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An Augmented Reality-Based Proving Ground Vehicle-in-the-Loop Test Platform

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Abstract. One of the biggest challenges in validating the electronic equipment of vehicles is finding suitable methods for virtual testing and simulating real-world scenarios as accurately as possible. Although computer simulations are safe and reproducible, there are significant simulation-to-reality gaps, making safety testing within simulations unreliable. Due to the lack of Precise sensor and traffic models, The data generated through simulation appears to be relatively realistic, still cannot replicate all the details of the real world. In this study, we propose to construct a secure and reliable assessment and validation platform by leveraging the combination of augmented reality technology and vehicle-in-the-loop simulation technique, which is called augmented reality-based proving ground vehicle-in-the-loop test platform. The method aims to combine real-world and virtual testing, making it easier and safer to test autonomous vehicles in critical scenarios while optimizing the validation process. Our proposed system offers an improved approach by combining simulated sensor data with real sensor data collect to generate augmented reality scenario data, which include AR based BUS sensor, AR based camera and AR based Lidar, providing more precise data support for the perception and decision-making processes of autonomous vehicles. In summary, the above-mentioned method provides a more comprehensive and accurate way of simulating scenarios, which can help improve the performance and safety of autonomous vehicles in the real world. Finally, we demonstrate the broader implications that such a simulation paradigm may have for autonomy, specifically showing how realistic sensor simulation can improve perception performance.

Keywords. Vehicle-in-the-loop, augmented reality, simulation, testing, intelligent connected vehicles

1. Introduction

The commercialization of self-driving cars requires two processes: development and testing validation. If road testing is solely relied upon, it is not only time-consuming and costly, but also puts others' safety at risk[1]. Simulating virtual environments[2] that emulate the real world for training or testing self-driving systems can increase efficiency[3] (allowing for continuous testing day and night) and achieve better testing

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results (as all testing scenarios are highly controlled and repeatable). It also provides startups with a fair chance to compete against large automakers and technology giants who cannot afford the lengthy and expensive road tests approach. However, virtual environments[4] are not physical reality, and it is essential to consider whether the self-driving systems developed in these environments can effectively handle the real-world physical environment[5]. Otherwise, it could result in ineffective development and testing. With the continuous development of AI and intelligent agents' learning capabilities regarding traffic scenes, some engineers believe that learning from errors occurring in virtual reality rather than on real roads might lead to better, faster, and safer training of intelligent agents. Companies such as Toyota, Uber, and Waymo have discussed in detail how they test self-driving cars on roads in cities such as Mountain View, Phoenix, and others. However, what is less known is that they also test vehicles in these cities' virtual reality environments[6].

The market for advanced driver assistance systems (ADAS) and autonomous driving technology is experiencing rapid growth. Due to the complexity of automotive control systems and the precise interaction between various electronic control units and actuators, accurate statements regarding quality and safety can only be achieved through real driving tests. However, as there is a high risk of collisions, many testing scenarios cannot be executed in reality. therefore, real open-road driving testing is not entirely applicable to ADAS/AD function validation. In addition to testing reliability and passenger safety, autonomous vehicles must be able to prevent and avoid collision accidents, which requires testing numerous collision accidents, even rare accidents that rarely occur in traditional cars, to verify the reliability and safety of autonomous driving. This requires the development of new, effective, economical, and safety-oriented testing methods for such situations. The test methods[7] based on the model-in-the-loop (MIL), software-in-the-loop (SIL), hardware-in-the-loop (HIL) and vehicle-in-the-loop (VIL)[8] have proved feasible and effective in vehicle function development and verification.

In this article, we propose an augmented reality based VIL testing method that combines the real world with virtual scenarios, which combines the realism of real road driving testing, the integration depth and flexibility of HIL methods, and the almost infinite possibility of collision testing. This combination is often referred to as augmented reality or mixed reality[9], especially in terms of visual perception. Perception also plays a crucial role in testing ADAS/AD functions, which receive signals from radar, lidar, and camera sensors. Therefore, it is feasible to use sensors to implement extended testing. It can be said that the VIL testing method covers the behavior of specific vehicles, enhances the well-known advantages of HIL, and provides new validation options for ADAS/AD control units with a high degree of realism.

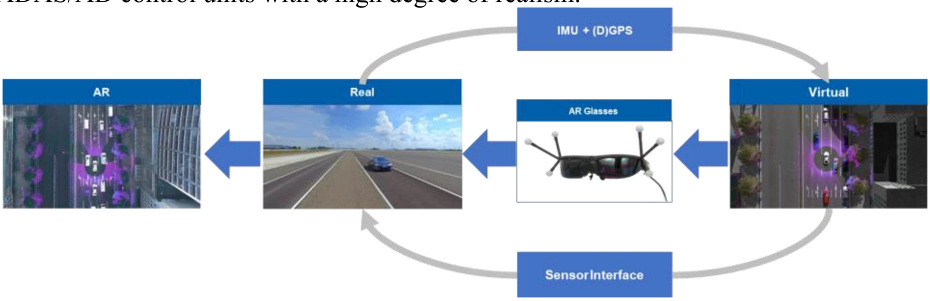


Figure 1. Augmented reality diagram for testing autonomous vehicles. The processed sensor information in the image is a combination of real and virtual objects. The vehicle drives in the real environment and virtual obstacles are added to the real environment.

