

RobotCycle: Assessing Cycling Safety in Urban Environments

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Abstract—This paper introduces RobotCycle, a novel ongoing project that leverages Autonomous Vehicle (AV) research to investigate how road infrastructure influences cyclist behaviour and safety during real-world journeys. The project’s requirements were defined in collaboration with key stakeholders, including city planners, cyclists, and policymakers, informing the design of risk and safety metrics and the data collection criteria. We propose a data-driven approach relying on a novel, rich dataset of diverse traffic scenes and scenarios captured using a custom-designed wearable sensing unit. By analysing road-user trajectories, we identify normal path deviations indicating potential risks or hazardous interactions related to infrastructure elements in the environment. Our analysis correlates driving profiles and trajectory patterns with local road segments, driving conditions, and road-user interactions to predict traffic behaviours and identify critical scenarios. Moreover, by leveraging advancements in AV research, the project generates detailed 3D High-Definition Maps (HD Maps), traffic flow patterns, and trajectory models to provide a comprehensive assessment and analysis of the behaviour of all traffic agents. These data can then inform the design of cyclist-friendly road infrastructure, ultimately enhancing road safety and cyclability. The project provides valuable insights for enhancing cyclist protection and advancing sustainable urban mobility.

Index Terms—Safety, Bicycle, Dataset, Benchmark, Urban Infrastructure

I. INTRODUCTION

With 15,693 cyclist casualties in UK road accidents in 2022¹, including fatalities and injuries, and 243 casualties in Oxfordshire alone in 2021², cyclists remain among the most Vulnerable Road User (VRU). Cyclists are continually exposed to risks due to the inherent design of roads, unpredictable behaviour of other users, and inadequate safety measures.

Our ongoing RobotCycle project aims to address these challenges by identifying how specific road features, such as road layout and traffic filters, along with the behaviour of other road users, can impact cyclist safety in urban environments. Incident reports and accident statistics lack crucial contextual information surrounding critical events since they

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¹Reported road casualties Great Britain, annual report 2022, available at <http://tinyurl.com/5n8zva74>

²Oxfordshire County Council (OCC) report 2021 on Road Traffic Collisions, available at <http://tinyurl.com/43ff89nc>



Fig. 1: Data-collection platform design (a) and deployment (b). The sensors and computing unit have been integrated into a backpack, allowing application flexibility without compromising the specifications and FOVs of the sensors.

mainly rely on post-event reporting and stationary sensing. These methods provide limited contextual information from a restricted set of sensors configured in fixed locations and viewpoints.

RobotCycle complements these approaches by gathering detailed information about traffic, road infrastructure, and behavioural patterns from the perspective of the VRUs, analysing all the factors contributing to cyclist vulnerability. We equip cyclists with a mobile sensing unit incorporating state-of-the-art technologies commonly found in Autonomous Vehicles (AVs) and further combine these rich ego-centric data with High-Definition Maps (HD Maps), trajectory tracking, and cyclist feedback to microscopically investigate the causes of safety-critical incidents and determine how road infrastructure and users’ behaviour impact cyclists’ safety during complex social interactions on urban roads. Figure 1 shows the final design of the sensorised backpack. We aim to identify previously unrecognized safety

issues as well as risky and complex behavioural patterns. Through this, we seek to inform the development of more effective interventions and deepen our understanding of social interactions in real-world road contexts, effectively enhancing cyclist safety.

II. STRUCTURE AND OBJECTIVES

The primary scope of the RobotCycle project is to investigate how cycling infrastructure influences cyclist behaviour and safety *during real-world journeys* to inform the design of cyclist-friendly road layouts, improving road safety and cyclability. Through our engagement with the key stakeholders, such as policymakers and cyclist associations, we formed the following three objectives:

- O1.** Design a novel, wearable sensing unit to collect rich multi-sensor data from the perspective of the cyclists;
- O2.** Develop a novel, annotated dataset for analysing the factors contributing to road safety, focusing on road infrastructure and traffic interactions;
- O3.** Propose a benchmark for assessing road safety for cyclists in urban environments through safety and cyclability indexes, identifying areas of high risk.

