Sense–Assess–eXplain (SAX): Building Trust in Autonomous Vehicles in Challenging Real-World Driving Scenarios

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Abstract—This paper discusses ongoing work in demonstrating research in mobile autonomy in challenging driving scenarios. In our approach, we address fundamental technical issues to overcome critical barriers to assurance and regulation for large-scale deployments of autonomous systems. To this end, we present how we build robots that (1) can robustly sense and interpret their environment using traditional as well as unconventional sensors; (2) can assess their own capabilities; and (3), vitally in the purpose of assurance and trust, can provide causal explanations of their interpretations and assessments. As it is essential that robots are safe and trusted, we design, develop, and demonstrate fundamental technologies in real-world applications to overcome critical barriers which impede the current deployment of robots in economically and socially important areas. Finally, we describe ongoing work in the collection of an unusual, rare, and highly valuable dataset.

Index Terms—Perception, Navigation, Introspection, Autonomous Vehicles, Robotics, Assurance, Ensurance, Insurance, Trust

I. INTRODUCTION

The perception and navigation capabilities of autonomous vehicles have been tremendously improved over the past decade. However, to increase the level of trust in autonomy in driving scenarios and to assure safety during operation, a range of open challenges need to be addressed. These challenges include:

1) **robust perception** of real-world environments under changing weather conditions,
2) **introspection** and **assessment** of perception and navigation processes, and the
3) **semantic interpretation** and **explanation** of scenes as well as the vehicle's performance.

In this work, as illustrated in Figure 1, we address the missing link between unconventional sensing modalities and environmental performance assessment in real-world scenarios, in conjunction with and coupled to explainability. Our work is built around the following concrete objectives with clear measurements of success through which we aim to impact the way in which we trust and assure autonomy of autonomous vehicles:

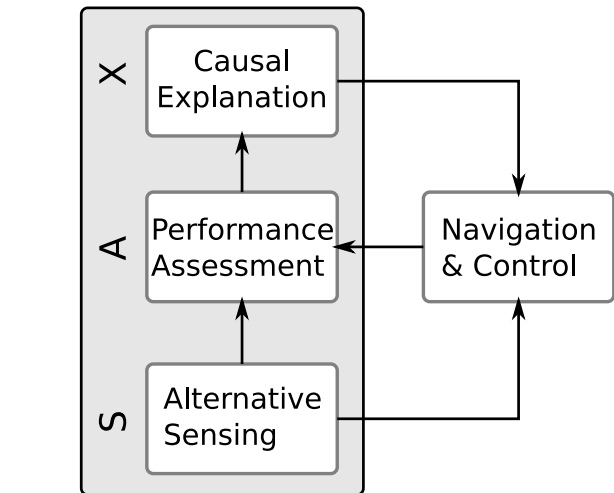* Matthew Gadd and Daniele De Martini contributed equally to this work.

Figure 1: An illustration of our Sense-Assess-eXplain (SAX) interpretation of trust and assurance of autonomous vehicle operations. *Alternative Sensing* is about the perception of the environment using unconventional sensing methods. *Performance Assessment* then develops methods necessary to assess perception systems as well as navigation and control aspects. *Causal Explanation* then anchors these representations in situated driving scenarios and develops methods for generating causal explanations. *Navigation and Control* is not the focus of our research agenda in this project. However, as it is an essential component of the overall integrated system we will leverage existing resources in this area.

O1: To robustly and reliably sense and interpret the environment in severe and changing weather conditions, overcoming the limitations of classic sensing modalities;

O2: To continuously assess and optimise the performance of perception as well as navigation methods;

O3: To demonstrate a system capable of explaining in non-engineering and human terms what a robot/vehicle has seen and how it has influenced its decision making.

This paper is organised as follows. Section II discusses related projects being undertaken in the community. Section III describes a thought experiment which we use to suggest a framing of the open issues in Section IV. Our particular

approach to these challenges is described in Section V. Section VI describes our initial findings, a valuable dataset that we are collecting, and the schedule for investigation going forwards. Sections VII and VIII discuss our contribution and future avenues for investigation.

