Realism Constructs for ADS Simulation Testing

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***Abstract*—As autonomous driving systems (ADSs) continue to expand into the public sphere, so too must our efforts to sufficiently validate their safety. Given the wide array of scenarios over which ADSs must operate and the inherent dangers in these scenarios, developers often rely on simulation testing to exercise the system. However, the well-documented simulation-reality gap limits the transfer of results from simulation testing to real world operation, hindering the ability to build sufficient assurance cases based on validation in simulation alone. This is a fundamental issue in the construct validity of simulation-based methods for validation of ADS systems. Recent efforts have sought to decrease the simulation-reality gap through improved simulation fidelity and developing methods for generating synthetic data from real data. However, these efforts do not come with a method to reason about the construct validity achieved by these improvements. Current methods to *measure* the distance between simulation and reality for ADS validation are insufficient for the task as they provide no basis on which to judge the validity of the simulated tests. For simulation testing to provide utility, we require methods to reason about this construct validity; i.e., whether and how much a given test or technique will yield failures that transfer to real-world deployment, or miss failures because of the lack of fidelity. We describe the continuing challenges in this domain, provide outlines of what is required of a solution, and set directions for future work in the community to this end.**

***Index Terms*—autonomous vehicles, validation, simulation testing, realism metrics**

I. Introduction

Autonomous Driving Systems (ADSs) promise to provide myriad benefits from increased safety, to improved efficiency, to broadened access to transportation. However, to meet these goals, ADSs must be rigorously validated over the rich space of real-world scenarios they will encounter to ensure they are sufficiently safe. Testing edge cases at the boundary of performance is vital to assure the correctness of safety-critical ADSs. Such edge cases—for example, scenarios where super-human sensing, perception, reaction, and maneuverability enable an ADS to avoid a collision that a human driver could not—are inherently unsafe to validate in the real world. To this end, simulation testing and methods that generate synthetic data for testing have become an integral part of the ADS validation pipeline due to their safety, controllability, speed, and cost. However, as researchers continue to develop and employ simulation and synthetic input testing, **we need methods to understand the construct validity of these tests with respect to the real world.**

We know that simulation does not match reality due to the well-documented simulation-reality gap which impacts many aspects of operating ADS in simulation [1]. Simulation uses environment models that abstract and approximate real-world objects, leading to lower-fidelity digital twins [2]. Simulation uses simplistic models to approximate physical processes, e.g. ground friction or deformation, narrowing the range of application [1], [2]. Simulation approximates the sensor input collection process and struggles to faithfully recreate sensor artifacts and noise [3]. Each of these differences contribute to developers' concerns about the construct validity of simulation testing as a means to build a safety case for ADS real-world deployment [1], leading ADS developers to retain real-world deployment testing within their validation pipeline [4].

Yet we lack methods to *measure* such gaps between simulation and reality to reason about the construct validity of such testing efforts. All sensor inputs are approximations of the real-world—what kind of gaps in realism are relevant, not to a human but to an ADS? Does a particular test input demonstrate safety or lack thereof for the system under test? Or is executing that input a waste of resources as even if a failure is found it will not translate to deployment? Is it possible to identify this a priori to reason about construct validity? Without the ability to answer these questions, we cannot build a reliable safety assurance case through simulation testing.

In order to develop a robust ADS testing infrastructure that can include simulation and synthetic testing, we must answer:

1) What does it mean for an input to be *real*?
2) What are the necessary and sufficient realism conditions for a test to inform an ADS safety assurance case?
3) How can we measure, compute, and decide this necessity and sufficiency?
4) How can this measurement be performed efficiently to enable practical utility in the ADS testing infrastructure?