In the remainder of the paper, we discuss each objective further and describe our approach to achieving them.

III. BACKGROUND AND RELATED WORK

Cyclist Journey Analysis. Recent studies investigate cycling safety and road users’ interactions by modelling driving, riding, and walking behaviours. These projects leverage various data sources to capture the environment, including sensors directly mounted on bicycles or cyclists and personalised IoT cycling gear [1], [2], [3], [4]. For instance, [1] conducts a thorough analysis, considering social and kinematic factors to evaluate cyclists’ safety and comfort in challenging environmental conditions. Capturing also social characteristics, [2] assesses highway design and its impact on cycling while [5] relies on IoT cycling gear for personalised cyclist training and safety assessment. Additionally, [3] captures stress and health data from cyclists and correlates them with image data, focusing on specific events. [4] proposes a method for detecting near misses from video captured from various positions, either on a bicycle or on the cyclist’s helmet. RobotCycle extends upon these works relying on wearable sensing, and capturing traffic interactions while mapping and modelling road infrastructure.

Backpack design. Due to their operational flexibility, backpacks have been previously employed for mapping and data collection projects, relying either solely on lidar scanners for capturing the surroundings [6], [7], [8], [9], [10] or also on cameras [11], [12]. Aiming to collect a rich multi-modal dataset, we designed and built a custom versatile backpack equipped with lidars, cameras, and inertial sensors achieving a complete 360° Field-Of-View (FOV) and close-to-far range detection around the cyclist, capturing geometry and appearance. This setup allows us to map the environment, capture close-range interactions, and analyse the trajectory of each participating actor in a traffic scene.

Sensor	Qty	Model	Description
Lidar	2	PandarXT-32	360x31° (HxV) FOV
Stereo	2	ZED2i	Stereo camera, intergrated IMU
Camera	2	Basler acA1920	Colour monocular, fisheye lenses
INS	1	Ellipse-N	RTK GNSS

TABLE I: Overview of the sensors used in the final version of the data collection platform. In post-processing, we utilise the fitted Inertial Measurement Units (IMUs) to mitigate noise caused by the cyclists’ body movements and road vibrations.

Behaviour, Risk, and Safety Modelling. Various studies focus on modelling traffic interactions and risk, while others propose alternative infrastructure to design safer road networks. For instance, [13] employs behaviour modelling to predict collisions and recommend avoidance manoeuvres. Meanwhile, [14] develops a safety model based on accident reports and mapping data to unveil behavioural patterns. In a different approach, [15] leverages risk and discomfort estimation models to generate personalised route recommendations by correlating accident and traffic data with street network topology. Additionally, [16] utilises simulation data to propose improvements in road infrastructure, while [17] leverages adversarial networks to redesign urban cities. In contrast, RobotCycle adopts a data-driven approach. We collect an extensive dataset capturing diverse road layouts, infrastructure characteristics, and weather and lighting conditions. Leveraging methodologies from AV research, we generate traffic, behaviour, and risk models. These models, in correlation with detailed HD Maps, enhance our understanding of road users’ interactions facilitating the identification of incident hotspots.

IV. WEARABLE SENSOR UNIT DESIGN

Our objective **O1** is to develop a comprehensive data-collection sensing unit incorporating state-of-the-art range and image sensors with inertial navigation systems. We aim to collect a robust dataset capturing short- and long-range infrastructure details and dynamic driving interactions in each traffic scene. This holistic approach ensures that the resulting dataset can be used to analyse and understand the intricacies of various driving scenarios.

We can summarise the requirements for the proposed sensorised platform with the following:

- R1.1.** Develop a portable, robust, and weather-invariant lightweight sensing unit to be used by different VRUs;
- R1.2.** Achieve a combined multi-modal 360° FOV short-to-long range sensing coverage, also capturing inertial and positional measurements;
- R1.3.** Record four hours of continuous cycling data per day for two weeks, capturing varying times of day, traffic volumes, and weather conditions;
- R1.4.** Aim for inconspicuous design.

