Autonomous vehicle validation - are we just guessing or can we predict the future?

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ABSTRACT

At present there exists no standardised, systematic or structured methodology for the validation of autonomous pod vehicles. The lack of process is compounded by minimal real-world collision or near miss data covering this vehicle type. This gap in knowledge may present a significant obstacle in autonomous pod vehicle development and consumer uptake from two sides; firstly, the scarcity of data for road safety practitioners to develop into appropriate test scenarios and secondly the lack of perceived transparency by the OEMs could form the perception that there is negligible vehicle development and manufacturer accountability, resulting in lack of trust from the end users.

To counter this knowledge gap this paper aims to provide more information on initial steps into the definition of a systematic reference dataset which reflects both autonomous pod use and the capabilities of the vehicles to be tested. Due to the lack of real world data in the short term, it will be necessary to develop vehicle validation scenarios for autonomous pods based entirely on non-autonomous collisions of comparable vehicle types. Although there are currently no specific well-tested frameworks to follow, the approach discussed applies proven methodological principals from the field of general product design which assumes that if the design envelope is set correctly then any product that meets this, no matter how outlandish, will be valid.

Keywords: Autonomous vehicles, autonomous pods, validation, test scenarios, accident data.

1 INTRODUCTION

In recent years there has been a rapid rise in the number of vehicles with autonomous features coming to market, and the race between manufacturers to get fully autonomous cars onto the road has driven quick advances in this technology with relatively little validation procedures compared to standard vehicles [1]. Additionally, these advances have led to the introduction of new vehicle types, as these partially-autonomous vehicles include not only traditional car designs (e.g. Tesla, Ford, BMW), but also smaller category vehicles such as the as-yet unclassified group of vehicles known as 'pod's (e.g. Gateway [2], Navya [3]).

At present there exists no standardised, systematic or structured methodology for the validation of these autonomous 'pod' vehicles. This is due, in part, to the small number of any types of vehicles with autonomous features that exist in the overall vehicle fleet, but also because useful information relating to any collision is typically very tightly regulated by the Original Equipment Manufacturer (OEM). For pods, the lack of process is compounded by minimal real-world collision or near miss data covering this vehicle type. This gap in knowledge may present a significant obstacle in autonomous pod vehicle development and consumer uptake from two sides; firstly, the scarcity of data for road safety practitioners to develop into appropriate test scenarios, and secondly the lack of perceived transparency by the OEMs could form the perception that there is a lack of vehicle development and manufacturer accountability, resulting in lack of trust from the end users.

To counter this knowledge gap this paper aims to provide more information on initial steps into the definition of a systematic reference dataset which reflects both the intended use of autonomous pods and the capabilities of the vehicles to be tested. Due to the lack of real world data in the short term, it will be necessary to develop vehicle validation scenarios for autonomous pods based entirely on non- or partially-autonomous collisions of comparable vehicle types. Although there are currently no specific well-tested frameworks to follow, the approach discussed applies proven methodological principals from the field of general product design which assumes that if the design envelope is set correctly then any product, no matter how outlandish, that meets this will be valid.

This approach applied to collision data underpins the autonomous pod validation framework and likewise assumes that any scenario derived from the dataset to the proposed pod vehicle will provide close alignment to only valid real-world collisions for use in the test scenarios. This new approach is currently being developed through the Capri (Connected & Autonomous POD on-Road Implementation) project, an industry-led research and development project funded by Innovate UK [4], which aims to build and test the next generation of autonomous PODs as well as the systems and technologies that will allow the vehicles to navigate safely and seamlessly in both pedestrian and road environments.

2 DATA APPROACH

Currently scenario generation for autonomous vehicles is a rapidly growing area of research. There are typically two ways of doing this, firstly by generating scenarios from a theoretical basis, for example basing the testing program on a list of accident types, and secondly from a practical 'beta-testing' basis, for example, pressing the vehicles into service to see what they encounter [5].

Both of these approaches will most likely be incomplete and may ultimately fail to deliver the range of scenarios necessary to build consumer trust. By their very nature collisions are rare events but they also vary considerably based on a huge range of independent factors. Without physically driving an autonomous vehicle for billions of event free kilometers or covering every available collision scenario imaginable through a theoretical testing plan there could always be scenarios which are unforeseen.

The use of real world collision data in test design is well founded. There are even examples where this approach has led to a huge increase in consumer knowledge and trust. The EuroNCAP testing program is one such example where evidence-based tests have been implemented with the outcome being safer cars, greater public awareness and crucially trust in the system [6].

