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Advancements In Mixed Reality For Autonomous Vehicle Testing And Advanced Driver Assistance Systems: A survey

Imane Argui, Maxime Gueriau, Samia Ainouz,

Abstract—Although the interest in autonomous vehicles and advanced driver assistance systems (ADAS) is significantly increasing, they won't be viable until their system outperforms human drivers and can adapt to face unpredictable scenarios. Over the years, several testing methods have been developed, allowing vehicles to evaluate models and algorithms. However, these methods face many challenges, including the differences between conditions in simulation and in real world during the transfer of models. In response to these challenges, mixed-reality technology has shown some great potential in ensuring safer experiments. It enables vehicles to interact simultaneously with physical and virtual objects, thereby, duplicating critical scenarios to help the vehicle to learn how to adapt. In this paper, we present a comprehensive literature review of the use of mixed-reality techniques for self-driving systems and ADAS. We explore various applications and limitations of this approach. Additionally, we discuss possible directions for future work, highlighting the necessity of ongoing progress in this developing field.

Index Terms—Mixed-reality, self-driving vehicles, testing methods, reality gap.

I. INTRODUCTION

Self driving cars evolved over the past few decades from experimental concepts to fully developed technologies that may be used on public roads. The National Highway Traffic Safety Administration (NHTSA) classified the level of vehicle autonomy into 6 levels based on the responsibilities and capabilities of both the vehicle and the human driver [1]. In this classification system, Level 0 denotes a fully manual driving experience in which the human driver is entirely in charge of operating the vehicle, and Level 5 denotes complete automation in which the vehicle is capable of handling all aspects of driving without the need for any human involvement. Despite the years dedicated to developing and improving the autonomy of the vehicles, it is still not possible to launch a fully autonomous vehicle (Level 5). However, self-driving cars are nowadays able to navigate autonomously, and smoothly break behind a stopped car, but the driver is still supervising and is responsible for maintaining control at all times. As self-driving technologies continue to evolve, Advanced Driver Assistance Systems (ADAS) play a crucial role in closing the divide between current vehicle capabilities and the future of fully autonomous driving [2]. ADAS are designed to strengthen vehicle safety and driving efficiency by providing crucial support functions such as adaptive cruise

control, collision avoidance, pedestrian detection, and more. ADAS implementations are instrumental in introducing drivers and the public to the functionalities that will become standard in fully autonomous vehicles. By incrementally integrating these technologies, manufacturers are able to refine sensors, algorithms, and user interfaces, which are essential for the reliable performance of Level 5 automation. Self-driving vehicles and ADAS are facing many challenges that have been summarized in [3]. While ADAS focus on improving driver and vehicle safety through specific features like emergency braking or lane keeping, the ultimate goal of fully autonomous vehicles is to take over the driving task entirely. Moral and ethical aspects are invoked when the vehicle must make good decisions in critical situations such as how to prioritize the safety of passengers and other road users in the event of an unavoidable crash. The robustness of the model is also considered a major challenge: variance in weather or road conditions may impact the behavior of the vehicle. Another concerning obstacle is the vulnerability of the car to cyber-attacks. Numerous aspects need to be taken into consideration before advancing ADAS features and launching a Level 5 vehicle. In [4], the authors demonstrate that autonomous vehicles would need tests over 14 billion kilometers of on-road testing in order to demonstrate their reliability in terms of fatalities and injuries. It may take hundreds of years to drive these miles, this is one of the reasons why it is necessary to find alternative methods to complement real-world testing such as simulations and virtual testing, mathematical modeling and analysis, pilot studies, etc. Thus, a driving test is crucial to evaluate the behavior of the vehicle and ADAS features in challenging situations as well as the security and robustness of algorithms. A wide variety of novel testing methods have been created to satisfy this demand as highlighted in recent comprehensive reviews [5, 6]. One of the common methods is simulation testing which has the advantages of low testing costs and strong repeatability. It entails simulating the surroundings and context the vehicle will experience in the actual world using computational models. Nevertheless, studies have shown that the difference in dynamics between the real-world model and the simulated model generates the reality gap [7]. It describes the difference between the simulation model and the real-world environment. It can also occur because of differences in sensor readings, or road conditions. Despite efforts made in this context of ameliorating simulation tools, for instance, projects such as VOICES (Virtual Open Innovative Collaborative Environment for Safety), that are funded by the U.S. Department

of Transportation (USDOT) to ameliorate the safety, efficiency and reliability of transportation systems. VOICES platform facilitates collaborative research and the testing of transportation technologies in a shared virtual environment where various transportation stakeholders can collaboratively test and develop systems in high-fidelity simulation of the transportation ecosystems [8]. However, challenges remain. The simulation model, for instance, might not accurately reflect the sensor data or the dynamics of the real-world environment, resulting in differences in the vehicle's performance. This gap highlights the need for more integrated and realistic testing methodologies. One solution that has been introduced is to combine the advantages of simulation with the characteristics of test drives leading to a hybrid method: Mixed-Reality (MR) testing. The purpose of using MR technologies is to facilitate testing and prototyping. The first applications in robotics were introduced for humanoids to combine the real and the virtual world for a reach-and-grasp task [9]. Chen *et al.* [10] used MR technology for autonomous navigation and observed the mobile robot Pioneer interact with both virtual and physical objects. Later, researchers applied MR to self-driving vehicles in different scenarios, trying to solve different challenges and simplify the testing of autonomous cars. The rise in the number of research papers on MR that have been published in IEEE over the past few years provides confirmation of the expanding interest in the topic. Figure 1 represents the number of MR-related papers published by IEEE each year, which demonstrates a consistent rise in research activity and interest over the past ten years. The main goal of this survey

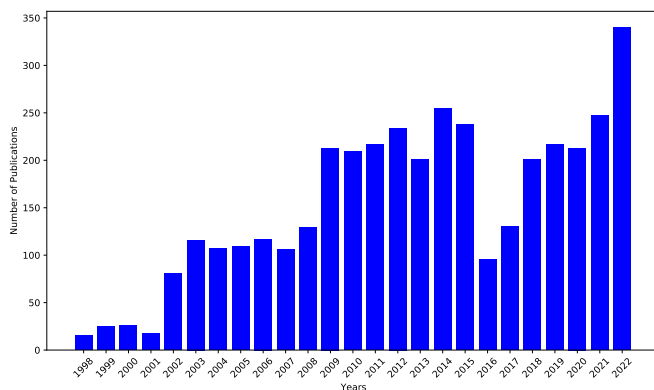


Fig. 1: The scientific interest towards MR [11]

is to examine various research efforts related to MR for self-driving cars and ADAS, assessing the benefits and challenges of this method. This paper specifically examines the application of mixed reality to improve the testing procedure for automated vehicles, addressing both current challenges and potential innovations. We aim to provide an assessment of the advantages and obstacles of this approach. For this purpose, it is important to clarify that the focus of this study lies specifically within the domain of agent/vehicle applications, distinct from user experience or head-mounted applications, where the augmentation of the user's perception is preminent. To achieve this objective, the survey will be structured as

follows :

- **Definition and context setting:** Mixed reality will first be defined in the context of autonomous vehicles and its various applications will be clarified. Additionally, the terminology used in this area will be navigated.
- **Exploring the benefits and technicalities:** An overview of the advantages of mixed reality for self-driving automobiles will be given in the survey. A necessary examination of the technical basis supporting MR's relevance to autonomous driving will come before this section.
- **Review of the state-of-the-art approaches:** A thorough analysis of the current state-of-the-art related to mixed reality in the context of autonomous cars will be conducted. This analysis will include a review of the various procedures employed, the methods used to determine their effectiveness, and any potential implementation-related limitations.
- **Research avenues:** This survey will conclude by revealing many unexplored research directions and untapped potential in the domain of MR for self-driving vehicles enabling to furnish readers with a comprehensive understanding of this testing approach and diverse avenues for improvement.

II. MIXED REALITY

The objective of this section is to first establish a solid foundation by ensuring that key definitions are clear. To achieve this, this section will start by providing a comprehensive definition of mixed reality in its larger context. Following that, various applications of mixed reality will be explored, shedding light on its diverse characteristics. Finally, the relationship between mixed reality and the concept of "X-in-the-loop," will be studied in order to be able to link these vital elements.

A. MR, VR, AR and AV

Before addressing technical details, it is important to specify the necessary concepts. Determining the definition of MR is not a straightforward task. There were a few attempts to define MR through a literature review, interviews with specialists in augmented reality (AR) and virtual reality (VR), and other methods [12]. The conclusion was that there is no universally single, agreed-upon definition of MR. However, a definition can be established based on the context. The Milgram continuum, depicted in Figure 2 is one of the most popular sources for MR definitions and serves as a good starting point. MR appeared for the first time in the work of Milgram

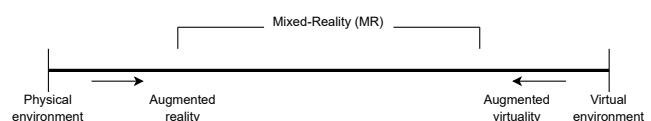


Fig. 2: The mixed reality continuum

and Kishino [13] where it was defined as follows: "The most straightforward way to view a Mixed Reality environment is

one in which real world and virtual world objects are presented together within a single display, that is, anywhere between the extrema of the virtuality continuum”, thus considering AR and augmented virtuality (AV) as subsets of MR. AR typically involves a real environment augmented with virtual objects. In this setup, virtual elements are overlaid on the real world, but the interaction is generally limited to the virtual objects within the real environment [14], while AV is a virtual world with real objects. Meanwhile, a specific MR environment would be a real environment, digitally represented by a virtual environment, allowing for an enriched interaction where real and virtual objects co-exist. It is also worth noting that some researchers might use the term AR when they are actually referring to MR. This misuse of terminology can lead to confusion and a misunderstanding of the capabilities and applications of these technologies. Table I summarizes the differences between MR and VR.