Importantly, project requirements are derived from and interlinked among the objectives. Indeed, **R1.2** is related to **O2**’s, **R2.3**, and **O3**’s analysis, and **R1.1** and **R1.3** to **O2**’s and **R2.4**.

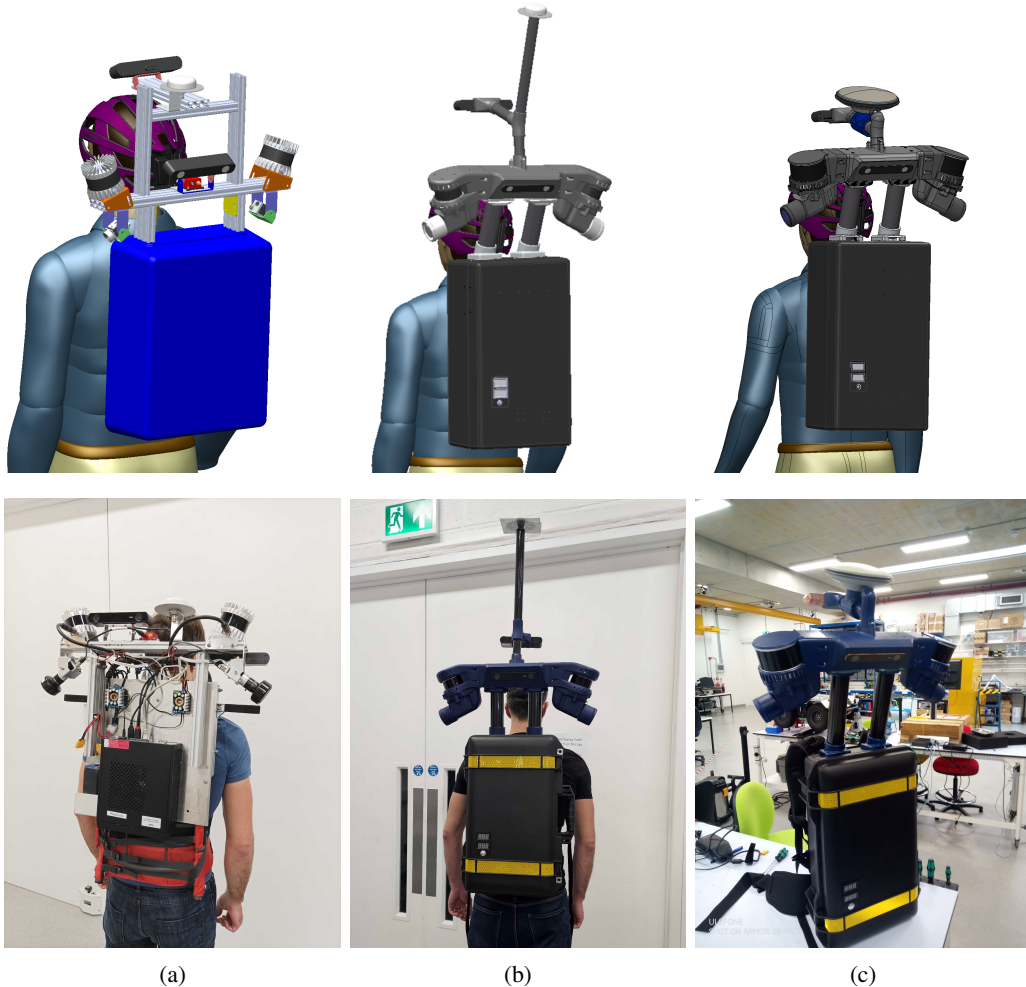


Fig. 2: Various design iterations of the RobotCycle backpack. From the left, the first iteration (a) allowed for sensors’ displacement to optimise their position and orientation. The second iteration (b) consolidated the sensors’ positioning, computing requirements, and networking, allowing extensive field testing. The final iteration (c), finalised the sensing configuration and design, maximising sensors’ FOV and optimising overall weight distribution.