When searching for evidence in any dataset of real world collisions it is important to understand what you are looking for and how this might inform your research. There are almost no situations where the data will be explored in an ad hoc manner or browsed through in an unstructured way. Most uses of in-depth collision data will begin with a research question. This question forms the focus of the search and defines the boundaries of what information is required. For example; the research question "what are the main causes behind single vehicle crashes involving 17-24 year old car drivers?" gives a range of boundaries which contain only the relevant collisions within the wider population of all collision types. The four degrees of freedom in this case are: collisions with; (i) collision causes available, (ii) single vehicle crashes, (iii) road users aged between 17 and 24yrs and involving (iv) cars. Figure 1 illustrates graphically the population of available collisions within a typical in-depth dataset, in this example the collisions are defined by a ten by ten square with an area representing 100% of all available collisions.

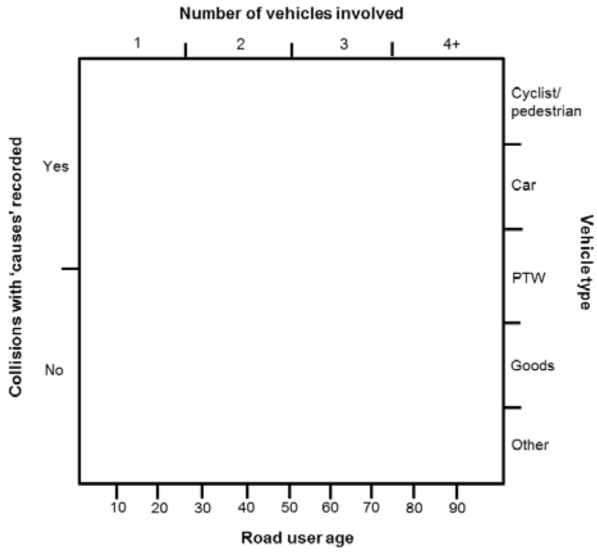


Figure 1 – Population of available collisions

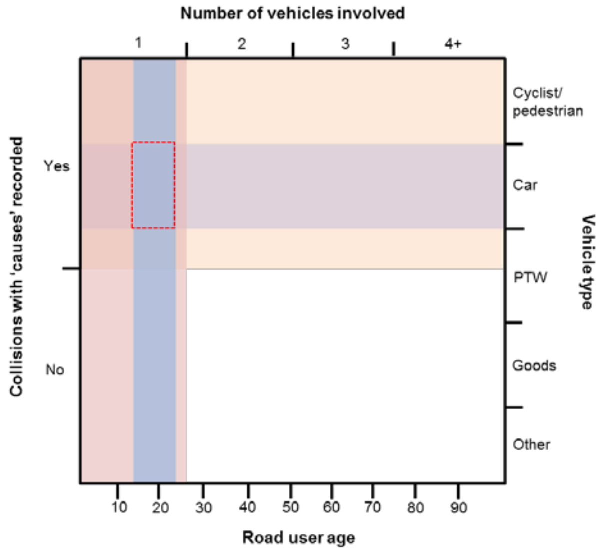


Figure 2 – Final selection for RQ

Overlaying the figure with only the relevant collisions for the research question it is possible to identify the population of collisions that fit the hypothetical research question. Figure 2 shows a representation of the final collision selection from the total sample available. In this hypothetical example the total percentage of cases remaining after the selection process would be 2%; using actual in-depth collision figures drawn from the DfT RAIDS database [7] this would represent a collision sample of 336 from a total sample of 16785.

In the example of autonomous pod vehicles this reduction in unrelated crash data is more difficult to achieve. Without knowing anything about the vehicle capabilities, the environment it will exist in, the users who will interact with it or the type of service it will provide it is extremely difficult to define a research question and consequently to identify a targeted population of suitable collision examples.

The method planned through the Capri project is to accurately define the degrees of freedom under which the search will be conducted; the result of any subsequent search will still ultimately not contain any autonomous pods however the data should look like autonomous pod collisions. Within the Capri project it is possible to see what an autonomous pod is like and what it is intended to do; from this the pod can be defined over a wide range of descriptors which can be found in the collision data.

Descriptors that define autonomous pods may be found in terms of their capabilities (acceleration, speed profiles etc.) the environments they use (road classifications, mix of traffic types etc.) and type of expected collision (crash type, impact speeds etc.). The outcomes of each descriptive element can be illustrated on a radar graph, of which each axis provides the values and the area contained within the graph providing an overall 'envelope' that describes the road user type. Figure 3 shows a simplified radar graph encompassing the descriptors of (i) acceleration, (ii) road type, (iii) mean Δv (collision speed), (iv) braking, (v) traffic mix, (vi) speed limit range. The area shaded in the following example shows the typical 'envelope' for a passenger car.