TABLE I: Differences between VR, AR, AV, and MR

	VR	AV	AR	MR
Virtual Env.	X	X		X
Real Env.			X	X
Virtual objects	X		X	X
Real objects		X		X

AR and VR technologies have been instrumental in advancing AV development by simulating driving scenarios, enhancing road safety, and improving the overall driving experience. By understanding the challenges and human factors issues associated with AR applications in vehicles, researchers can better prepare for the integration of MR in AVs, ensuring seamless user interaction and system performance [15]. MR builds upon and improves the foundations established by AR, making the experience more immersive and realistic. One way to visualize MR is as an additional layer of AR, which not only overlays virtual objects onto the real world but also enables simultaneous interaction with both virtual and real objects. This seamless integration of virtual and real environments is the defining feature of MR. Because MR enhances AR, many of the technical implementations used in AR can be reused and adapted for MR. These include: (i) Real-time data processing, (ii) Hardware and software integration, (iii) Scalability. The major difference with MR is its ability to combine the virtual and real worlds, allowing virtual and real objects to coexist and interact within the same environment. This capability requires additional technical considerations to ensure that the interactions between virtual and real elements are not only synchronized but also realistic and meaningful.

B. Different applications of MR

Many different sectors, including education, healthcare, architecture, and robotics are integrating MR technology at an increasing rate. In the educational context, MR is used to offer interesting, interactive learning experiences that let students explore challenging ideas with more engaging opportunities [16], [17], and [18]. In healthcare, MR is exploited to

visualize and replicate medical operations as well as to train doctors in a secure environment [19], [20], [21], and [22]. To conceptualize and test designs before production starts, MR is used in architecture and engineering to simulate construction projects and build virtual prototypes [23], [24], and [25]. In robotics, MR is exploited to validate prototypes and reduce the reality gap [26], [27], and [28]. It is also used in mobile robotics to simplify debugging and reduce the cost of testing [10] and [29]. Overall, MR technology has shown the ability to change how users engage with digital information and the real world, as well as to open up new avenues for immersive and interactive experiences in a variety of contexts.

C. X-in-the-loop

Researchers have shown a growing interest in the problem of testing and validating advanced automotive software, which made them develop and improve the effectiveness of testing techniques based on virtual environments. In the literature, the X-in-the-Loop (XiL) framework exploits the most recent developments in communication technologies and vehicle automation as well as testing and validation needs [6]. X refers to different system elements, *e.g.* software, hardware, vehicle, and scenario.

- **Software-in-the-loop** involves running the actual software in a virtual environment [30].
- **Hardware-in-the-loop** operates on parts or complete hardware of the vehicle in the simulation loop. Actuators or sensors can be incorporated into the simulation instead of their models to improve its validity [31]. It gives realistic feedback, but the vehicle still uses a virtual model [32].
- **Vehicle-in-the-loop** implies testing the real vehicle in a fully virtual environment [33]. It can be compared to virtual reality settings since everything is virtual (environment and objects).
- **Scenario-in-the-loop** can be considered one step closer to real-world testing, because some elements of traffic control components can actually be placed, in addition to the vehicle and the surface being real [34]. This setting offers a mixed-reality framework where objects from real and virtual worlds can be introduced.

In summary, XiL testing methods have been successful in testing and validating advanced automotive software in virtual environments. Many surveys investigate the feasibility and reliability of these methods in order to test and validate autonomous vehicles [6], [35], and [36]. Efforts have been made in this context, for instance, the CARMA XiL simulation project, developed by the U.S. Department of Transportation’s Federal Highway Administration, represents a framework designed to improve the testing and validation of cooperative driving automation systems [37]. This project integrates various simulation modalities (SiL, HiL, ViL) to provide holistic testing environment. One can clearly observe that the definitions are the same despite the fact that the names are different. This connection between SciL and MR shows how virtual worlds have the potential to offer a realistic testing environment for autonomous car systems.

III. MR IN AUTONOMOUS VEHICLE TESTING AND DEVELOPMENT

The primary goal of AV testing is to identify and evaluate the vehicle's response to critical and risky scenarios [38]. These scenarios are rare in real-world conditions but are crucial for ensuring the safety and reliability of autonomous systems. Traditional simulation-based testing, while essential, often lacks the necessary realism to fully assess and validate AV systems [39]. MR provides a robust alternative by enabling direct testing on real vehicles within an actual environment, while still simulating these critical scenarios. This section provides a thorough summary of MR application for AD systems and ADAS. MR testing enables for an easy interaction between the automated driving agent and virtual and real elements within the same environment by leveraging the concept of digital twinning. This enables the vehicle's sensors to detect virtual elements (ranging from static objects such as traffic signs and red lights to dynamic entities including pedestrians and other vehicles) as if they were real. It is achieved through advanced sensor integration and fusion techniques and contribute to an augmented testing environment by simulating complex, real-world scenarios in a controlled yet dynamic MR setting. The potential advantages of applying MR in AD and ADAS, the technical prerequisites for implementing such systems, and the architectural components of a successful MR frameworks are discussed in the following sections.

A. Potential benefits of MR in self-driving vehicles.

The potential benefits of mixed reality (MR) in self-driving vehicles are significant. One of the challenges in testing autonomous vehicles is the reality gap [7], where it can be difficult to simulate all real-world sources of variation for realistic modeling of robot sensory input and motion characteristics, leading to an incomplete and inaccurate representation of the real world. Lighting, noise, fluid dynamics, thermal dynamics, and the physics of the soil, sand, and grass are some of these sources of variance [10]. Even though the models of the vehicles, sensors, and road topology are simplified by simulation tools, they are unable to accurately represent the complex details of the real world [40]. Due to these limitations, it is difficult to replicate robot sensory input and motion characteristics realistically. This emphasizes the need for MR testing techniques that can close the reality gap and offer a more accurate reflection of the real world. Reduced resource requirements for experimentation are another benefit of MR in the development and testing of self-driving cars. To provide accurate results and uphold safety requirements, traditional testing techniques frequently need an important amount of technical assistance, equipment, and human resources [10]. However, since many aspects of the testing procedure can be replicated in a virtual environment, MR can significantly reduce the need for physical equipment and personnel. Additionally, MR can enable more frequent testing and iteration by minimizing the need for physical testing environments, which will ultimately result in a faster and more reliable development of self-driving technology. Furthermore, testing self-driving cars in real-world traffic situations can be dangerous for both

the car and the individuals, especially when navigating around moving objects like pedestrians or other vehicles. In extreme circumstances, specific test scenarios might even be explicitly forbidden in order to protect the reliability of the vehicle under test. These risks can be reduced by using MR technology to build regulated, safe virtual worlds that match real-world scenarios. MR testing provides also a cost-effective and low-risk way to test algorithms and machine learning models in realistic settings, while still being grounded in reality [41].

B. Bridging Simulation and Real-World AV Testing

Public road testing, proving ground testing, and simulation testing are generally recognized as the three pillars of safety certification in the field of autonomous vehicle (AV) testing [42]. Collectively, these techniques guarantee that AV systems are properly evaluated in a variety of controlled and real-world conditions, offering a framework for validating the reliability as well as safety of autonomous vehicles. While proving ground testing provides controlled circumstances for specific evaluations, simulation testing enables thorough scenario modeling and analysis, including edge cases and rare events. Public road testing involves real-world driving scenarios. MR technology bridges the gap between these traditional methods, providing a hybrid testing environment that improves the overall evaluation process of AV systems. It complements the three traditional pillars of AV safety certification by integrating the strengths of public road testing, proving ground testing, and simulation testing. The following will detail the differences and similarities between MR and these three techniques.

1) Simulation testing:

• Similarities

- To test AV systems, MR uses virtual models, identical to simulation testing. Software is used in both approaches to generate and assess driving scenarios and vehicle responses.
- Similar to traditional simulations, MR can imitate a wide range of scenarios, including edge cases and rare events that could be challenging to meet in real life.

• Differences

- MR creates a hybrid testing environment by fusing virtual aspects with real-world data, whereas traditional simulation testing is fully virtual. This method offers an assessment of AV systems that is more complete.
- MR has the potential to provide more realistic and immersive sensory feedback than traditional simulations. MR tests can more nearly replicate real-world situations by combining with genuine vehicle hardware and sensory systems.

2) Proving ground testing:

• Similarities

- Certain scenarios can be evaluated repeatedly in controlled environments thanks to proving ground testing and machine learning. By including virtual

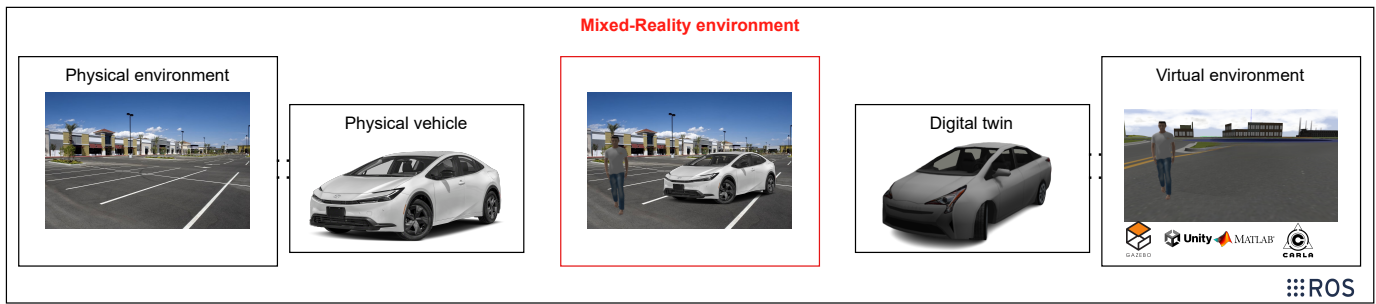


Fig. 3: Architectural elements of a MR framework

components in addition to the physical setup, MR can improve these conditions.