To satisfy the design requirements, we opted for a sensorised backpack. This wearable solution enhances deployment flexibility as it does not depend on external or fixed infrastructure, such as the bicycle frame, and can be easily worn by different VRUs at the cost of increased load on the user, trading off R1.1 and R2.4. In addition, this solution does not limit our sensor selection and mounting options while simplifying the overall wiring setup.

The sensors equipped can be seen in Table I, sample data are visualised in Figure 5, and the final design is depicted in Figure 1; it should be noted that we prioritised R1.2 over R1.4 to satisfy the data analysis procedures. The backpack also fits an onboard computer, a hardware synchronisation system, and various storage devices, designed to meet the 4-hour runtime requirement (R1.3) while allowing quick and easy battery replacement in the field.

A. Iterative design

We optimised the mounting configurations and sensors specifications to achieve an unobstructed 360° FOV coverage

around the ego-cyclist after several design iterations, as seen in Figure 2. The initial design, in Figure 2a, relied on custom articulated joints and mounting points, allowing us to experiment with different sensors’ positioning and orientations, as well as different sensor types, specifications, and FOVs. Figure 3 shows one of our custom joint mechanisms enabling six degrees of freedom movement, facilitating experimentation with various sensors’ positioning. With this flexible and adjustable setup, we optimised the design, taking into account various mounting points. For instance, in Figure 3, the front camera is mounted on the side of the rider, illustrating one of the possible configurations we explored.

In a second iteration, shown in Figure 2b, we optimised the platform for a rugged and robust design while allowing basic height and tilt adjustments adaptable to each rider. We also focused on developing a computing unit to suit our data bandwidth requirements and finalised the wiring and cooling setup. We then run extensive system tests in the field, recordings of which can be seen in Figure 5.

Following these tests, we finalised the hardware design

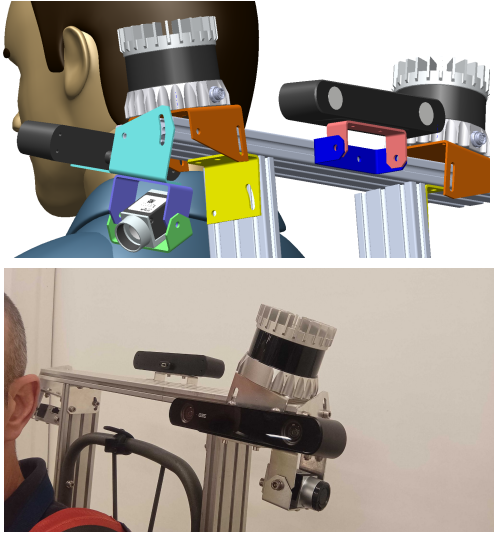


Fig. 3: Detail of the articulated systems that enabled extensive experimentation with various sensors’ positioning to optimise the sensing setup.

and the sensors’ configuration and positioning as seen in Table I and Figure 2c. By integrating noise shielding, reinforcing mounting points, and optimising weight distribution, we made the overall system more robust, compact, and comfortable for prolonged bike rides.

V. DATA COLLECTION

Our goal **O2** is to record a comprehensive and detailed dataset encompassing all traffic interactions and infrastructure details across diverse environmental and traffic conditions. To achieve this, we have identified and prioritised areas of interest while remaining compliant with existing data and traffic regulations. In particular, our data-collection strategy was formulated based on the following requirements:

- R2.1.** Ensure compliance with Data Protection and Privacy Regulations;
- R2.2.** Ensure compliance with Road Safety Regulations;
- R2.3.** Capture diverse types of road layouts and different traffic volumes, road signs, cycling styles as well as various illumination, weather, and road-surface conditions;
- R2.4.** The trial length is depended on the risk assessment and must be agreed upon with the cyclists;
- R2.5.** Collect data bidirectionally in high- and low-peak traffic hours in specific semantically rich and diverse loops.