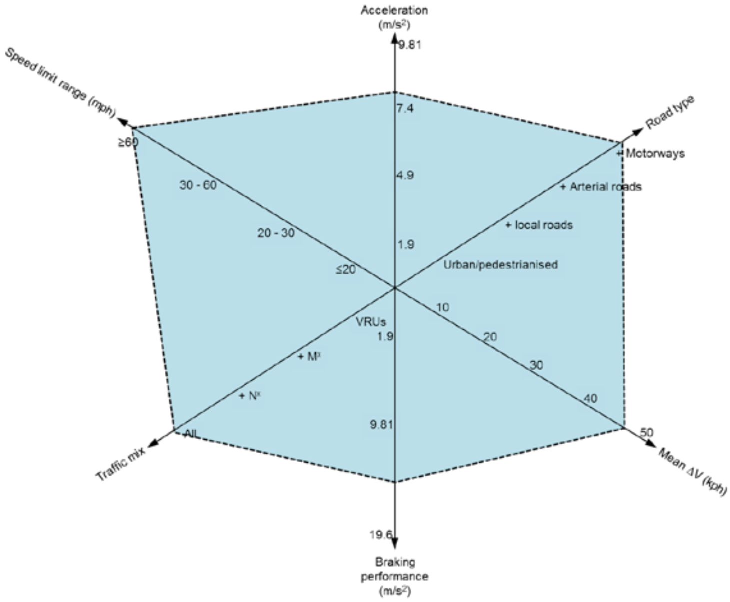


Figure 3 – Radar plot showing traditional passenger car envelope

Adding in further road user types in the same manner provides a clear comparison of the different amounts of data that could be available within an in-depth collision dataset. The following image (figure 4) shows the same envelope for passenger cars but with the addition of separate envelopes for cyclists and mobility scooters.

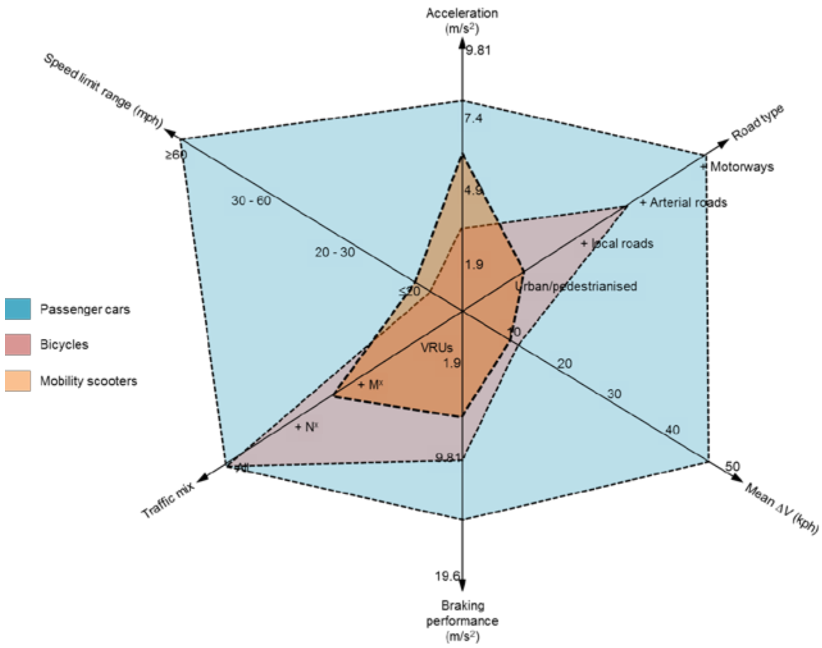


Figure 4 – Radar plot showing traditional passenger car, cyclist and mobility scooter envelope

This technique also shows the crossover between the different road user types and allows data from all road user groups to inform the research question, this is especially important when looking for evidence to support vehicles which are not present in the in-depth collision data such as autonomous pods. In other words, this technique does not exclude collisions that do not explicitly fit the profile (i.e. not a pod vehicle) but instead includes all road users and all collision types that fit the general envelope (i.e. looks like a pod vehicle). It is therefore possible to provide a potential envelope for autonomous pods; Figure 5 graphically illustrates the expected population of in-depth collisions that reflect autonomous pods despite no such vehicle being present within the dataset.