- Without requiring any physical modifications to the infrastructure, MR can increase the variety of situations examined in testing grounds. It is simple to make virtual changes to test various scenarios.

• Differences

- Proving grounds are actual sites that need substantial resources to be adjusted for various testing. With MR, there is a more adaptable option that allows virtual surroundings to be changed fast and affordably.
- In proving grounds, physical setup and adjustments can be costly and time-consuming. By enabling virtual upgrades and alterations, MR lowers these expenses.

3) Public road testing:

• Similarities

- When AV systems are being tested on public roads, MR can overlay virtual aspects onto real driving scenarios, giving them the opportunity to experience uncommon or dangerous circumstances under controlled conditions. This improves test realism without sacrificing safety.
- MR can produce more precise and context-aware simulations, increasing the tests' relevance and dependability, by including real-time data from open road tests.

• Differences

- Driving on public roads during public road testing exposes the car, the driver, and the general public to possible risks. On the other side, MR offers a risk-free testing environment by simulating hazardous situations.
- Because the environment is changeable, it can be difficult to reliably recreate certain scenarios during public road testing. Exact scenario replication is made possible by MR, guaranteeing repeatable and consistent testing.

C. Technical background

MR testing methods for self-driving cars commonly rely on simulation environments in order to replicate the real world,

including roads, traffic, pedestrians, and other elements that the vehicle may face. This focus on MR specifically aims to improve the testing protocols for automated vehicles by providing a comprehensive and dynamic testing framework that closely mimics real-world conditions.

Various simulators have been used in different applications of MR testing for self-driving vehicles. The most popular ones are Unity3D, MATLAB, CARLA, SUMO, and Gazebo. For example, the open-source CARLA simulator [43] has attracted a lot of interest recently because of its incredibly realistic surroundings and physics engine, which enable pre-

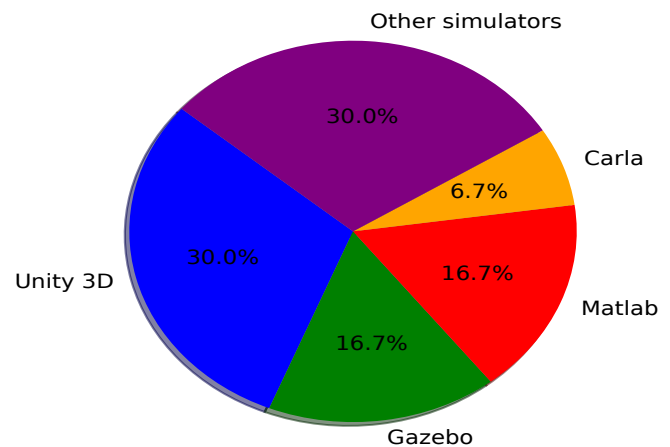


Fig. 4: Different simulators used in the literature

cise representation of real-world circumstances. On the other hand, GAZEBO [44] is an open-source multi-robot simulator that offers a realistic 3D scenario for testing and evaluating autonomous systems.

Moreover, MATLAB [45] is frequently used for mathematical modeling and control system design. Finally, a well-known gaming engine called Unity3D [46] can be employed to build simulated environments for training and testing autonomous driving systems. In addition to these tools, the NeuralNDE simulator is a simulator proposed in recent researches [47] that leverages deep learning techniques to generate high-fidelity, naturalistic driving environments and that closely mimic real-world conditions. This simulator enables for the dynamic interaction of virtual and real elements to facilitate the testing and validation process of autonomous vehicles. Figure 4 provides

a summary of the different simulators used in the literature for MR testing of self-driving vehicles.

To offer accurate and realistic representations of the environment around the vehicle, MR testing of self-driving cars depends on the integration of several types of sensors. Perception sensors are an essential component for augmenting the scenes. These sensors include Light Detection and Ranging (LiDAR), cameras, and ARUCO tags. LiDAR sensors are used to provide a high-resolution 3D map of the vehicle’s surroundings, while cameras capture images of the environment in real time. ARUCO tags are markers that have a distinct pattern that cameras can recognize. They are frequently used for object tracking and pose estimation in MR environments. ARUCO tags are a popular option for augmenting environments because they are lightweight and easy to use, some researchers relied on these sensors for MR testing [48]. Creating an MR environment can be done by adding virtual elements to the real environment. For instance, virtual and real LiDAR data can be combined to create an accurate point cloud of the surroundings. Several researches have tested this technique such as [40, 48, 49, 50].

The augmentation of LiDAR sensors must take into consideration all occlusions between real and virtual objects. The fusion of the virtual sensor’s data and the actual sensor’s data [48] can be expressed in the Equation 1.

$$R_f = \{(\min(r, R_v(\theta, \phi)), \theta, \phi), \forall p \in P_s\} \quad (1)$$

Where R_f represents the fused point cloud, $\min(r, R_v(\theta, \phi))$ calculates the minimum range value for a point, it compares the range r of the point from the actual sensor with the range of the closest point in the virtual sensor’s data, θ and ϕ are the polar and azimuthal angles in spherical coordinates for each point in the fused point cloud. Similarly, to create an MR environment for evaluating the vehicle’s perception and object detection abilities, virtual objects can be overlaid over the real camera image, few studies have investigated this approach [51, 52]. Equation 2 represents the augmentation strategy used in the state of the art to enable the agent to perceive the fusion of two environments by comparing the real depth map I_1 and the virtual depth map I_2 [51].

$$I_1 = (I_1 \cap (I_1 > I_2)) \cup (I_2 \cap (I_2 > I_1)) \quad (2)$$

Odometry data is a very common source of information to measure a vehicle’s position and velocity. This data can be augmented in MR testing through the combination of real and virtual odometry data to produce a more precise representation of the movement of the vehicle in the simulated environment. The experiments that explored this strategy are [53], [54], and [55].

D. Architectural Elements of MR Framework

Self-driving car testing frameworks need to be built using a systematic approach that integrates numerous architectural components. These components are essential to creating an environment that accurately assesses the skills of autonomous cars while also simulating real-world scenarios. Figure 3 provides a visual representation of the components of the MR framework.

1) *Physical environment*: It is considered important within the framework, serving as the essential foundation for conducting all tests. Even before the initial stages, it establishes priority forming the primary element that prepares the way for subsequent additions. The physical environment smoothly interacts with the virtual world in the MR framework. An immersive and dynamic testing environment for self-driving cars is created by overlaying virtual features on top of this physical location.

2) *Physical robot*: The existence of a physical or real robot is essential to the mixed reality framework. This component plays a crucial role in the testing and validation process by providing a practical platform to evaluate the effectiveness and applicability of self-driving models and algorithms in real-world scenarios. The incorporation of the physical robot ensures that the theoretical developments made in virtual simulations can be cautiously evaluated under real-world conditions.

3) *Virtual environment*: It is a fundamental component of the simulation. The digital world is meticulously designed to mirror the real world while combining augmented elements. A distinctive characteristic of the virtual environment is its scalability, allowing it to be expanded or adjusted to match the requirements of the testing objectives. This flexibility guarantees that the testing process stays extremely adaptable, taking into account a wide range of scenarios and difficulties experienced in self-driving vehicle applications.

4) *Digital twin*: The digital twin has a crucial role in the MR framework. It is considered as the virtual instance of a physical system (vehicle or robot) that is continually updated with the latter’s performance, maintenance, and health status data throughout the physical system’s life cycle [56]. The digital twin facilitates an integrated “in-the-loop” connection between the physical robot and the virtual environment. The system’s physical and virtual components can interact and exchange feedback continuously as a result of this integration. With the incorporation of the digital twin, the physical robot can fully understand the combination of the physical and virtual environment.

E. Technical implementation in MR for AV testing

To ensure reliable and accurate simulation environments, the technical implementation of Mixed Reality (MR) for Autonomous Vehicle (AV) testing requires complex data synchronization and temporal delay control procedures. This section explores the approaches used to combine virtual simulation elements with real-world sensor data, emphasizing how important it is to preserve synchronization and reduce latency.

1) *Data Synchronization*: Data synchronization is essential for ensuring that all the components of simulation work together when MR environments are implemented for AV. The synchronization procedure involves coordinating the time of diverse data streams to uphold uniformity throughout the system. This system creates a realistic testing environment by integrating many sensors with simulation tools. The Robot Operating System (ROS), which serves as a middleware to manage and synchronize data from various sources, including

actual and simulated entities, is one of the key components. Because of its ability to communicate across processes, ROS makes it easier to integrate different models and real-world events (*c.f.* Figure 5). The simulation kernel is a specific ROS node that manages topic and service-based communication and data exchange. In order to maintain system synchronization, this node controls the information flow between the simulation and real-world components [57]. Data streams are managed using ROS, which makes it easier for the actual robot and the simulator to communicate. The integration of a *rosbridge* suite library facilitates communication protocol, guaranteeing instantaneous data transfer between simulators and ROS [29].

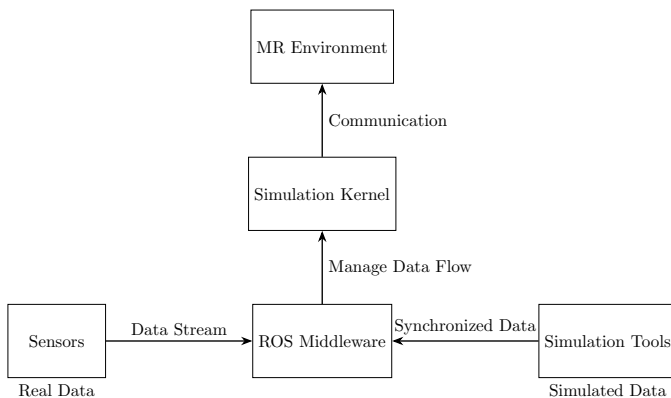


Fig. 5: Data synchronization process in an MR environment.