Oxford is known for its diverse infrastructure and road network, which has led to the collection of several extensive AV datasets [18], [19], [20]. Yet, to ensure coverage of varying traffic volumes and various types of cycling infrastructure – including roads without cycle paths, roads with shared cycle paths, and roads with exclusive cycle paths – we conducted an extensive analysis of the city’s road network. Indeed, we first qualitatively classified Oxford’s road network according to traffic, location, and functionality, also leveraging data from detailed Cycling Network Maps³,

³<http://www.transportparadise.co.uk/cyclemap/>

and then further prioritised different road segments according to the diversity of road layout, infrastructure features, and prevailing traffic conditions. Results of this analysis can be found in Figure 4, leading to an estimated 15 bidirectional runs on each route, encompassing different times of the day and weather conditions (**R1.1**). The specifics of executing a single trial are contingent upon agreement with each cyclist, considering the weight of the total sensor package (**R2.5**) and the cyclist’s durability (**R2.4**).



(a) St. Giles’ fork: Cyclists must navigate the car lanes, moving from the main bicycle lane to the lane on the right of the fork. Meanwhile, vehicles can travel and merge from either side.



(b) Woodstock Rd: The bicycle lane begins on one side of the road and later transitions to the opposite side requiring cyclists to cross the road and share the lane with pedestrians.

Fig. 4: (Left) CycloSM⁴bicycle oriented map rendered from OpenStreetMap (OSM) [21]. (Right) Visualisation of places of interest on Google Maps.

VI. DATA ANALYSIS

To the best of our knowledge, this is the first project capturing data from the cyclists’ perspective using a multi-sensing backpack. Our sensing platform described in Section IV provides a 360° FOV, offering a comprehensive perspective of the cyclist’s surroundings, capturing dynamic and static elements in roads of diverse traffic volumes and infrastructure designed in Section V. This section describes the analysis we will perform on these data to assess, predict, and monitor the cyclists’ safety on the road, as indicated in our objective **O3**. To this end, we are focusing on building HD Maps, data annotation, and traffic models, which will be used in conjunction to calculate a safety score that will holistically comprehend risks associated with traffic events, allowing us to address safety concerns effectively and develop strategies to mitigate them. In this analysis, HD Maps are central as they are a fine-grained representation of the environment, which we can augment with semantic and road quality information (smoothness, potholes, etc.) –

