

2.2.1.1. Defining sensing requirements

Practical guidance – automotive

Author: Dr Daniele Martini, University of Oxford

Operating scenarios for Autonomous Vehicles (AVs) comprehend both structured, human-built environments and the vast scope of natural scenery. Hazards span from many-participant traffic environments to treacherous surfaces and lighting and weather conditions. Defining the operating scenarios as a combination of both scene and possible threats, we advocate that different combinations will require different sensor payloads as specific sensing modalities provide robust performances under particular circumstances. Moreover, we argue for an extension of the most common sensor suite used in AVs to include unusual sensing modalities, which can be less affected by challenging environmental conditions [1].

A diverse dataset

A primary contribution of the SAX project [2] is the collection of a variegated dataset. It contains a broad combination of scenes -- urban, rural and off-road -- and hazards -- mixed driving surfaces, adverse weather conditions, and other actors' presence. The main goal of this dataset is to show how specific sensors behave in particular scenarios. Our sensor suite extends the pool of sensors traditionally used for AVs with uncommonly-used sensors that show great promise in challenging scenarios. Among the first, we can list cameras, LiDARS, GPS/INS and automotive radar; we also collect data from a Frequency-Modulated Continuous-Wave (FMCW) scanning radar, audio from microphones in the wheel arches and all the internal states of the vehicle.

The dataset will give us a deeper understanding of the behaviour of the sensors under such different conditions, highlighting strengths and limitations. To do so, we accompany the data with ground-truth labels for various tasks – object detection/segmentation, drivable surface segmentation, odometry – to train and validate algorithms.



Figure 1. Vehicle Platform and Sensor Suite and the location in the UK for the collection sites.

FMCW scanning radar

Although radar has been a typical sensor modality for automotive applications for several decades, FMCW scanning radar has only been introduced to commercial uses in the past few years due to reductions in costs and dimensions. Radar can benefit safety greatly in scenarios in which traditionally exploited sensors like cameras and lasers will fail due to its inherent robustness to weather conditions and long sensing range.

We showed how AVs could utilise radar independently from other sensors for low-level autonomy tasks, ranging from odometry [3] and localisation [4] [5] [6] to scene understanding [7] [8] to path planning [9].

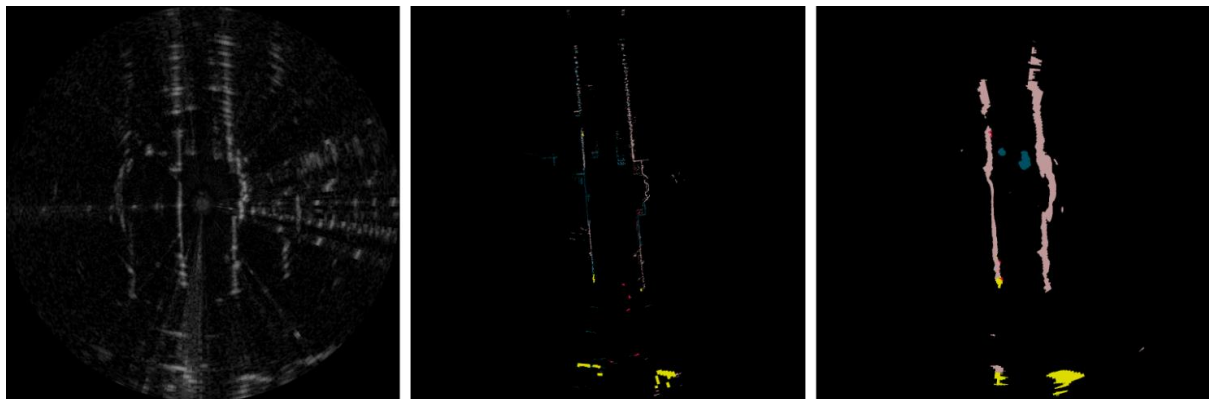


Figure 2. A radar scan (left) is labelled using camera and lidar data (centre) for training a semantic segmentation pipeline (right) [7].