2) *Time delay management*: Maintaining the simulation’s realism requires controlling temporal delays, particularly when real-time data is being used. The system’s smooth operation is ensured by addressing multiple sources of delay in the implementation. Delays, for instance, may happen when pose data is transferred from Unity3D to ROS and vice versa. The performance and accuracy of real-time simulations can be impacted by factors like processing time and network latency, which are the source of the delay [50]. The overall system delay can be broken down into: (i) *Message transmission delay*: The amount of time it takes for messages to move from ROS to the simulator and vice versa. (ii) *Processing delay* Time required by processors to interpret and act on received data. (iii) *Actuation delay* Actuators’ response time to commands in physical form. The use of ROS services, such as the “step()” function, helps to maintain time consistency between different simulation components. This is particularly important when integrating various models like SUMO for traffic simulation and Menge for pedestrian behavior simulation [58]. Moreover, 5G technology significantly optimizes time delay, ensuring ultra-reliable low-latency communication (URLLC) essential for MR testing. This optimization allows for real-time data synchronization and processing, crucial for accurate simulation and real-world integration. The 5G network’s high bandwidth and low latency capabilities enable seamless connectivity and interaction between virtual and real environments, enhancing the fidelity and reliability of MR testing for AV systems [6].

3) *Sensor fusion*: When testing and validating autonomous vehicles (AVs) in Mixed-Reality (MR) situations, sensor fusion

is an essential element. One way to produce a more accurate and complete picture of the environment around the vehicle is to combine data from many sensors. The integration of several sensors improves the dependability and resilience of AV systems by offering supplementary and redundant data, which is important when maneuvering through intricate and ever-changing surroundings. Furthermore, sensor fusion increases mapping and localization accuracy, enabling AVs to function effectively and safely. Additionally, in MR testing, sensor fusion allows for the realistic simulation of complex scenarios that would be difficult or unsafe to recreate in the real world, providing a controlled yet flexible environment for rigorous testing. The use of a variety of sensors-based autonomous driving vehicles can help the development of an MR simulators. For instance, a system that uses a MEMS-based IMU, UDS, and 2D LiDAR has been proposed to collect details environmental data [29]. The integration of these many sensors makes it possible for the simulator to faithfully imitate real-world circumstances, which validates the autonomous platooning algorithms and improves the efficacy of the testing procedure. Figure 6 represents an example of schematic with the framework of an MR simulator, including the tools and simulator used as well as the communication between each element. The integration of odometry measurements

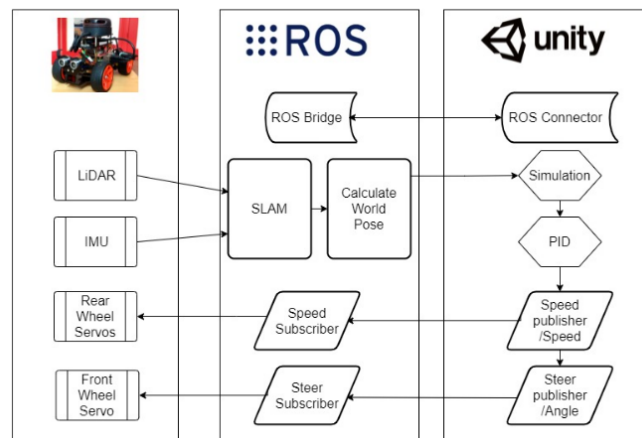


Fig. 6: An example of the architecture of an MR framework [29].

with LiDAR data through an Extended Kalman Filter is also another way to improve the vehicle localization accuracy. This approach allows the vehicles to better navigate and operate in a real-world environment, as well as in an MR simulation. The localization algorithm for the real vehicle is based on an Extended Kalman Filter (EKF), which fuses odometry measurements with LIDAR data. The odometry information consists of vehicle speed and steering angle, captured from the real vehicle’s CAN bus. These values are used as inputs for a kinematic bicycle model, which is integrated numerically to produce an estimate of the vehicle’s position and orientation on the driving plane at 40Hz. This process, known as the model update, accounts for the low-velocity application typical in parking lots. Due to the non-linear nature of the model’s

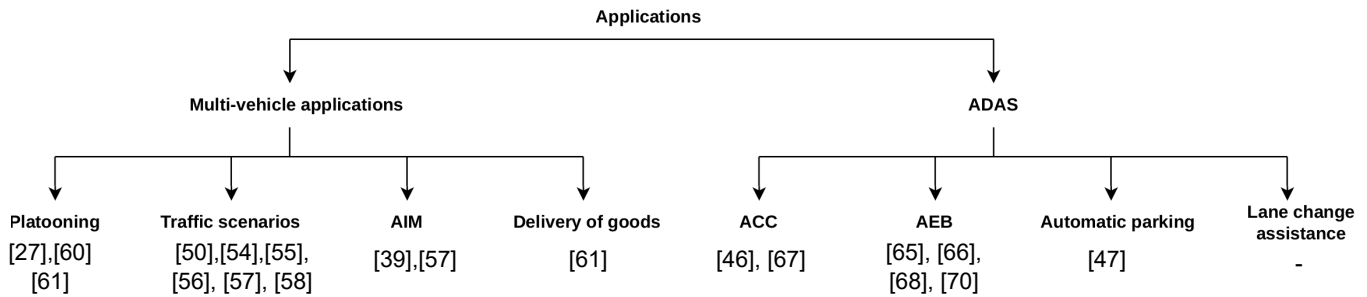


Fig. 7: SOTA applications of MR for self-driving cars.

differential equations, they are locally linearized for each execution of the Kalman filter’s model update [50].

IV. REVIEW OF MR FOR SELF-DRIVING APPLICATIONS

The use of mixed reality frameworks in self-driving cars has the power to significantly change how human drivers view and engage with these vehicles. Mixed reality offers a wide range of opportunities for strengthening safety and improving efficiency by smoothly fusing virtual aspects with the real environment. MR proves indispensable for rigorous, scalable testing procedures across multiple vehicle systems, enabling the replication of near-real conditions with both virtual and physical components. This subsection outlines and investigates several significant mixed reality framework applications in the context of autonomous vehicles. These applications incorporate both existing state-of-the-art implementations and anticipated future developments. The aim is to demonstrate the wide range of potential that mixed reality may bring to the field of autonomous cars. Applications of mixed-reality for self-driving vehicles can be divided into two big parts: multi-vehicle applications and advanced driver assistance systems (ADAS), illustrated in Figure 7.

1) *Multi-vehicle applications*: The use of MR offers novel capabilities to completely transform how vehicles interact, communicate, and navigate in complex traffic scenarios by providing additional information to the autonomous system as well as optimizing the performances and reducing the risks. In this part, we will examine several case scenarios for multi-vehicle applications and explore how MR technology can be integrated into each one.

- **Traffic scenarios**: The dynamic and unpredictable nature of traffic events makes training autonomous vehicles a difficult task on many levels. A thorough testing strategy is necessary because of the complexity of simulating different traffic circumstances, interactions with other cars, and responding to unforeseen events. Autonomous vehicles can maneuver through simulated traffic environments using MR, where interactions with other cars, pedestrians, and barriers are reproduced realistically. This provides a safe testing environment for the vehicles while simulating the complexities of real-world traffic in a controlled manner. Additionally, MR makes it possible to introduce uncommon and dangerous events [57] that might be too risky to be replicated in the real world, such

as high-speed collisions or bad weather. As demonstrated by the work of [53], [57], [59], [60], [61], and [62], some researchers investigated in the application of traffic scenarios in MR environments.

- **Platooning**: It involves a group of automated vehicles that are linked together and exchange information to drive in a coordinated manner [63]. Through the use of a virtual environment where multiple vehicles can be simulated in addition to one physical vehicle, MR might potentially lower the cost of testing. This virtual environment can be used to replicate different situations and evaluate the coordination and communication between the vehicles without the requirement for numerous physical cars. Furthermore, by creating a virtual environment that

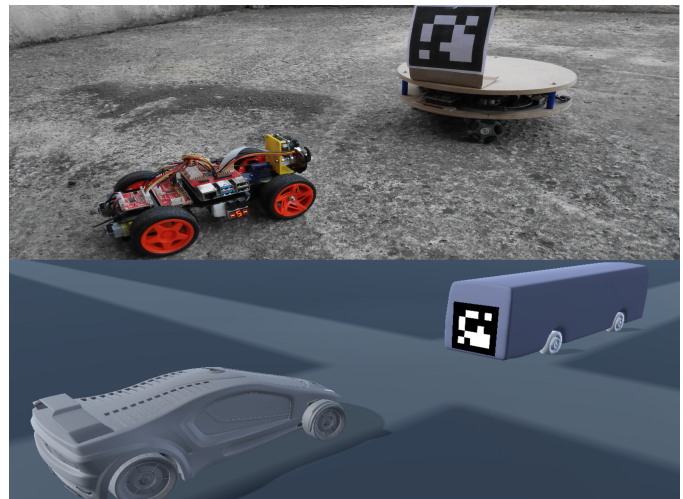


Fig. 8: Miniature car in a MR environment [58].

replicates real driving conditions, MR can help reduce the cost and logistical challenges of testing platooning systems in the real world [58]. Previous research have explored the application of MR in platooning scenarios, as evidenced by the work presented in [64], [58], [29]. Figure 8 is a representation of a platooning application at a miniature scale where the car is guided by a simulated one following ArUco markers in MR environment [58].