II. CONTEXT FOR THIS STUDY

This project is firmly embedded within and aligned with the outcomes of the Assuring Autonomy International Programme (AAIP)[1] – addressing global challenges in assuring the safety of robotics and autonomous systems. Related AAIP work which may be of interest to the reader includes [1]–[6].

In the broader community and as exhibited in focused sessions [7], [8] we find that the works of [9]–[22] have a bearing on this research agenda. In particular, works dealing with validation and proving safety [15], [20], critical scenarios and hazardous events [10], [21], human values and comfort [11], [19], human-understandable descriptions [22], safety-oriented architectures [17], [18], and mitigating hazardous events [14] all related to our objectives. Furthermore, from a robotics perspective, the role of perceptual components in safety systems [9] as well as demonstrators [12], simulators [13] and datasets [16] for tackling these research challenges are all approaches that inspire the work presented.

In this work, we draw on our experience in robust navigation [23] and scene understanding [24] as demonstrated in trials that we have executed in challenging scenarios [25]–[27]. Specifically, we continue to advocate the use of commercially promising but unusual sensing technology which is inherently robust to inclement weather and illumination [28]–[31].

III. MOTIVATION

To illustrate the assurance paradigm we advocate in Section IV and the approach we describe in Section V to solve the inherent issues this paradigm captures, let us consider the following concrete example scenario:

> While driving off-road, a vehicle enters a region it has not traversed before. It leverages external services to retrieve satellite images which provide a large-scale overview of the region ahead. Based on these images, the vehicle creates a map, performs a semantic segmentation of driving surfaces, and plans a route through them according to their traversability. While following the route, radar and audio sensor measurements are used to refine and update the surface segmentation in the map – in the long-range and short-range respectively. The vehicle will also explain to a human driver **what** route was taken, and **why**: *"The vehicle will take a route over an area of gravel. The route is slightly longer than the direct route, as there is an non-traversable body of water in the direction of the goal."*

> Next, consider that as it starts to rain heavily, the vehicle notices a drop in its localisation performance using its cameras. Due to the change of weather conditions – which is also detected through audio (change of surface properties) and confirmed by external weather services –

the vehicle seamlessly adapts its localisation system from camera to radar and reduces its velocity. Although this process happens in the background, the vehicle can **explain** the cause of its decision to the human driver: *"Due to the heavy rain and slippery surface conditions, the vehicle has reduced its speed."* An explanation to a developer and/or system auditor will provide more technical details: *"Due to a 5% drop in localisation performance using the camera the vehicle switched to a localisation method using radar."*

For full capability in these scenarios in a fashion that is understandable and comfortable for a human occupant or auditor, the autonomous vehicle must:

1) be able to robustly sense and understand its environment,
2) have a good understanding of how well its various (perceptual or otherwise) subsystems are performing for the task at hand in the current driving conditions, and
3) relay this information to a human occupant/auditor in a rational and digestible format.

We capture these three aspects in Section IV which frames our research agenda. Section V describes our proposed approach in order to answer these research questions. We acknowledge alternative approaches, however, and hope that the paradigm itself finds use in the broader community.

IV. THE SENSE-ASSESS-EXPLAIN (SAX) PARADIGM

The proposed approach to trust and assurance addresses these challenges using a paradigm called **Sense-Assess-eXplain (SAX)** which comprises three complementary strands of research: To summarise, we *explain* at different levels of abstraction what we have *sensed* and *assessed*. This means that, while driving, the vehicle is able to explain what it has perceived and how this has influenced its own decision making. Moreover, the vehicle will be able to explain how its performance depends on the current and predicted environmental conditions.