II. Motivation

Recent research has attempted to close the simulation-reality gap for sensed inputs on two fronts: by increasing the fidelity of the simulation [5]–[7], or by generating synthetic sensor inputs from sensor inputs collected from the real world to preserve its realism [8]–[10]. In these works, improvement in closing the simulation-reality gap is measured either through qualitative appeals to human preference on how real an input *feels* [11], or by quantitative metrics calibrated to the same human preference [12]–[16]. Many studies in this field have claimed sufficient realism, i.e. construct validity, for ADS validation by relying on these metrics, demonstrating that the average or minimum observed metric value during the study is above a given threshold. However, with a plethora of metrics that can be applied, prior techniques are evaluated over a diverse set of metrics for realism that prohibit comparison between techniques. Further, absent a rigorous basis to connect these metrics to the safety assurance case for an ADS, i.e. to reason about construct validity, the techniques that rely on these metrics for sufficiency may prove futile in transitioning to field deployment—why should a score above X threshold for a particular metric be considered real enough to assure against future deployment failures of the ADS? Or it could be that a given threshold for a given metric is sufficient—*we simply do not know*. This lack of a common set of metrics for realism and a connection between these metrics and the safety case for ADS present a crucial obstacle for the field as new techniques are developed. This impedes progress toward several important research goals: test input generation techniques cannot be compared with regard to their ability to transfer to real-world deployment, test adequacy metrics cannot account for deficiencies arising from the simulation-reality gap, and simulator and synthetic test generation techniques have no sufficiency criteria to judge when they have met their realism goals and thus resources should instead be allocated elsewhere. **Most critically, we cannot reason about the construct validity of current ADS simulation testing.**

III. Looking Forward

We seek to call the community's attention to the need for further investigation to identify methods for measuring, computing, and deciding the necessary and sufficient realism required for the use of simulation for the ADS research and testing pipeline, if such methods exist. A useful measure to this end should enable reasoning about the realism sufficiency of a test input to form the basis for a valid test. This sets several research questions for the community to address:

RQ1: *What does it mean for an input to be real to an ADS?*

Building from the discussion in Section II, other research fields have developed particular definitions and goals of realism based on their intended application, e.g. improving the end-user experience in virtual reality [17]. The community must align on a common definition and set of goals for what it means to be sufficiently real as it pertains to ADS validation to determine how this aligns with the construct validity of ADS testing techniques. Only once a definition is identified can we work toward methods to measure, compute, and decide realism.

RQ2: *What parameters are required for a realism measure: the test input; the SUT; the types of faults being investigated; the method of input generation; the intended use as part of a broader assurance case?*

To begin to understand the practicability of leveraging realism measures to decide the validity of an ADS test case, we must first understand what parameters must be considered. An overarching realism oracle for arbitrary inputs would represent a substantial advance even beyond ADS validation, with applications in image manipulation detection [18] and deepfake detection [19]. However, as discussed, ADS test validity rests on determining whether gaps in realism are relevant *to the ADS*. Specifically-targeted approaches requiring additional parameters can still provide utility—even a measure that can be used to decide if a given input from a particular SUT targeting a particular failure-mode is realistic is useful.

RQ3: *What realism measures are suitable to this task; do different SUTs or testing paradigms require different measures or can the community build an infrastructure around one shared measure? If no shared realism measure exists, how do we demonstrate validity?*

The community has employed several measures claiming to address realism in recent years. However, as these measures have thus far been disconnected from explicit arguments about their connection to validity for ADS testing, no clear consensus has emerged on which measures are suitable—one of the existing measures may rise to the front, or further research may be required to develop novel measures, or identifying such a measure may be infeasible. While a common measure or set of measures would advance the community's ability to compare research, the practical utility for the end-user relies on demonstrating the construct validity of their chosen test methodology. In the absence of a suitable measure, the community must shift focus to developing alternatives for demonstrating this validity while building comparable, extensible, and valid ADS testing methodologies.

RQ4: *How can these methods be efficiently computed and pragmatically integrated into the ADS research and testing infrastructure?*

Measures that meet the prior criteria would represent a meaningful step forward in advancing research to this end. However, as an applied exercise in validating ADS, identified methods must be amenable to efficient computation. Given the complexity of the problem, this requirement must be explicitly designed for within the ADS research and testing infrastructure to permit practical use.

IV. Conclusion

In this position paper we highlight the critical need for a richer understanding of methods to reason about construct validity of simulation- and synthetic input generation-based methods for ADS validation and its connection to realism and the simulation-reality gap. We outline the shortcomings of existing realism metrics that have been applied to this end and provide the contours of what this unique paradigm requires of future methods. We aim to begin the conversation in earnest for the community to build a common understanding of how we can create reliable methods for measuring realism or identify other avenues to demonstrate validity for the ADS testing pipeline. In this way, we set the stage for future work in this direction toward building a robust infrastructure for ADS research and testing.

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