- **Autonomous intersection management (AIM)**: AIM is a research area that focuses on creating intelligent systems for controlling intersections that involve autonomous vehicles. The goal of AIM is to improve

safety, efficiency, and sustainability by enabling AVs to communicate and cooperate with each other and with the intersection infrastructure [65]. AIM requires a fleet of autonomous vehicles, which is both expensive and potentially dangerous due to the possibility of crashes during testing [41] and [61]. Integrating AIM within MR frameworks offers a promising way to test and refine these systems, mitigating challenges related to cost, safety, and reliability. Within a simulated intersection scenario, a single physical car can interact with virtual vehicles that have different trajectories. Researchers can evaluate the viability and efficiency of different optimal trajectories.

- **Delivery of goods:** Autonomous delivery vehicles can be used to transport a variety of items, including food, packages, and other items, with minimal intervention required. The use of MR offers a new approach to training, testing, and optimizing self-driving models before their deployment as well as replicating dense urban environments, complete with intricate road layouts and parking challenges. Autonomous delivery cars can be tested in situations where they must navigate through congested streets, find acceptable parking spaces, and plan the most effective routes to delivery locations. The work presented in [66] serves as a promising foundation for the efficient delivery of goods in a multi-robot environment, laying the groundwork for further advancements.

2) *Advanced Driver Assistance Systems:* The integration of MR to ADAS holds the potential to improve different aspects of vehicular safety and performance.

- **Adaptive Cruise Control (ACC):** It is an advanced driver-assistance system designed to help vehicles maintain a safe following distance and stay within the speed limit on the road. MR testing for ACC systems makes it possible to explore a variety of traffic scenarios and road conditions. These scenarios cover a variety of dynamics, such as unexpected stops and changes in the flow of traffic. Additionally, the effectiveness of ACC systems depends on how well their sensors detect moving objects and cars. Through the simulation of various settings and sensor outputs, mixed reality acts as a facilitator. This simulation helps developers understand potential sensor limitations and calibration requirements, leading to improved ACC system performance. A good demonstration of this application can be found in [49] and [70].
- **Automatic Emergency Braking (AEB):** It is designed to help prevent or mitigate collisions by automatically applying the brakes if a potential collision is detected and the driver does not respond in time. AEB system testing in MR environments offers a safe and controlled environment for simulating emergencies, like as sudden barriers and pedestrian crossings. Without putting actual drivers or pedestrians in danger, this controlled simulation enables thorough analyses. AEB systems may also come across uncommon situations like animal-versus-vehicle collisions or specific road hazards. Simulation of these uncommon conditions is made possible by the use of



Fig. 9: AEB testing in a MR environment [73].

mixed reality, providing developers with invaluable information about how the system would function in such situations. Different researchers showed interest in testing AEB in a MR settings such as [68], [69], [71], [73]. Figure 9 is a representation of the application of AEB in MR settings.

- **Automatic parking:** The ease and accuracy of parking operations for drivers could be greatly improved by Automatic parking systems. These systems are created to detect parking spaces and autonomously direct automobiles into these spaces with a minimum of driver involvement. This technology not only makes it easier to park in confined places, which can be difficult, but it also lowers the risk of collisions and improves overall road safety. For testing and training purposes, automatic parking systems can benefit from MR. It provides a flexible platform for training parking techniques in a range of configurations and conditions. Moreover, MR goes beyond training by enabling testing of autonomous parking systems in challenging circumstances. For instance, it is possible to replicate challenging real-world scenarios by having virtual vehicles interacting with it. Such tests evaluate the system's technical ability as well as its flexibility in dynamic parking conditions. The findings outlined in [50] provide a solid initial step towards optimizing algorithms of automatic parking, offering valuable insights for future developments in this area.
- **Lane change assistance (LCA):** Before executing a lane change, LCA systems must precisely determine the speed and location of other vehicles [74]. Engineers can evaluate how well the system responds to diverse car behaviors and road dynamics by simulating complex traffic interactions using MR. Emergency scenarios such as abrupt lane encroachments or forceful lane changes by neighboring vehicles must be handled by LCA systems. By testing these scenarios safely and methodically with MR, developers can assess how well the system will respond. This application represents a forward-looking perspective for future research. As of now, no studies have been identified that specifically explore the use of MR for evaluating LCA systems under such dynamic scenarios.

Table II gives a thorough summary of the work that has been

TABLE II: Related Work on Mixed Reality for Self-Driving Vehicles

Reference	Vehicle	Sensors	Simulator	Application
Chen et al., 2009 [10]	Differential robot Pioneer	Onboard laser rangefinder	Gazebo	Obstacle avoidance
Quinlan et al., 2010 [41]	Marvin Vehicle	GPS information	UDP + AIM Simulator	AIM
Gechter et al., 2014 [67]	Car	Laser rangefinder	Unity 3D + PhysX	Detection of virtual objects
Matsunaga et al., 2018 [64]	Vehicle STAVi	Hololens	Not mentioned	Platooning
Feng et al., 2018 [68]	Lincoln MKZ Hybrid	Onboard Unit	VISSIM Simulator	Automotive Braking
Zofka et al., 2018 [49]	Car	LiDAR	Gazebo	ACC
Zofka et al., 2018 [40]	CoCar	LiDAR	Gazebo and CoCar	Detection of pedestrian
Mitchell et al., 2020, [53]	DeepRacer Robot	Optitrack	IDM + MOBIL	Traffic scenarios
Szalai et al., 2020 [55]	Car	GPS data	Unity 3D + SUMO	Detection of virtual objects
Kneissl et al., 2020 [50]	Audi A4 B9	LiDAR	VTD Simulator	Automated Parking
Varga et al., 2020 [54]	Toyota Prius 3	Radar	Unity 3D	Detection of virtual objects
Zofka et al., 2020 [57]	Car	LiDAR and optical cameras	SUMO + UE	Traffic scenario
Feng et al., 2020 [59]	Lincoln MKZ	Real-Time Kinematic GPS	VISSIM	Traffic scenario
Ghiurău et al., 2020 [69]	Volvo Cars	RGB cameras	Unity 3D	Assistive braking
Baruffa et al., 2020 [58]	3-wheels robot	ArUco markers	Unity 3D	Platooning
Liu et al., 2020 [66]	Turtlebot3	LiDAR	Unity 3D	Delivery of goods
Che et al., 2021 [70]	Car	GPS	Not mentionned	ACC
Szalay et al., 2021 [71]	Smart Fortwo passenger car		Traffic simulator	Automated parking + AEB
Chand et al., 2021 [29]	RC car	Telemetry data + LiDAR	Unity 3D	Platooning
Drechsler et al., 2021 [52]	Car	Camera	Unity 3D	AEB
Goedicke et al., 2021 [72]	Toyota Prius Alpha	Headset	Unity 3D	Basic driving
Drechsler et al., 2022 [73]	Car	Telemetry data	Carla	CCRS
Shao et al., 2022 [61]	Car	Signal controllers	Carla + SUMO	Traffic scenario + AIM
Shao et al., 2023 [60]	Car and truck		VISSIM + SUMO + Simulink	Traffic scenario
Genevois et al., 2022 [48]	Renault Zoe	LiDAR	Gazebo	Collision mitigation
Argui et al., 2023 [51]	Summit XL	Depth cameras	Gazebo	TTC
Feng et al., 2023 [62]	Lincoln MKZ	Real-Time Kinematic + camera	SUMO	Traffic scenario

done so far on the use of MR in the context of self-driving cars, classified by years. It is interesting that several investigations have been carried out on a smaller scale, aiming to address distinct objectives. The "Vehicles" column in this context indicates whether the research was conducted on real vehicles or robotic platforms. For instances where "Car" is indicated in this column, it signifies that the tests were performed using car-like configurations, yet specific vehicle models are not explicitly delineated. The table categorizes the sensors used to enhance data or create virtual representations of robotic things. Furthermore, it arranges the studies according to the simulation platforms used in the study projects. Finally, the applications of the research are presented in the last columns.

V. EVALUATION TECHNIQUES

The evaluation of the MR-based approaches presented in the literature is a critical next step after their integration in the context of self-driving vehicles. MR technology improves evaluation techniques by providing metrics that bridge the gap between simulated models and real-world dynamics which can be crucial for comprehensive validation of vehicle safety and efficiency. This section will first make a systematic analysis of diverse metrics that have been employed within the literature,

offering valuable insights into the efficiency, robustness, and potential of these MR frameworks. Furthermore, this section goes beyond the existing metrics by proposing novel evaluation criteria, thereby contributing to the development and advancement of evaluation methodologies in this developing area.

A. Qualitative observations

To begin this investigation, the section will go through the qualitative results and observations that have come from a variety of research relevant to the MR frameworks that have been given. These qualitative observations, which are frequently drawn from practical and real-world applications, provide valuable perspectives on the efficiency and performance of these frameworks. Before diving into the quantitative measures and innovative evaluation criteria that will follow in this section, a fundamental understanding can be created by first looking at the qualitative components. From the observation of researchers, it has been shown that the real robot successfully interacts with simulated objects, enabling navigation while avoiding obstacles [10]. Some researchers proposed different criteria for qualitative evaluation [49] that are summarized in the table III. Various research studies

initiated their investigations by first providing detailed observations of vehicle behavior, describing the specific events and outcomes. Subsequently, they proceeded to quantify these observations using a range of diverse metrics and measurement criteria [55], [40], [51], [73].

TABLE III: Criteria for qualitative evaluation [49]

Criteria	Definition
Observability	The ability of a testing system to provide information and understanding about the true values of all entities participating in the test.
Safety	The potential harm or risk of damage that can be posed to both the system under test (SuT) and any additional pedestrians.
Flexibility	The work involved in producing novel and unforeseen traffic scenarios.
Throughput	The number of experiments that can be performed given a fixed time interval.
Realism	The degree to which the system is triggered in accordance with the behavioral realism of the scenario context.