A. Sense

We shall *sense* the world through a set of unconventional but complementary sensors – including Frequency-Modulated Continuous-Wave (FMCW) scanning radar and acoustic sensors – that will allow us to perceive and interpret the environment in novel ways beyond the current state-of-the-art. These alternative sensing methods will allow us to make robust perceptions where traditional sensing modalities might fail under severe weather conditions. We take the view that these new additional modalities, so rarely used, offer both an axis of assurance and validation viz-a-viz conventional established techniques *and* an expansion of the operating envelope. In particular, we focus on the perception of driving surfaces in on-road and off-road scenarios under various weather (including torrential rain and snow) and lighting conditions using radar as well as the interpretation of complex, unstructured environments using auditory sensing. Finally, to increase the vehicle's environmental awareness we sense the environment through a set of available data services such as rain radar (from weather services) and satellite imagery.

Figure 2: Our primary vehicle, a Jaguar Land Rover, while traversing an off-road scenario during one of the data-collection trials.

B. Assess

We *assess* both environmental conditions (a priori) and the vehicle's perceptual as well as navigational performance in order to increase its environmental awareness and to adapt its behaviour accordingly. To this end, we shall continuously assess the performance and effectiveness of perception and navigation methods and adapt them if necessary.

C. eXplain

This "explanatory" thread lies at the heart of our assurance and trust research agenda. We feel it is sorely lacking in much of the autonomous vehicle (AV) research endeavour where, with good reason, black boxes abound; however, the narrative is clearly changing. We have to be able to offer users pathways to trust and assurance of *what* machines are doing and *why*. They have to be able to explain, almost justify, what they are doing, what they see, what it means, and what they plan to do next and why. The inputs to this explanatory process are, of course, the *Sense* and *Assess* threads, and their value is exponentiated when they are used to give humans common-sense everyday explanations of intended action and perception. We posit that human users demand this as a precursor to trust, and we know that commercial insurers will require it.

V. THE SENSE-ASSESS-EXPLAIN (SAX) METHODOLOGY

In this project we build on our perception, mapping, and localisation capabilities – the ideal substrate to perceive challenging environments. In our approach for sensing, assessing, and explaining the environment we harness the power of deep learning, while we utilise structure, priors, and models to guide the learning process. By combining deep learning with Artificial Intelligence (AI) reasoning methods and structure we can overcome some of the critical barriers for assuring autonomy. For example, a vehicle will be able to provide detailed causal explanations of its decisions at different levels of abstractions for different stakeholders. As discussed in Section VI, our approach will be validated in complex, real-world driving scenarios using the Jaguar Land Rover (JLR) platform shown in Figures 2 and 4.

A. Alternative Sensing

In the last decades, many advances have been made in AV navigation and localisation. Nevertheless, these are still open problems, especially when AVs are deployed into the real world, exposing challenges that are hardly predictable in the laboratories, particularly in the perception of the environment. Harsh weather and lighting conditions in particular pose non-trivial challenges to AV development, above all with the usage of traditional sensing systems, as cameras and Light Detection and Ranging (LiDAR).

Since all autonomous tasks are built on top of environment perception, the availability of robust sensing information, as well as algorithms and techniques to interpret it, is crucial for all robotic platforms. The objective of this line of work is therefore to investigate the exploitation of uncommon sensing modalities and configurations, such as scanning radars and audio, and external weather and map services, for the vehicle's motion estimation and surface classification.

Furthermore, new techniques such as deep learning can be extremely effective tools to model the data streams coming from such sensors. For those models to be robust and accurate, though, a thorough and consistent dataset, representing a variety of experiences and conditions, is necessary.

Work in this area includes:
1) Radar-based motion estimation and localisation,
2) Auditory sensing,
3) Leveraging external services (such as satellite imagery),
4) Multi-modal terrain classification, and
5) Data collection.

Figure 3 shows exemplar records taken from some of the sensors that our platform shown in Figure 2 is equipped with.

B. Performance Assessment

Predicting the likely performance of a robotic sub-system based on past experience in the same workspace is applicable to both navigation [23] and perception [32]. In this context we will further equip AVs with accurate situational awareness for safe autonomous operation in complex environments.

Here, we consider that some environments are less lenient than others to even small lateral or rotational deviations from a known trajectory, so that localisation can be lost if the taught trajectory is not followed within some tolerance. Furthermore, predictive uncertainty estimates from standard neural networks are typically overconfident, often making them too unreliable to be deployed in real world applications.