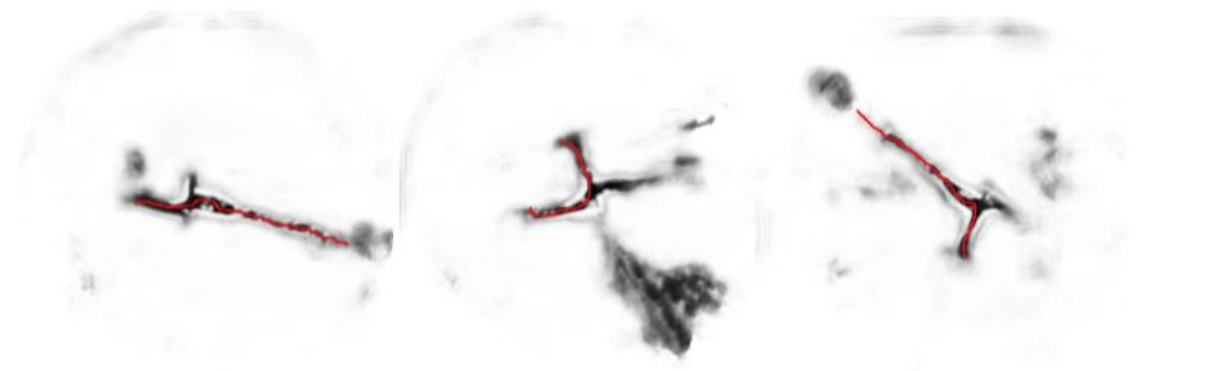


Fig 3: Radar is used to understand the driveability of the scene (black and white), giving us representations through which the AV can plan its motion (red) [9].

Audio

Recent research showed how audio can be a suitable sensing modality for various tasks, either with or without fusing its information with other sensors [10]. We have studied how audio can benefit road-surface classification [8]. Audio has the advantage to be inherently invariant to the scene illumination, although it contains only very punctual information – i.e. in the contact point between the wheel and the ground. For this reason, we coupled the audio data with odometry estimation to build an automatic annotation tool to teach a radar

segmentation network to distinguish road surfaces with the advantage of an extended field of view.

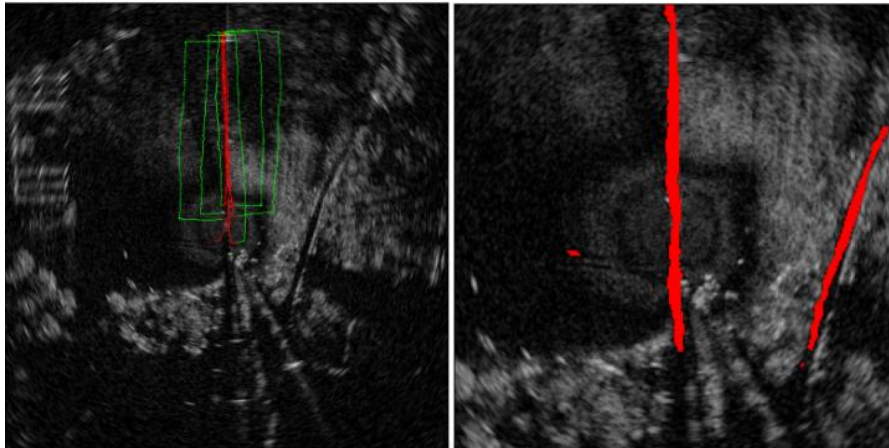


Figure 4. Audio data is used to label a radar scan (left) for training a semantic segmentation pipeline (right) to distinguish between road surfaces [8].

CAN

The dataset also contains data recorded from the CAN bus of the vehicle. The variables recorded span from the steering wheel angle to the rotational speed of each wheel to the engaged gear. Such variables contain critical information for several tasks, which can treat them either as sensory data – e.g. for driver identification [11] – or as control signals – e.g. for training behavioural-cloning algorithms [12].

External services

We challenge the definition of a sensor by including services provided by external operators, particularly *satellite imagery* and *weather forecasts*. Although these are, in practice, sub products of GPS queries, the information they contain can be valuable for tasks such as localisation [13] [14] or route planning.

On this matter, we explored how services like Google maps can serve as readily available maps of never-seen places where an AV can localise using range sensors, like LiDAR and radar. We showed that deep learning approaches could overcome the domain difference between the external service and the sensor stream and achieve accurate displacement estimation between the overhead image and the AV in an urban environment.