B. Quantitative evaluation

In the literature, diverse metrics have been employed to evaluate MR frameworks, and the selection of these metrics typically depends on the specific purpose and application of the MR system. It is important to note that not all of the metrics used will be addressed in this study because some of them are strongly linked to particular applications. Instead, the focus will be placed on outlining metrics that are considered to be of a common nature and introducing new ones. Due to the requirement of digital twinning between the robot and its corresponding real vehicle, time delay poses one of the most significant issues in the development of MR frameworks. It is critical to ensure exact temporal alignment between the signals the virtual robot receives and the actions of the actual robot since timing errors might negatively affect the efficiency and security of MR applications. Different studies tried to quantify delays in sensor data transmission [58], [73], [29], [6], [41]. Figure 10 is an illustration of a result of the measurements of delays between the time of the reception of a message and the time of the action of the agent [58].

Another approach to assess digital twinning in an MR environment involves measuring the positions and velocities of both the real vehicle and its digital twin, as demonstrated in [10] where a pose correction algorithm was employed, using pose estimation techniques. The results indicated that the residual error between the positions of the real robot and the virtual robot was approximately 0.012 meters. The metrics employed in different studies vary based on the particular application and specifications. For instance, two different scenarios can be considered to demonstrate this variability:

- In the context of training an agent within an MR environment, a valuable evaluation approach involves assessing the agent’s learning progress within this environment. Metrics such as the number of collisions per scenario before and after MR training can provide insights into the effectiveness of the MR training process as presented in [53]. This approach is particularly pertinent when

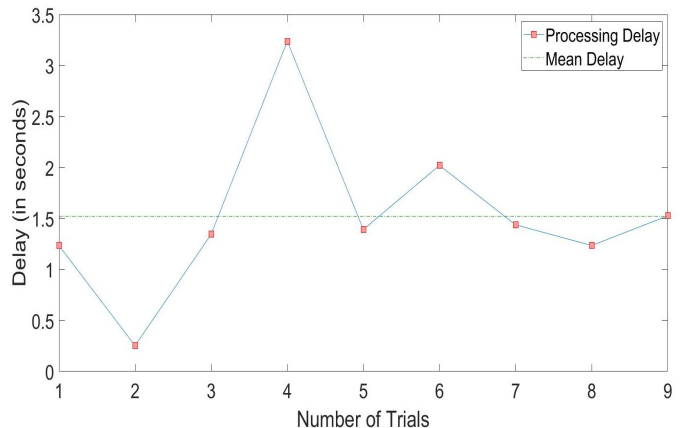


Fig. 10: Delay between the reception of message and the agent moving, extracted from [58].

the objective is to improve the agent’s performance and reduce collisions. Furthermore, authors in [62] employed other metrics to provide a robust framework for evaluating the performance of the agent’s training: (i) crash rates and types (*e.g.*, rear-end, side-swipe), (ii) reduction in required testing iterations by speeding up the development cycle and reducing resource expenditure, (iii) variance reduction in policy gradient estimates that improves the stability and reliability of the learning process, (iv) efficiency metrics by demonstrating that the proposed method could accelerate the evaluation process by multiple orders of magnitude compared to traditional methods, (v) generalization across scenarios, by demonstrating how the trained agents could generalize their learned behaviors to new, unseen environments. This metric is critical in assessing the robustness of the MR training process.

- On the other hand, researchers have adopted alternate metrics like Time-to-Collision (TTC) [75]. It is a traditional metric used to calculate the time it would take a following vehicle to collide with a leading vehicle. It can be calculated as follows:

$$TTC = H \cdot V_r = \theta \cdot \left(\frac{d\theta}{dt} \right) \quad (3)$$

Where θ is the visual angle subtended by the lead vehicle, V_r is the relative velocity, H is the headway, $\frac{d\theta}{dt}$ represents the rate of change of the subtended vehicle. This metric was used in the literature when the main goal was to guarantee that the agent perceives virtual and real-world obstacles in a consistent manner [48, 51]. The framework may be comprehensively tested using TTC, and outcomes can be contrasted between simulations, real-world, and MR scenarios.

Traditional metrics, while well-established in other domains, have not been widely applied in the context of MR testing. These metrics can be considered for further evaluation depending on the applications or purposes of the framework. Exploring a selection of illustrative scenarios with these metrics could

reveal new assessment angles and improve understanding of MR's impact:

- **Agent's perception and detection metrics:** A number of metrics can be used when the MR framework's augmentation approach significantly relies on augmenting the agent's perception. These metrics are primarily concerned with measuring the ability of the agent to recognize and locate virtual objects in a mixed reality environment. The essential metrics in this examination are the common performance metrics used for object-detection for example, including:
 - The average precision, the average recall, the false positive, true positive and false negative rates [76].
 - Root-mean-square-error (RMSE) and mean absolute error (MAE) [77].
 - Depth perception prediction metrics [78].
- **Safety assessment metrics:** The system's safety evaluation is a separate area of study that received significant attention from various organizations and researchers, especially when it comes to following safety regulations like ISO 26262¹. This is particularly important when taking into account the use of MR frameworks in simulated or real-world settings. Some studies proposed a methodology of designing metrics for safety assessment [79]. Nevertheless, there are many metrics used for safety assessment that can be deployed in the context of MR testing, for example, operational safety assessment (OSA) are metrics introduced by the Institute of Automated Mobile (IAM) that enable to quantify the operational safety of AVs [80]. Some OSA metrics are:

- Minimum Safe Distance Violation (MSDV).

$$MSDV' = \begin{cases} 1 & \text{if } d^{lat} < d_{min}^{lat} \wedge d^{long} < d_{min}^{long} \\ 0 & \text{else} \end{cases} \quad (4)$$

$$MSDV = \begin{cases} 1 & \text{if } MSDV' = 1 \wedge \text{Originated by AV} \\ 0 & \text{else} \end{cases} \quad (5)$$

- * d^{lat} : lateral distance between two vehicles.
- * d^{long} : longitudinal distance between two vehicles.
- * d^{long}_{min} : minimum longitudinal distance
- * d_{min}^{lat} : minimum lateral distance between two vehicles.

- Time-to-Collision Violation (TTCV).

$$TTCV = \begin{cases} 1 & \text{if } TTC \leq \text{threshold} \\ 0 & \text{else} \end{cases} \quad (6)$$

- Modified Time-to-collision Violation (MTTCV).

$$MTTC = \frac{-\Delta\vec{V} \pm \sqrt{\Delta\vec{V}^2 + 2\Delta\vec{A}\vec{D}}}{\Delta\vec{A}} \quad (7)$$

$$MTTCV = \begin{cases} 1 & \text{if } MTTC \leq \text{threshold} \\ 0 & \text{else} \end{cases} \quad (8)$$

- * $\Delta\vec{V}$: Relative velocity.

- * $\Delta\vec{A}$: Relative acceleration.

- * \vec{D} : Relative space gap.

- Post-Encroachment Time Violation (PETV).

$$PET = t_2 - t_1 \quad (9)$$

$$PETV = \begin{cases} 1 & \text{if } PET \leq \text{threshold} \\ 0 & \text{else} \end{cases} \quad (10)$$

- * t_2 : Arrival time of vehicle 2 at conflict point.

- * t_1 : Arrival time of vehicle 1 at conflict point.

- **Scalability metrics:** They are important in situations when the MR framework is intended for deployment in various contexts. They assess how well the framework is scalable to account for various dimensions and operational complexity. This assessment could include looking at how well the framework performs, communicates, and adapts as the scope of the activity or the number of parties involved changes. There are different metrics to achieve this purpose. In this context, Response Time (RT) is a metric commonly used in real-time systems to ensure that tasks complete within their deadline [81]. One approach to use this metric is to calculate RT and observe whether it remains consistent as the number of participants or the complexity of the system increases. RT can be calculated using a recurrence equation that upper-bounds the interference by higher priority tasks during an interval of duration R_i . The equation is:

$$R_i = C_i + \sum_{j \in hp(i)} \lceil \frac{R_i}{T_j} \rceil C_j + s(\hat{C}_e(R_i), \hat{C}_m(R_i)) \quad (11)$$

where C_i is the worst-case execution time of task i , T_j is the period of task j , and $s(\hat{C}_e(R_i), \hat{C}_m(R_i))$ is a function that computes the stall time caused by memory bandwidth regulation. Another metric that can be used to evaluate the scalability of the framework is the U-statistics that can capture the differences in the performance measures between different scenarios [82]. In Equation 12, U-statistics was calculated to verify whether a simulated network was implemented similarly to the actual road, using the actual speed V_a and the simulated speed V_s .

$$U = \frac{1}{\sqrt{\sum (V_a - V_s)^2}} \left(\sqrt{\sum V_a^2} + \sqrt{\sum V_s^2} \right) \quad (12)$$

It can be calculated to measure how well the MR framework scales with an increasing number of vehicles or actors in the scenario.