Work in this area includes:
1) Predicting localisation performance, and
2) Estimating model confidence.

We plan in this challenge to draw on works such as [33] to intelligently and seamlessly select the sensing modality which has the most support in the region of the world currently experienced and its environmental condition.

C. Causal Explanation

It is of key importance that users, developers, and regulators understand what a robot is doing, what it did, what it intends to do, and why. *Explanations* are identified by AAIP as one
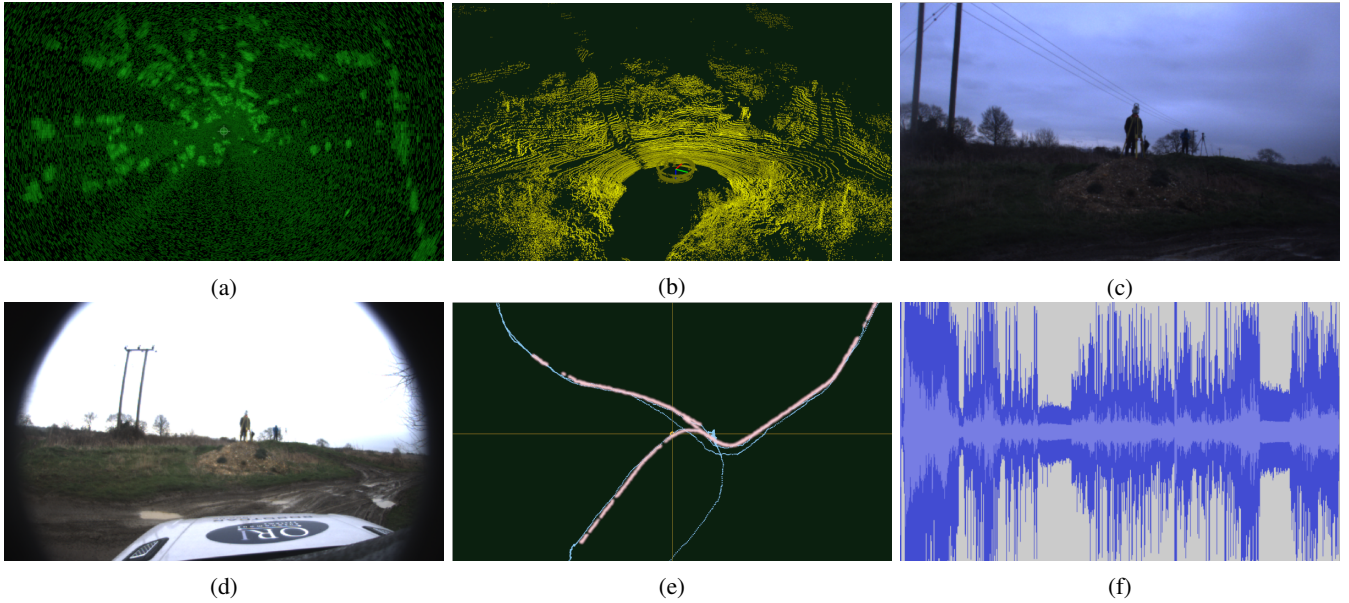
Figure 3: Samples of sensor streams taken at the same time as in Figure 4. (a) shows a radar scan in its cartesian form; (b) shows 3D LiDAR data; (c) and (d) show the camera data taken by the from stereo and mono cameras respectively; (e) shows the manually-overlaid Global Positioning System (GPS) and ground-truth data – see Section VI; (f) is the audio stream from the microphones in the wheel archs.

of the critical barriers to assurance and regulation. Regulators are already requiring some form of *interpretability* and *explainability*.

In this project we will build robots that semantically understand their environment and can provide causal explanations for their own decisions. Transparent and interpretable representations will enable developers to analyse the robot's behaviour and assure its safe autonomous operation. Users will benefit from explanations by developing trust in autonomous systems.

Work in this area includes:

1) Scenario-based requirement analysis,
2) Semantic scene representation, and
3) Learning and inference for causal explanation.