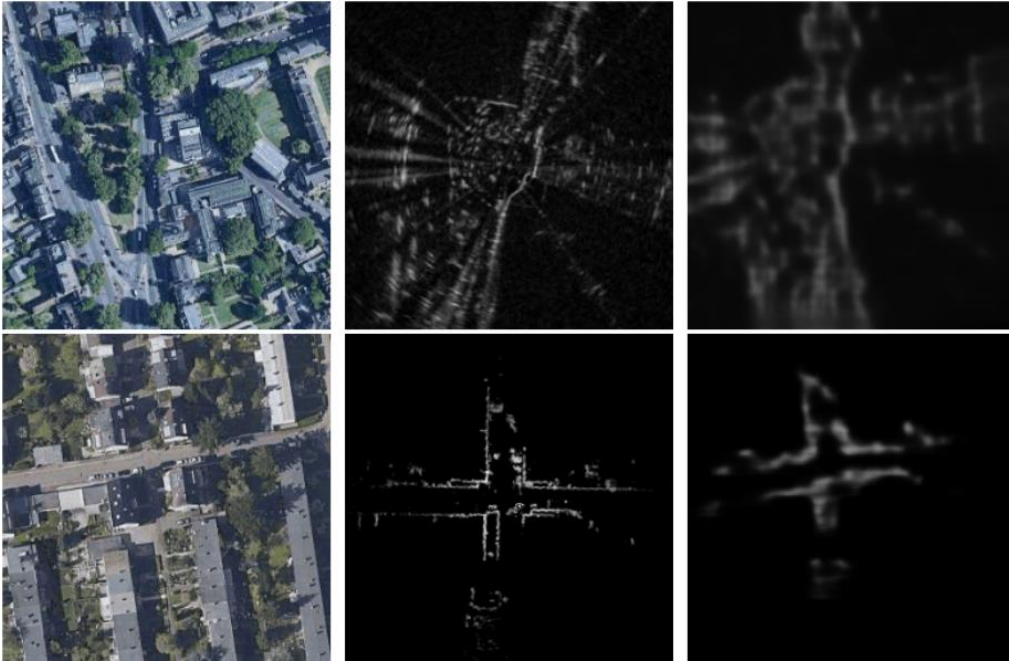


Figure 5: Satellite images used as a map for radar (top) and LiDAR (bottom) sensors. The satellite image is converted into a synthetic sample of the sensor domain to estimate the translational and rotational offset between the two [13].

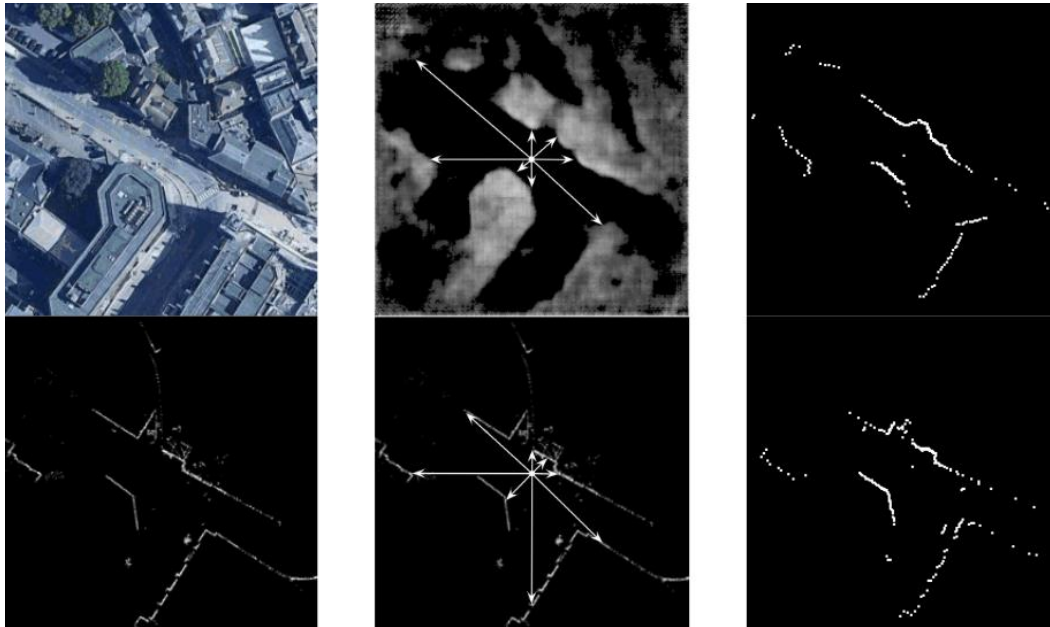


Figure 6: A satellite image is converted into a point cloud by estimating an occupancy map for offset estimation with a LiDAR scan [14].

Summary

In summary, we present a universal view of AV sensing requirements and how uncommon sensing modalities can be suitable for overcoming challenging operational scenarios. Ideally, we would like our vehicles to be deployable and performant in any situation. The sensing capability of the AV plays a critical role, and to evaluate the suitability of specific sensors in specific scenarios, we collected a dataset with broad combinations of environments and

weather conditions. Alongside the sensing data, we provide labels for various tasks, which can be used for training and evaluation purposes.

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