⁴<https://github.com/cyclosm/cyclosm-cartocss-style/>

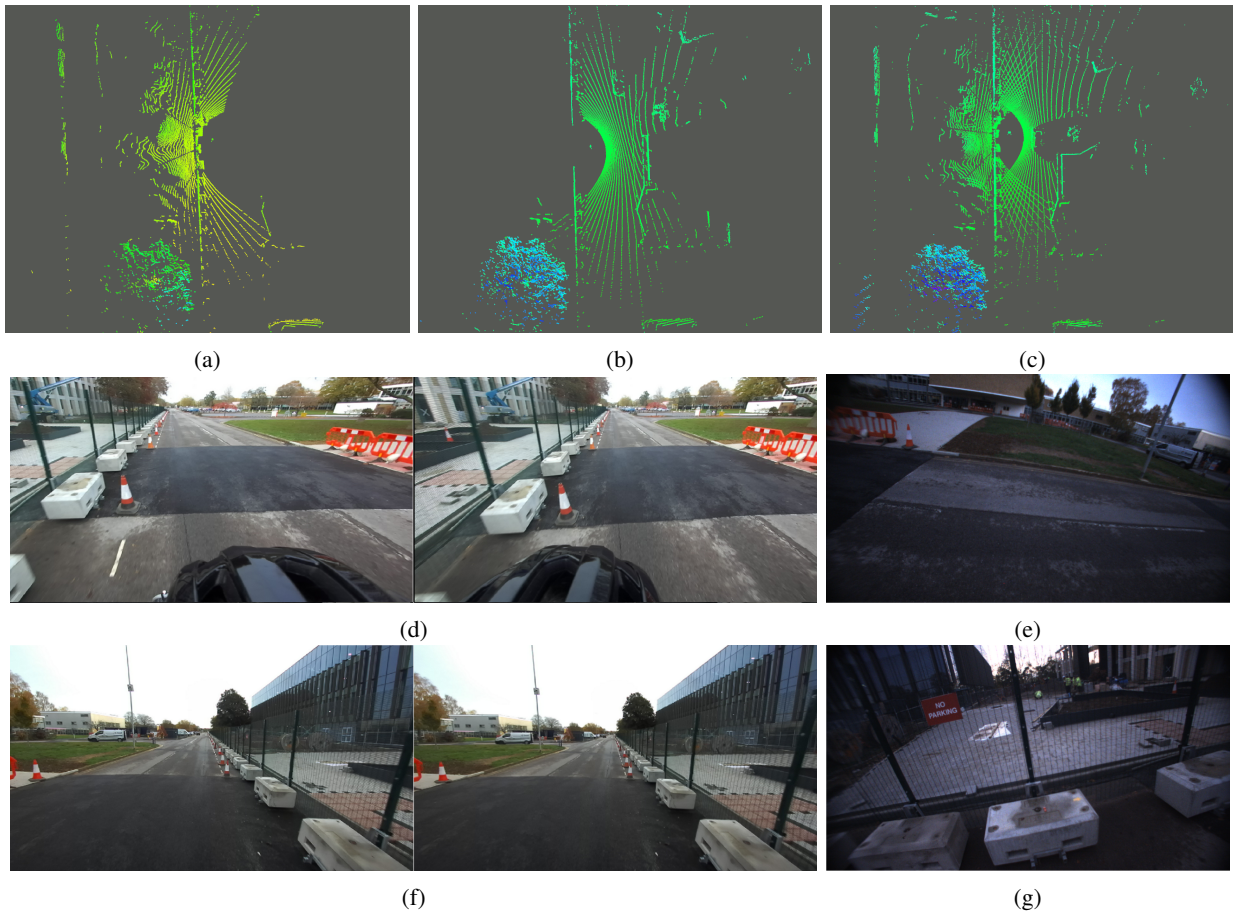


Fig. 5: Sensor samples from the second iteration of the backpack in Figure 2b. Raw 3D scans of the side lidars are visualised in (a), (b), and combined in (c); undistorted image data from the front and rear stereo cameras are shown in (d) and (f); raw images from the monocular side cameras are seen in (e) and (g). The side cameras are synchronised with the lidars through the Pulse Per Second (PPS) signal from the GPS and a custom signal repeater; GPS data can be seen in Figure 6.

retrieved from IMU data – and dynamic agents locations. Semantic elements, such as objects and local geometry, have been previously used to explain the performance and behaviour of AV systems [22], [23]. We aim to follow a similar approach using semantics to enhance HD Maps and explain the behaviour of our ego-cyclist in correlation with elements in the environment. By correlating those with traffic and trajectory models we can assess the safety of the road network. Preliminary results are shown here on a test dataset we recorded with the proposed sensing platform at the Culham Science Center in Abingdon (UK) – here *culham* – and the uniD dataset [24].

A. HD Maps

HD Maps are invaluable for providing detailed contextual information about the environment, including precise lane locations, road boundaries, curbs, and landmarks. In addition, they capture local and global morphology, such as surface and geometry, detailing static infrastructure. This level of accuracy offers insights into complex intersections and infrastructure, aiding in localising all road agents and allowing us to correlate their behaviours to traffic flows and interactions. A preliminary example of an HD Map applied

to *culham* is depicted in Figure 6.

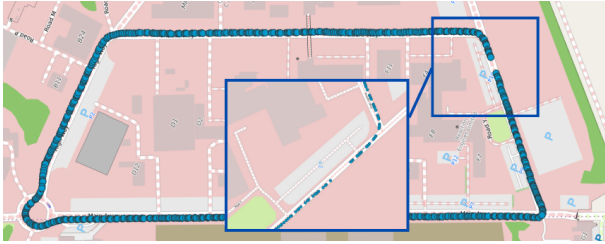
B. Data Annotation

To analyse the data and extract trajectory and behavioural patterns, we need to detect and track semantics of interest in the dataset. We will annotate all dynamic agents and road-layout-specific classes in the dataset, extending existing class definitions – e.g. the extensively-used CityScapes’ [25] – including infrastructure elements critical to a thorough description of the scene. Table II summarises our semantic class definition of interest and Figure 7 depicts labelled images in our *culham* dataset.