These examples highlight the flexibility in selecting metrics, allowing for the adaptation of evaluation to match the particular objectives and specifications of the MR framework. A more comprehensive understanding of the framework's capabilities and limitations can be gained by considering novel measurements, ultimately resulting in improvements in its applications and potential

¹<https://www.iso.org/standard/68383.html>

C. Reliability of virtual elements in MR framework

In the MR framework, various virtual elements are integrated to create a complete simulation environment. These virtual elements, which can include sensors, objects, and dynamic entities, may exhibit different levels of reliability. It is crucial to evaluate the reliability of each virtual element to ensure the overall effectiveness and accuracy of the MR environment. We can find potential deficiencies and raise the simulation's fidelity by methodically evaluating these components' robustness and performance. This section explores the assessment of the reliability of virtual components and presents strategies to guarantee their harmonious operation in order to maintain an accurate and realistic MR framework. To evaluate their reliability, a variety of methods can be used, including subjective quality evaluations for dynamic point clouds and meshes [83], scenario development to assess environmental immersion, and interaction effectiveness in synchronous mixed reality systems [84]. Furthermore, some researchers suggested to assess retrieval accuracy by placing cubes of various sizes in real and virtual worlds, showing a close relationship between localization accuracy and retrieval success [85]. Other studies in different fields of studies suggest to evaluate the reliability through object detection, tracking methods, and rendering in real-time, ensuring accurate and stable interaction between physical and virtual objects [86]

D. Transferability of MR testing to Real-World Applications

The increasing use of MR in automated vehicle testing raises important questions regarding the applicability of these tests to real-world scenarios. Effective evaluation not only requires rigorous testing within the simulated environments but also necessitates a robust framework for evaluating the transferability of these results to real-world conditions. In this section, we suggest some ways to evaluate the transferability of MR testing to Real-World application.

- **Validation of simulation accuracy:** The accuracy with which MR environments replicate real-world conditions is fundamental to the validation of simulation models used in the testing of automated vehicles. The first aspect that needs evaluation is the accuracy of the sensors, as they are considered critical components of autonomous vehicles, with their data serving as the primary input for decision-making processes. Studies such as [87] have shown that discrepancies in simulated sensor data can lead to statistical variances affecting the simulated and real-world data correlation. Further research emphasizes the need for high-resolution sensor models in MR to maintain data fidelity, which is critical for accurately translating simulated environments into practical, operational contexts without losing essential details to smoothing filters commonly used to manage point cloud data [88].
- **Mixed Reality-to-Reality disparity measure:** There are some quantitative metrics that have been used in past researches to assess the effectiveness of robotic controllers when transitioning from simulated to real-world environments [89]. This measure quantifies the

discrepancies between behaviors observed in simulations and those seen in real-world operations: Simulation-to-Reality Disparity Measure (STR Disparity). It evaluates the behavioral fidelity by comparing the actions of a system in a simulation with its actions in real-life scenarios, and whether the outcomes achieved by the system in a simulated environment can be replicated in the real-world without significant loss of functionality or efficiency. Given the complexity and safety-critical nature of autonomous driving tasks, adapting the STR disparity to the context of MR testing could improve the transferability and validation process. This metric would involve the measurement of the time it takes for an agent to respond to dynamic changes in the MR environment, and compare it to response times in real-world tests, the evaluation of the precision and reliability of sensor interpretations in MR settings against those obtained from real-world data, and the assessment of the accuracy of vehicle path tracking, obstacle avoidance, and other navigation-related maneuvers in MR versus road tests.

E. Validation of MR results

A Mixed Reality (MR) environment needs to be validated against real-world testing to ensure that the simulation accurately represents reality. The reliability of MR experiment results depends on this validation. Research highlights the significance of verifying simulation environments through the use of real-world and simulated data comparisons, like LiDAR point cloud comparisons [90]. MR can be used for various purposes, including training and validation of Autonomous Vehicles.

1) *Training in MR environment:* In the context of AV development, MR serves as a tool for generating large datasets, providing realistic data, and creating challenging corner cases that are difficult to replicate in real-world conditions. Researchers and developers can improve the training of AV models and make sure they are prepared to handle a variety of scenarios by using machine learning. If MR is used solely for the training of models, the validation process for these models will remain unchanged and follow the traditional methods of validating trained models as illustrated in Figure 11. However, to guarantee the accuracy and safety of these models under real-world driving circumstances, the conventional validation procedure is still necessary. In order to evaluate the models' performance, a comprehensive real-world testing procedure is used, where the models are implemented in actual settings. The models undergo evaluation in relation to known performance indicators, including robustness, accuracy, and reliability. In order to confirm that the models fulfill the performance and safety requirements established by regulatory organizations, regulatory compliance is also checked.

F. Testing in MR environment

Validating MR results when using MR as a testing tool involves several key steps to ensure accuracy and reliability. Initially, MR environments can be used for pre-testing and

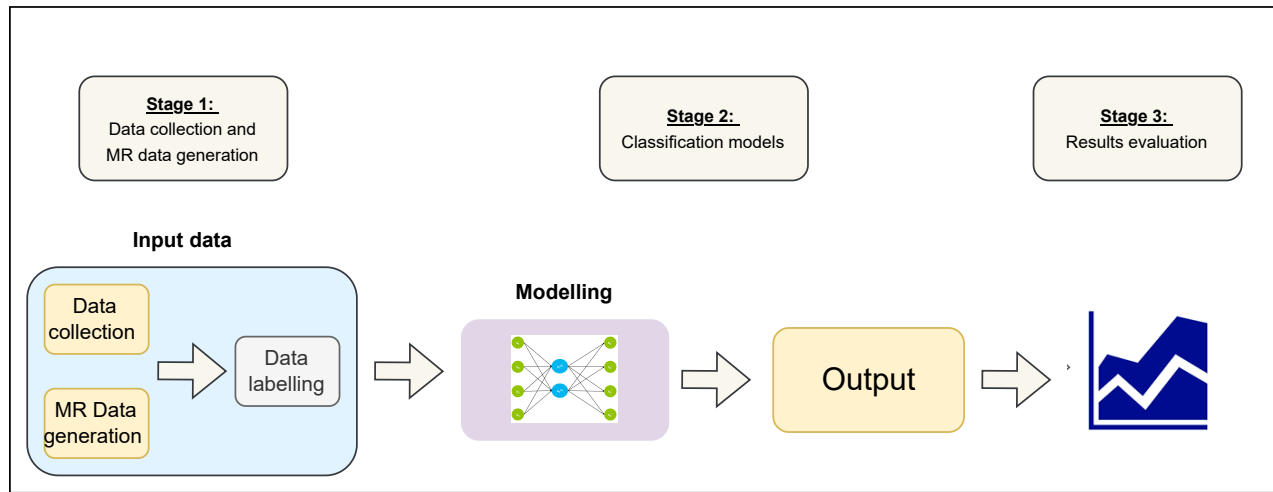


Fig. 11: Evaluation of models trained in MR generated data.

initial validation, where AV models are subjected to various simulated scenarios to identify and rectify potential issues early. This pre-testing phase helps save time and resources by addressing problems before real-world deployment. By benchmarking performance metrics from MR-based tests against real-world benchmarks, developers can fine-tune AV models to meet necessary standards. However, to fully trust the results of MR testing, it is crucial to perform final validation through traditional real-world testing. This step provides the ultimate confirmation of an AV model's performance, ensuring that it operates reliably under actual driving conditions. Real-world testing also verifies that the training and improvements made in the MR environment translate effectively to real-world scenarios. Additionally, real-world testing is essential for meeting regulatory requirements and obtaining safety certifications, demonstrating the AV system's capability to handle real-world complexities and adhere to safety standards. MR is not intended to replace traditional validation processes but to complement them. By combining MR with conventional testing, we can improve the thorough assessment of AV systems and take advantage of the advantages of both methodologies to create autonomous vehicles that are more reliable and safe. By using this complementary method, it is ensured that MR maintains the strict criteria needed for real-world deployment while also adding to the adaptability and dependability of AV systems.

VI. POTENTIAL CHALLENGES

While the adoption of MR frameworks for testing different aspects of ADAS is expanding, it is important to understand that this approach is not without its share of technical challenges. Specifically, MR is instrumental in simulating complex driving environments that test the responsiveness and effectiveness of ADAS under varied conditions, thereby bridging the gap between virtual simulations and real-world unpredictability. This section will examine three main challenges, extracted from the literature, in an effort to identify key areas that require careful consideration and resolution.

A. Digital twinning

The vital role of the digital twin within the mixed reality framework has been emphasized in Section III-D. A digital twin must accurately reflect the real counterpart's visual and functional characteristics. But this replication goes beyond just the design; it demands an accurate imitation of the physical characteristics such as mass, inertia, material properties, friction and contact models, etc. Fortunately, present simulators make it easier to mimic the physical characteristics of robots or vehicles through Unified Robot Description Format (URDF) files for example². The digital twin can be created by fusing data from multiple sensors and processing elements on the vehicle and road side infrastructure. It is important to estimate the state of the vehicle in the digital twin, thus using Kalman filter is a common approach to estimate and synchronize the vehicle's state in real time [91]. However, creating a strong digital twin architecture poses a variety of complex problems. This design must show that it can control the complicated interactions between various parts of the physical system as well as the external environment. Additionally, it must demonstrate the ability to continuously update in real-time, properly reflecting changes made to the physical system [6]. Assessing the accuracy of pose estimations and velocity estimations for both the physical and virtual counterparts is critical for ensuring the effectiveness of the digital twin. The use of OptiTrack technology has been suggested as a worthwhile strategy for carrying out this evaluation [53]. Even if Optitracks have proved their efficiency, low latency and high accuracy [92], they are typically installed in fixed locations. This limits their portability and may not be suitable for applications that require tracking in various environments.

B. Time delay

Potential technical restrictions in a MR framework intended for autonomous driving are mostly caused by time delays

²<http://wiki.ros.org/urdf>

inside the system. The operation of the system is impacted in numerous ways by these delays [29]:

- **Components of time delay:** There are three main factors that influence the system’s overall time delay. These include the processing time for data, the updating of world pose data from ROS to the simulator, and the time it takes for messages to travel from the Robot Operating System (ROS) to the simulator.
- **Lag in the vehicle’s movements:** The introduction of a considerable lag is one notable effect of time delay. The agent’s movements and the simulation can be noticeably out of sync due to this lag. As a result, this asynchrony may jeopardize the system’s ability to produce accurate results.
- **Effect on control strategies:** Time delay has a significant impact on control strategy effectiveness beyond simple asynchrony. Effective control requires anticipating delays, making it a crucial element for improving system performance as a whole.
- **Jitter effects:** The difference in timing between messages, sometimes known as “jitter,” poses a further difficulty. Jitter can cause significant delay discrepancies between various queries. Therefore, the accuracy, effectiveness, and overall consistency of the system may be compromised by these differences in time delay.