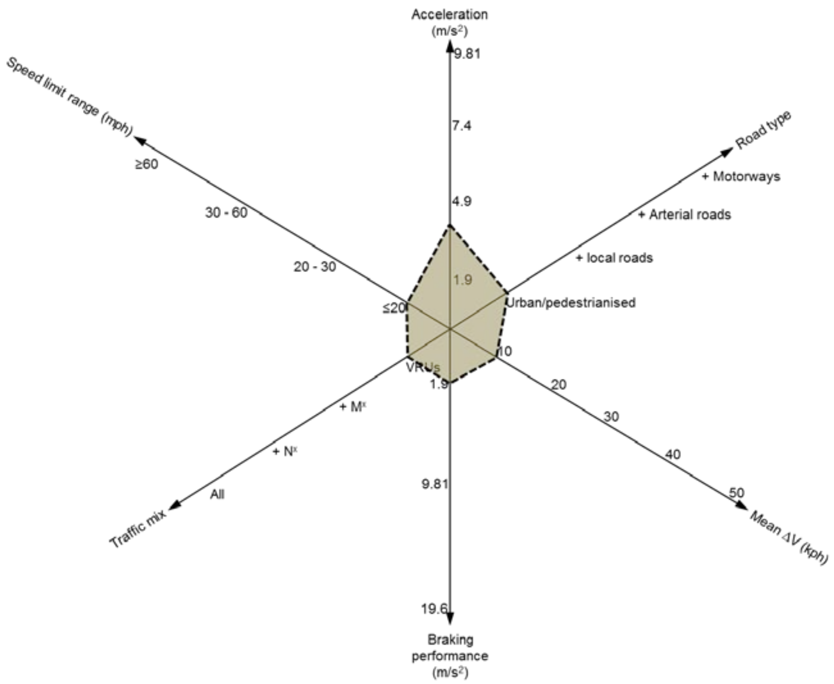
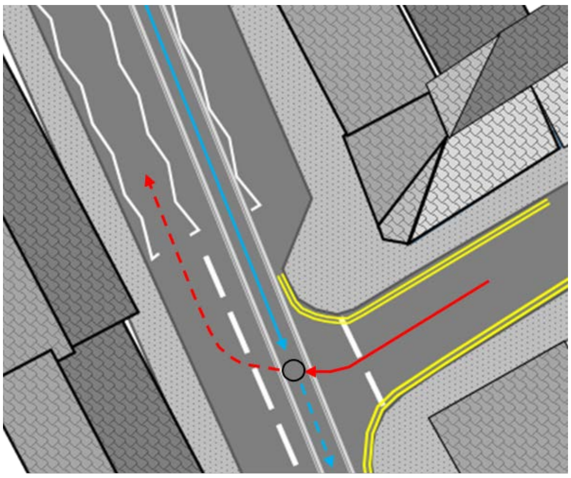


Figure 5 – Radar plot showing an example autonomous pod envelope

2.1 Example Outcome

As an example of how the sampling methodology selects relevant cases the following collision from a UK dataset demonstrates how a non-autonomous standard vehicle collision can reflect an autonomous pod collision:



V1 MPV attempts to turn right out of private road onto major public road with shared tram facilities. V2 tram approaches from V1 right at ~20mph. View of V2 approach obscured by parked van directly adjacent to right of V1. V1 edges slowly out onto major road (<1mph). V2 driver fails to see front of V1 emerging from behind parked van and N/S of tram contacts N/S front of V1. Damage only, non-injury collision.

This example demonstrates that the vehicle paths and characteristics reflect well the type of behaviour and use an autonomous pod will need to contend with. The example collision provides a clear framework from which to base both physical and simulation testing scenarios. In this case either (or both) vehicle(s) can be assumed to be the pod in scenario generation.

3 DISCUSSION

The work outlined within this paper describes the very first steps in defining and determining a relevant collision dataset for autonomous pod testing scenarios. There is currently a need for a robust and detailed dataset for this purpose, analogous to the way in-depth collision datasets have informed the development of regulatory tests for human driven vehicles. There is little doubt that autonomous vehicle development and testing will continue, however it can be seen that specific test scenario generation has until now been based on a more theoretical approach or from the outcomes of real world testing. These methods, although valid in the complete development lifecycle, could miss critical information and could ultimately damage the perception autonomous pods have on consumers.

The approach outlined has some key benefits over the current testing methods. These include:

- Providing a clearer dataset for further analysis into autonomous pod scenario setting.
- More validity in scenario setting – scenarios are underpinned by data on collisions that actually happened rather than a purely theoretical approach.
- Closer alignment with the real-world pod capabilities – for example it will not be necessary to undertake testing scenarios that are beyond the scope of the pod use.

By employing methods to extract all relevant information from the datasets already at our disposal it will be possible to fill in existing gaps and develop more robust testing scenarios. This step will, in turn, also increase consumer confidence in the testing and safety outcomes of these vehicles as the real-world basis of the testing scenarios are more visible and understandable.

In the initial stages the proposed methodology for identifying pod testing scenarios will need to be set with large confidence margins on the descriptor values. This will ensure that a wide enough net is cast to capture all relevant collisions in the real-world datasets. It is likely that further refinement on each descriptor will be required to tune the model as this approach represents the 'first best guess' of an iterative process.

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