Here, we will investigate a range of driving scenarios to understand what types of explanations are required by stakeholders. In particular, we will focus on scenarios which involve different types of surfaces and changing weather conditions.

Additionally, we will extend our graph-based scene representation [34] to encode information of traffic participants and other semantic aspects of the environment including the type of surfaces as well as weather information in a well-defined language (ontology).

D. Integration and Demonstration

Our AV demonstrator is used in transportation tasks in real-world environments. The vehicle will perform these tasks in on-road and off-road settings on a range of different terrains and under different weather conditions.

The overall aim is to demonstrate that a vehicle can explain its observations of environmental conditions (e.g. surface, weather) as well as its own performance.

To this end, we will adopt the following principles:

- The vehicle uses a set of uncommon, multi-modal sensors (incl. radar and acoustic sensors) to mitigate against failure of traditional sensors such as cameras in severe weather conditions, and
- The robot assesses its performance in perception and navigation tasks and detects anomalies that are outside of learnt confidence bounds.

We will address our aim by exploring and validating the following practices:

- Use of real-world datasets to learn sensor models including confidence bounds, for representative environments, and
- Validation of learnt models through use in real driving scenarios using our JLR RobotCar.

Work in this area includes:

1) Dataset release, and
2) Real-world demonstration.

Thus, the demonstrator will deliver a method for explaining observations of the environment as well as its assessments of perception and navigation routines, a dataset of unconventional sensors, and a taxonomy of explanations. The taxonomy will provide guidance for regulators and system developers for the accreditation of AVs.

VI. PRELIMINARY AND UPCOMING OUTCOMES

Our early investigation has been focused on robust and effective motion estimation [35], [36], localisation [31], [37], and semantic scene understanding [38] using FMCW scanning radar. We have also produced work showing effective localisation between satellite imagery and radar in [30], towards leveraging external services. Finally, we have released the largest radar-focused *urban* autonomy dataset collected to date [39].

Figure 4: The Leica laser tracker used for ground-truth recording during one of the off-road trials.

However, many urban datasets have been released in recent years [40]–[42]. For this reason, we are in the process of collecting a new dataset with the intention of encouraging research into *introspection* and *explainbility* of Autonomous Driving (AD) systems in totally under-investigated driving scenarios. To this end, our focus for data capture revolves around *unusual sensing modalities*, *mixed driving surfaces*, and *adverse weather conditions*.

Specifically, we are completing driving in rural and off-road England with our *Jaguar Land Rover RobotCar*. We choose not to perform this investigation with smaller robotic platforms such as [43] as despite the reach of these platforms into interesting scenarios which are important to economic sectors such as agriculture they are not *also* suitable urban driving.

Indeed, we are capturing data in a wide set of atmospheric and illumination conditions while traversing a variety of surfaces including highways, country lanes, mud paths, and cobblestone streets. Our sensor suite is comprised of sensors traditionally exploited for AD including cameras, LiDARS, and GPS/INS. However, we also include sensors which are not traditionally exploited but show great promise including FMCW radar and audio. Furthermore, we provide synchronised streams from external services including satellite imagery and publicly available weather information. Towards building trust in AVs in challenging real-world driving scenarios, we also plan to provide human-derived metadata tags on the actions taken by the driver at interesting occasions during each foray.

Commonly for autonomous vehicles operating outdoor, high precision GPS is a viable way to record a ground-truth signal for algorithms to be tested and verified [44]; nevertheless, an Real-Time Kinematic (RTK) solution is dependant on the availability of a Global Navigation Satellite System (GNSS) base station in close proximity [45] and fairly affected by occlusions – trees and buildings – and longitude. Leica Viva TS16[2] is an accurate instrument used for surveying and

building construction. Since TS16 has robotic mode, it is able to lock onto the specific target and track it regardless of the amount of distractions in the field. We axploit this excellent ability to provide a ground truth for accuracy evaluations.