Thus, it is important for researchers to address the issue of time delay, and test different solutions. For instance, ROS 2 has proved to improve real-time support and better timing precision compared to ROS 1 [93]. ROS 2 offers the advantage of reducing communication delays by enabling direct communication between nodes, eliminating the necessity for a ROS master intermediary.

C. Validation methods

While designing the architecture and implementing Mixed Reality (MR) frameworks has been the focus of a significant amount of previous research in the area, this first stage is only one of the validation procedures. A thorough validation procedure necessitates a broader viewpoint and a careful analysis of sensor model precision. The precision and accuracy of sensor models are a fundamental presumption in many MR frameworks. But when the objective is to thoroughly validate the entire process, presuming their accuracy is not enough. It is crucial to turn our attention to understanding how potential measurement inaccuracies in actor poses—including those of vehicles, pedestrians, and other actors—can spread across the entire system and inevitably affect evaluation outcomes. It becomes required to carefully examine each component of the processing chain in order to get a thorough validation. This necessitates a detailed analysis of sensor models and their ability to accurately represent real-world data [40]. Researchers may develop a more reliable validation framework that accurately reflects the performance and dependability of MR systems by diving into the specifics of sensor model behavior and their sensitivity to measurement mistakes.

VII. RESEARCH AVENUES

A. Domain Adaptation

The complexity and unpredictability of real-world driving conditions make safety one of the biggest challenges in the implementation of autonomous driving technology. AVs must be able to handle a wide range of scenarios, from normal daily traffic to extreme weather, unpredictable pedestrian behavior and unanticipated road obstacles. For this matter, simulators are essential for addressing this challenge by offering a controlled, risk-free environment for testing and validation. However, the gap between the simulated conditions and real-world scenarios is an ongoing issue despite the fact that most research on autonomous driving is conducted using simulators [94]. Addressing the reality gap is crucial for the safe deployment of AVs. There are different approaches proposed in the literature to bridge the gap between simulation and reality. A common approach is domain adaptation, a machine learning technique that aims to reduce the disparity between the source and target domains, however, it should be mentioned that domain adaptation is not without its challenges (discrepancy between domains, limited labeled data, scalability, etc.) [95]. In this context, MR can be a useful tool to address these challenges and facilitate domain adaptation. Since MR can provide a realistic rendering of virtual content [96], it can be used as a tool to create diverse scenarios, including variable weather conditions, different road kinds and traffic circumstances. The obstacle of having a limited data diversity in domain adaptation would be reduced by the diversity in the training data produced by MR. It is without saying that ensuring that both real and virtual elements within the MR environment should be detected and processed effectively in order to expand the diversity of training data. Past researches has applied object detection Faster R-CNN to images created by fusing real depth with virtual depth data from Gazebo simulators and demonstrated encouraging outcomes [97]. Indeed, the results has shown that the algorithm can detect both virtual and real elements within the MR environment. Despite the lack of quantifiable metrics to assess the effectiveness of object detection in these images, this avenue remains promising and calls for more investigation in order to produce a more diverse dataset for overcoming the low data variety issue in domain adaptation.

B. Training AI-based models in MR environments

The process of training and testing models comprises the training of autonomous vehicle AI models in simulated environments, followed by the transfer of these pre-trained models to real-world self-driving cars after fine-tuning the parameters of the models. Yet, this approach has some notable limitations. The model transfer process usually takes place offline and can be very time-consuming. In addition, real-time feedback and cooperation between the pre-trained and fine-tuned models - which are being taught in a variety of real-life scenario - are frequently lacking [98]. To address these issues, researchers and engineers might consider exploring ways to establish a more dynamic and feedback-driven training process for self-driving vehicles that will allow the fine-tuning model to con-

tinuously interact with real-life scenarios. The goal would be to reduce the time required for model adaptation and improve its capacity to adjust to a variety of real-world situations. A number of interesting opportunities and advantages are presented when MR testing is introduced as a viable method for training models. It might transform the development and testing of AVs by obtaining a dynamic and real-time feedback. While the AI model is being trained, it can actively interact with the simulated environment, receive data, and make immediate adjustments. Some researches tested these assumptions by training a robot in a multi-vehicle, multi-lane environment by using MR testing. Several results were observed after the training of the reinforcement learning model in this settings including the reduction of collisions with virtual and real obstacles compared to a model trained only in simulation and the improvement of reward collection [53]. Those results suggest that training models in MR environment can lead to improve performance and generalization compared to training only in simulation. MR training presents a promising avenue for improving the training of AI models, and constitutes a valuable path to explore for further validation of these findings.

C. Increasing complexity and realism

As researchers continue to explore MR for self-driving vehicles by building frameworks using different sensors and approaches, it is equally important to consider the next stages of framework development. This entails progressing toward more complicated scenarios by adding more complexity in the virtual environment and determining whether or not the system can handle them successfully. For instance, autonomous driving at intersections is a challenging issue due to the different types of participants (vehicles, motorcycles, bicycles, pedestrians, etc.), the intersection structures, and the conflict points at intersections [99]. For this purpose, MR testing can be employed to introduce other variances such as simulating dynamic traffic signals, temporal signs that change in real time, sudden road closures, and complex road topologies such as crossroad, X-intersection, roundabout, ramp merge, misaligned intersection, etc.. Another critical issue faced by the development of AVs is the poor performance of the driving system under adverse weather conditions such as rain, snow and fog. This is due to the fact that these weather conditions can cause significant degradation on the sensors, leading to inaccurate information and wrong decisions [100]. Regarding this challenge, the availability of simulation tools is essential. Virtual simulators enable researchers to create difficult road environments within scenarios that would be costly to replicate in real-world field experiments [101]. Nevertheless, these simulation systems remain restricted to virtual worlds while it can be conceivable to conduct tests directly in a real environment with adverse weather conditions without taking costly risks. The safer approach would be to introduce dynamic virtual obstacles in foggy or rainy conditions to train models and assess their robustness while respecting real-world safety. However, it's necessary to acknowledge that incorporating these additional layers of complications can be demanding. It requires the development of sophisticated simulation models

and the creation of realistic scenarios that push the boundaries of the self-driving system. Exploring this research avenue may contribute to the development of more resilient and adaptable self-driving systems.

D. Shared MR environments

An emerging technology that is attracting the attention of researchers more and more is V2X communication, which stands for Vehicle-to-Everything. V2X is a communication technology, that enables data interchange between vehicles and numerous environmental aspects including other vehicles (V2V), pedestrians (V2P), infrastructure (V2I), and networks (V2N). This technology is intended to improve traffic safety, reduce travel times, increase efficiency, reduce accident rates, and savings in fuel consumption [102]. One use case of V2V communication is for connected and automated vehicles to exchange information with other vehicles on the road in order to improve traffic stability and move in a coordinated and more efficient manner. However, CAVs will need to co-exist with traditional vehicles a mixed-traffic flow, which can be challenging [103]. MR testing can make it possible to safely and carefully evaluate CAVs in mixed-traffic conditions. This can be done by creating accurate simulations of complicated and dynamic traffic conditions involving the interaction of CAVs and human-driven vehicles. Therefore, developers can adjust their algorithms, control schemes, and optimization tactics. In this case, it is also conceivable to integrate traffic flow simulators (*e.g.*, SUMO, VISSIM, MATSim, etc.) with MR frameworks to simulate additional traffic vehicles and establish connections between the real vehicle and virtual ones. This integration can create a shared connected environment that will allow for comprehensive testing and evaluation of the vehicle's behavior. A prominent research study has examined V2X communication within MR environment [71]. In this study, the authors conducted real-life 5G-based V2X communication scenarios to demonstrate vehicular communication with 5G support using MR approach. These scenarios involved the exchange of sensor and control information among vehicles, their surrounding environment, and their digital twins. MR testing was employed on the purpose to enable the simulation of certain actionable triggers near the digital twins rather than being physically present around the vehicles while establishing the communication between the vehicle and the other actors of the experiments via 5G network ensuring near real-time connection. This approach allowed vehicles to respond to obstacles and traffic situations in both physical and simulated environment before the deployment in real-world environments. These are favorable outcomes, demonstrating the feasibility of employing MR testing even within complex and shared environments for evaluating diverse communication approaches in different scenarios.

VIII. CONCLUSION

In summary, this analysis has investigated the field of Mixed Reality (MR) testing for autonomous driving systems, highlighting a variety of uses, prospective advantages, and technological foundations. The review has examined the

existing state of the art, and shows how MR offers great potential to improve autonomous system development and testing. Although the study has identified areas of limitations that require additional investigation, it has also identified promising research directions that will drive this developing field forward. It is becoming increasingly noticeable that MR testing is key to improving the evaluation and improvement of self-driving technology as developments continue. The ability to simulate complex real-world scenarios and train autonomous systems more effectively is made possible by the immersive, interactive and adaptable characteristics of MR settings. Critical difficulties like domain adaptation, robustness in adverse conditions, and mixed-traffic integration will benefit significantly from these features. Future research on the cost-effectiveness of MR technology in comparison to conventional testing methods is one promising area. It can provide valuable insights into the economic benefits and cost savings associated with MR technology. This includes an analysis of initial investments, operating costs, and long-term savings. Self-driving car development, validation, and deployment are made safer and more effective with the help of MR testing, which acts as a link between the virtual and real worlds.

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IX. BIOGRAPHY SECTION