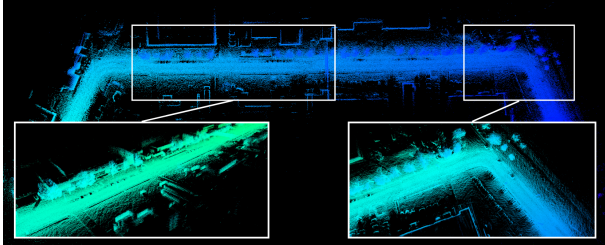
C. Traffic and Trajectory Models

Since this dataset will be taken from the perspective of a VRU instead of a vehicle, it will contain diverse VRU-to-VRU and VRU-to-Vehicle interactions. These interactions have higher variability as VRUs do not necessarily follow allocated lanes, traffic lights, and road rules. Especially cyclists, because they operate at higher speeds, pose a danger to other types of road users, making predicting cyclist trajectories crucial for a comprehensive safety assessment.

We have begun developing these processes by leveraging the uniD dataset [24]. Figure 8 shows results for road agents’



(a) GPS trace overlaid onto OSM [21] using the on-board INS unit from Table I. A noticeable gap in the traces highlights moments when the GPS signal was briefly lost, providing insights into the signal interference challenges faced during data collection.



(b) Preliminary results of the HD Map generated after fusing the scans from the two side lidars sensors, generating a rich and detailed 3D structured representation of the environment.

Fig. 6: GPS trace and HD Map visualisation from our culham dataset.

Category	Subcategories
ground	road, pavement, cycle-lane, bus-lane, parking-spot, bus-stop, lane-marking, roundabout, crossing, traffic-island, other
structure	building, fence, wall, barrier, stop-shelter, road-works, overhead-bridge, other
nature	vegetation, trunk
object	pushchair, sign, fence, pole, traffic-cone, traffic-light, wheelchair, other
vehicle	car, truck, bicycle, motorcycle, e-scooter, mobility-scooter, van, bus, on-rails, other
animate-agent	animal, pedestrian, rider, other

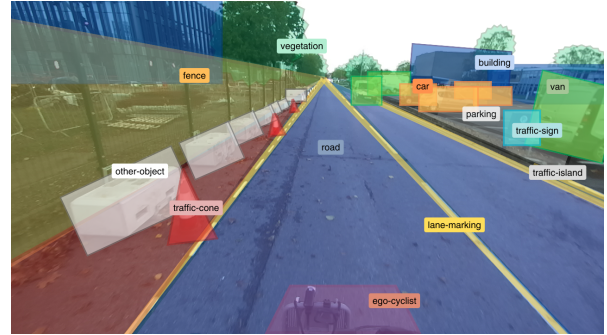
TABLE II: Target categories and derived subcategories for semantic labelling of image and pointcloud data focusing on infrastructure elements and dynamic agents.

tracked directions and velocity, divided by kind. As expected, VRUs tend to occupy a larger portion of the road surface exhibiting a wider range of behaviours.

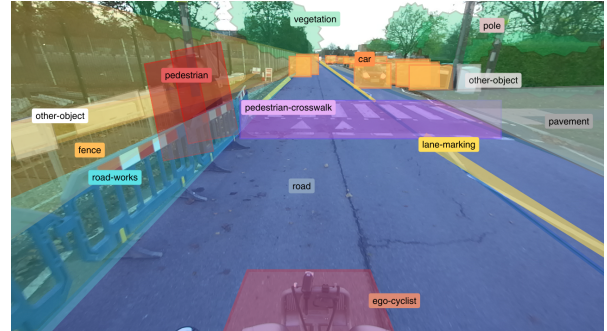
VII. FUTURE WORK AND OPEN ISSUES

As the outlined work packages have provided encouraging preliminary results, further refinement and analysis are imperative for the project’s success. We aim to conduct a data-driven safety analysis leveraging behavioural modelling and trajectory prediction methods from AV research. In addition, an in-depth causality analysis is required to identify the intricate causes and effects of each event captured.