VII. Open Issues

The work proposed in this research agenda is in a nascent field, with many open issues. In this section we briefly list import challenges in this area which is either pending or out of scope of the work proposed here – as framed by the paradigm discussed in Section IV.

a) Sense: Multi-modal hazard identification, safe environment perception in open environments, and dealing with the unknown.

b) Assess: Safety argumentation for machine learning based systems, probabilistic guarantees, self-perception, self-awareness, introspection, related approaches of other communities, and determination of environment perception performance.

c) eXplain: Performance evaluation of explanations, metrics and benchmarks for risk and safety, abstraction-levels and hierarchies for explanations, human-machine interfaces, and explanation in the context of regulation.

VIII. Conclusion

This paper presented an overview of the ongoing work in demonstrating world-leading research in mobile autonomy, focused on challenging on-road and off-road driving scenarios. We discussed our approach for addressing the fundamental technical issues to overcome critical barriers to assurance and regulation for large-scale deployments of autonomous systems. We foresee a future where robots can robustly sense their environment, can assess their own capabilities, and, vitally in the purpose of assurance and trust, can provide causal explanations for their own decisions.

References

[1] Z. Porter, I. Habli, H. Monkhouse, and J. Bragg, "The moral responsibility gap and the increasing autonomy of systems," in *International Conference on Computer Safety, Reliability, and Security*. Springer, 2018, pp. 487–493.

[2] J. A. McDermid, Y. Jia, and I. Habli, "Towards a framework for safety assurance of autonomous systems," in *Artificial Intelligence Safety 2019*. CEUR Workshop Proceedings, 2019, pp. 1–7.

[3] S. Burton, L. Gauerhof, B. B. Sethy, I. Habli, and R. Hawkins, "Confidence arguments for evidence of performance in machine learning for highly automated driving functions," in *International Conference on Computer Safety, Reliability, and Security*. Springer, 2019, pp. 365–377.

[4] R. Bloomfield, H. Khlaaf, P. R. Conmy, and G. Fletcher, "Disruptive innovations and disruptive assurance: Assuring machine learning and autonomy," *Computer*, vol. 52, no. 9, pp. 82–89, 2019.

[5] S. Burton, I. Habli, T. Lawton, J. McDermid, P. Morgan, and Z. Porter, "Mind the gaps: Assuring the safety of autonomous systems from an engineering, ethical, and legal perspective," *Artificial Intelligence*, vol. 279, p. 103201, 2020.

[6] C. Menon and R. Alexander, "A safety-case approach to the ethics of autonomous vehicles," in *Safety and Reliability*. Taylor & Francis, 2019, pp. 1–26.

[7] M. S. Elli, I. Alvarez, J. Ota, J. Weast, and M. Maurer, "2nd special session on solving the automated vehicle safety assurance challenge," in *International Conference on Intelligent Transportation Systems (ITSC)*, 2019.

[8] R. McCall, M. Baumann, I. Politis, S. S. Borojeni, I. Alvarez, A. Mirnig, A. Meschtscherjakov, M. Tscheligi, L. Chuang, and J. Terken, "1st workshop on situational awareness in semi-automated vehicles," in *Adjunct Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 2016, pp. 233–236.

[9] R. Salay, M. Angus, and K. Czarnecki, "A safety analysis method for perceptual components in automated driving," in *2019 IEEE 30th International Symposium on Software Reliability Engineering (ISSRE)*. IEEE, 2019, pp. 24–34.

[10] G. Bagschik, A. Reschka, T. Stolte, and M. Maurer, "Identification of potential hazardous events for an unmanned protective vehicle," in *2016 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2016, pp. 691–697.

[11] J. C. Gerdes, S. M. Thornton, and J. Millar, "Designing automated vehicles around human values," in *Automated Vehicles Symposium*. Springer, 2019, pp. 39–48.

[12] S. Pechberti, D. Gruyer, D. Gingras, and F. Dupin, "Design of a modular demonstrator for safety application systems: The cvis project," in *2010 IEEE Intelligent Vehicles Symposium*. IEEE, 2010, pp. 1146–1151.

[13] L. Cui, J. Hu, B. B. Park, and P. Bujanovic, "Development of a simulation platform for safety impact analysis considering vehicle dynamics, sensor errors, and communication latencies: Assessing cooperative adaptive cruise control under cyber attack," *Transportation research part C: emerging technologies*, vol. 97, pp. 1–22, 2018.

[14] J. K. Johnson, "The colliding reciprocal dance problem: A mitigation strategy with application to automotive active safety systems," *arXiv preprint arXiv:1909.09224*, 2019.

[15] K. D. Julian, R. Lee, and M. J. Kochenderfer, "Validation of image-based neural network controllers through adaptive stress testing," *arXiv preprint arXiv:2003.02381*, 2020.

[16] W. Zhan, L. Sun, D. Wang, H. Shi, A. Clausse, M. Naumann, J. Kummerle, H. Konigshof, C. Stiller, A. de La Fortelle *et al.*, "Interaction dataset: An international, adversarial and cooperative motion dataset in interactive driving scenarios with semantic maps," *arXiv preprint arXiv:1910.03088*, 2019.

[17] G. Bagschik, M. Nolte, S. Ernst, and M. Maurer, "A system's perspective towards an architecture framework for safe automated vehicles," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018, pp. 2438–2445.

[18] N. Mohan, M. Törngren, and S. Behere, "A method towards the systematic architecting of functionally safe automated driving–leveraging diagnostic specifications for fsc design," *arXiv preprint arXiv:1912.03178*, 2019.

[19] M. Naumann, M. Lauer, and C. Stiller, "Generating comfortable, safe and comprehensible trajectories for automated vehicles in mixed traffic," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018, pp. 575–582.

[20] P. Koopman, B. Osyk, and J. Weast, "Autonomous vehicles meet the physical world: Rss, variability, uncertainty, and proving safety," *ArXiv*, vol. abs/1911.01207, 2019.

[21] C. Wang and H. Winner, "Overcoming challenges of validation automated driving and identification of critical scenarios," in *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*. IEEE, 2019, pp. 2639–2644.

[22] T. Menzel, G. Bagschik, L. Isensee, A. Schomburg, and M. Maurer, "From functional to logical scenarios: Detailing a keyword-based scenario description for execution in a simulation environment," in *2019 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2019, pp. 2383–2390.

[23] W. Churchill and P. Newman, "Experience-based navigation for long-term localisation," *The International Journal of Robotics Research*, vol. 32, no. 14, pp. 1645–1661, 2013.

[24] L. Kunze, T. Bruls, T. Suleymanov, and P. Newman, "Reading between the lanes: Road layout reconstruction from partially segmented scenes," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018, pp. 401–408.

[25] M. R. Balme *et al.*, "The 2016 UK Space Agency Mars Utah Rover Field Investigation (MURFI)," *Planetary And Space Science*, p. (Early Access), 2019. [Online]. Available: http://oro.open.ac.uk/58259/

[26] M. R. Balme *et al.*, "UK Space Agency "Mars Utah Rover Field Investigation 2016" (MURFI 2016): Overview of mission, aims and progress," in *48th Lunar and Planetary Science Conference*, March 2017. [Online]. Available: http://oro.open.ac.uk/48661/

[27] B. Yeomans, H. Porav, M. Gadd, D. Barnes, J. Dequaire, T. Wilcox, S. Kyberd, S. Venn, and P. Newman, "MURFI 2016 - From Cars to Mars: Applying Autonomous Vehicle Navigation Methods To a Space Rover Mission," in *Proceedings of the 14th Symposium on Advanced Space Technologies in Robotics and Automation (ASTRA)*, Leiden, Netherlands, 2017.

[28] L. Marchegiani and P. Newman, "Learning to listen to your ego(-motion) : Metric motion estimation from auditory signals," in *Towards Autonomous Robotics Systems (TAROS)*, 2018.

[29] L. Marchegiani and I. Posner, "Leveraging the urban soundscape: Auditory perception for smart vehicles," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Singapore, June 2017.