Our initial data collection is limited to private and constrained environments, capturing very few driving interac-



(a)



(b)

Fig. 7: Sample labelled images from two locations depicting different traffic scenarios in our culham dataset. Label categories can be seen in Table II.

tions; in the final iteration of our project, we will collect the Oxford dataset described in this paper, which we commit to making publicly available. Using this novel dataset, we aim to develop a generalisable approach to assessing safety, which, based on infrastructure, traffic volumes, and historical data, can generate insights into potentially unsafe situations, even on roads not traversed within the dataset. Within the scope of this project, our focus lies on urban environments. However, an extension to off-road areas can provide valuable insights into the behaviour of VRUs across more diverse and challenging environments [26].

VIII. CONCLUSION

This paper introduces the RobotCycle project which aims to evaluate the safety of cycling infrastructure by leveraging advancements in AV research and technologies. Here, we have described the development process of a wearable data collection device, the design of the data collection process, and the data analysis rationale. Our primary focus has been on building and testing the sensing backpack to ensure that it satisfies all design requirements so that we can achieve the project’s objectives. Initial results demonstrate the device’s ability to capture diverse and rich datasets, which are then used to extract semantic elements, HD Maps, and traffic patterns. The RobotCycle project is an innovative undertaking with a mission to enhance the safety and sustainability of urban cities. We aim to generate valuable insights into the ongoing discourse on urban development, setting a benchmark for further advancements in the field.

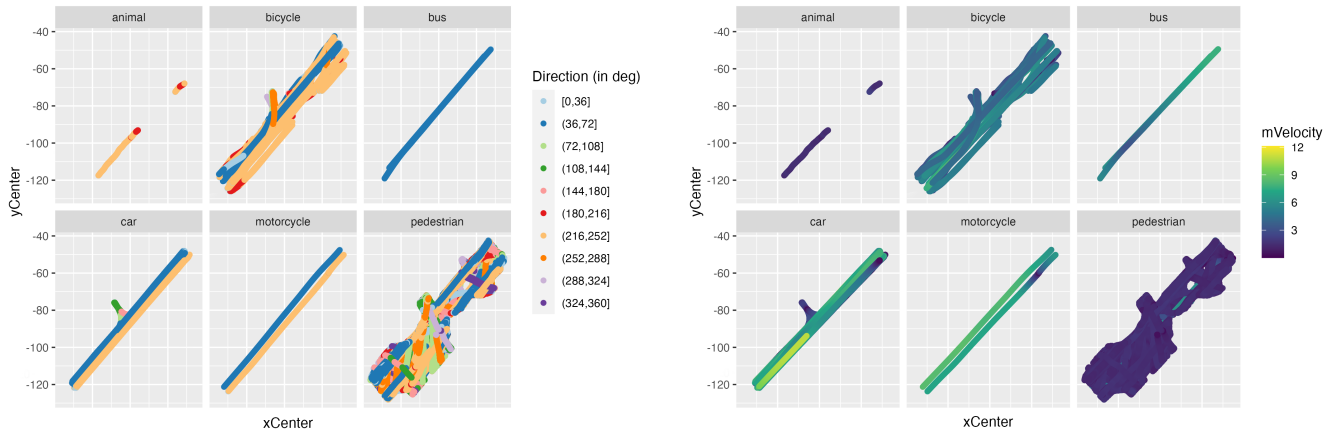


Fig. 8: Preliminary analysis results for road agents' direction (a) and velocity (b) on the uniD dataset [24]. Interestingly, VRUs exhibit a more varied behaviour w.r.t. engine-powered vehicles, which follow road lanes more closely.

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