[30] T. Y. Tang, D. De Martini, D. Barnes, and P. Newman, "RSL-Net: Localising in Satellite Images From a Radar on the Ground," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1087–1094, April 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8957240

[31] S. Saftescu, M. Gadd, D. De Martini, D. Barnes, and P. Newman, "Kidnapped radar: Topological radar localisation using rotationally-invariant metric learning," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Paris, 2020.

[32] J. Hawke, C. Gurău, C. H. Tong, and I. Posner, "Wrong today, right tomorrow: Experience-based classification for robot perception," in *Field and Service Robotics*. Springer, 2016, pp. 173–186.

[33] C. Gurău, C. H. Tong, and I. Posner, "Fit for purpose? predicting perception performance based on past experience," in *International Symposium on Experimental Robotics*. Springer, 2016, pp. 454–464.

[34] L. Kunze *et al.*, "Reading between the lanes: Road layout reconstruction from partially segmented scenes," in *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, 2018.

[35] R. Aldera, D. De Martini, M. Gadd, and P. Newman, "Fast Radar Motion Estimation with a Learnt Focus of Attention using Weak Supervision," in *IEEE International Conference on Robotics and Automation (ICRA)*, May 2019, pp. 1190–1196.

[36] R. Aldera, D. De Martini, M. Gadd, and P. Newman, "What Could Go Wrong? Introspective Radar Odometry in Challenging Environments," in *IEEE Intelligent Transportation Systems Conference (ITSC)*, Auckland, New Zealand, October 2019.

[37] M. Gadd, D. De Martini, and P. Newman, "Look Around You: Sequence-based Radar Place Recognition with Learned Rotational Invariance," in *IEEE/ION Position, Location and Navigation Symposium (PLANS)*, 2020.

[38] P. Kaul, D. De Martini, M. Gadd, and P. Newman, "RSS-Net: Weakly-Supervised Multi-Class Semantic Segmentation with FMCW Radar," in *Proceedings of the IEEE Intelligent Vehicles Symposium (IV)*, 2020.

[39] D. Barnes, M. Gadd, P. Murcutt, P. Newman, and I. Posner, "The Oxford Radar RobotCar Dataset: A Radar Extension to the Oxford RobotCar Dataset," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Paris, 2020. [Online]. Available: https://arxiv.org/abs/1909.01300

[40] F. Yu, W. Xian, Y. Chen, F. Liu, M. Liao, V. Madhavan, and T. Darrell, "Bdd100k: A diverse driving video database with scalable annotation tooling," *arXiv preprint arXiv:1805.04687*, 2018.

[41] H. Caesar, V. Bankiti, A. H. Lang, S. Vora, V. E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan, and O. Beijbom, "nuscenes: A multimodal dataset for autonomous driving," *arXiv preprint arXiv:1903.11027*, 2019.

[42] R. Kesten, M. Usman, J. Houston, T. Pandya, K. Nadhamuni, A. Ferreira, M. Yuan, B. Low, A. Jain, P. Ondruska, S. Omari, S. Shah, A. Kulkarni, A. Kazakova, C. Tao, L. Platinsky, W. Jiang, and V. Shet, "Lyft level 5 av dataset 2019," https://level5.lyft.com/dataset/, 2019.

[43] S. Kyberd, J. Attias, P. Get, P. Murcutt, C. Prahacs, M. Towlson, S. Venn, A. Vasconcelos, M. Gadd, D. De Martini, and P. Newman, "The Hulk: Design and Development of a Weather-proof Vehicle for Long-term Autonomy in Outdoor Environments," in *International Conference on Field and Service Robotics (FSR)*, Tokyo, Japan, August 2019.

[44] W. Maddern, G. Pascoe, M. Gadd, D. Barnes, B. Yeomans, and P. Newman, "Real-time Kinematic Ground Truth for the Oxford RobotCar Dataset," *arXiv preprint arXiv: 2002.10152*, 2020. [Online]. Available: https://arxiv.org/pdf/2002.10152

[45] A. Rietdorf, C. Daub, and P. Loef, "Precise positioning in real-time using navigation satellites and telecommunication," 2006.