However, traditional VIL on proving ground[10][11] or test beds[2][12] still uses the method of pure virtual perception injection, lacking consideration for the complexity of the real-world environment, such as the influence of factors like clutter, noise, temperature, weather, etc. on sensors, and many key physical factors cannot be modeled and reproduced in simulations. This requires the use of AR technology[13] to improve traditional VIL testing. As shown in Figure 1, it incorporates virtual information while retaining the perception of the real environment. AR technology can increase the testing speed of connected and autonomous vehicles by 1,000 to 100,000 times and reduce the extra testing costs to almost zero[14]. There are many research papers on related AR testing methods[15][16], but most of them lack engineering feasibility and practical implementation. This article focuses on the research and application of system real-time performance and practical engineering applications.

In this article, we propose an AR based lidar simulation model that augments real point clouds using synthetic virtual obstacles such as vehicles, pedestrians, and other movable objects. A vehicle equipped with a lidar can be easily deployed to scan interesting streets to obtain background point clouds, which can then generate annotated point clouds automatically.

We also propose an AR based camera simulation model in this article, which is a geometric calibration and image synthesis process that augments real images by extracting dynamic virtual objects from simulation scenarios. A vehicle equipped with a camera can be easily deployed to capture real background, which can then generate annotated objects and lane automatically.

Based on the sensor simulation models mentioned above, this article integrates an augmented reality-based vehicle-in-the-loop testing platform, and ADAS/AD functions validation has been achieved on this platform.

2. Methodology

2.1. AR based VIL on proving ground

The VIL on test beds refers to the use of the entire vehicle turntable to integrate the real vehicle into the simulation scenario. Since the vehicle is fixed on the turntable, the vehicle dynamics still need to be simulated by the dynamic simulation software Carmaker, while VTD simultaneously simulates the traffic scenario, forming a closed-loop simulation test that combines virtual and real elements.

The VIL on proving ground refers to the joint simulation test between a real vehicle and a virtual scenario, mainly traffic, in a closed field. In the VIL on proving ground, the user does not need to perform detailed modeling and parameterization of the vehicle dynamics or simulate the driver model but can use a real driver or driving robot. The Carmaker simulation model is run through the on-board real-time system installed on the tested vehicle. The virtual road is completely matched with the real road, and the real-time positioning of the vehicle is synchronized to the virtual scenario through the GPS and IMU mounted onboard, while the traffic object set in the virtual scenarios is injected into the ECU through sensor model to make corresponding control decisions, thus forming a highly integrated testing solution.

The augmented reality vehicle-in-the-loop simulation test platform constructed in this paper belongs to the VIL on proving ground. The overall structure mainly consists of three parts: the traffic simulation scenario, the autonomous driving control system, and the physical vehicle on proving ground. The required simulation scenario for the development test is built based on VTD, including a complex virtual scenario simulation of vehicles, pedestrians, traffic signs, road markings, roadside surroundings, and buildings. The digital twin vehicle in the simulation scenario collects the virtual scenario data through sensor models. We fuse the simulated sensor data with real sensor data through AR fusion software, then send the data to the controller of the test vehicle for perception fusion and control decision-making. The vehicle control commands generated are sent to the chassis actuator of the physical vehicle via the bus. After responding appropriately on the real road, the vehicle posture and position information are sent to the digital twin vehicle in the simulation world to complete the vehicle position and time synchronization, thus achieving real-time closed-loop simulation of the entire system.

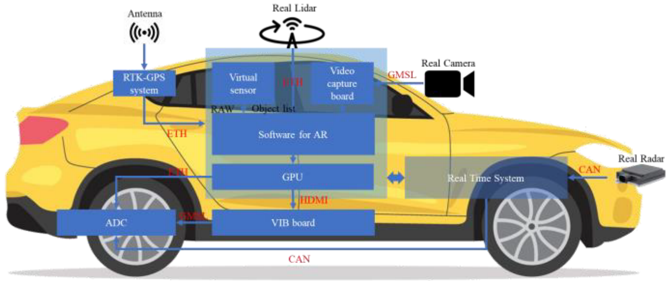


Figure 2. System architecture of augmented reality-based proving ground vehicle-in-the-loop test platform.

As shown in Figure 2, the test equipment includes a real-time machine installed in the trunk of the test vehicle, a graphic workstation, and injection devices. Both the virtual ego car and the physical ego car are equipped with the same sensors, mainly including radar, GPS, lidar, and cameras. The simulation process is synchronized with the real vehicle through IMU and GNSS. Real sensor data is collected via CAN-BUS, Ethernet or GSML and then fused with virtual data through AR software. Finally, the augmented data is injected into the domain controller through VIB devices and ETH conversion boxes. The bus-class sensor data need to be directly sent to the bus through the real-time machine card to complete the virtual-real data fusion at the bus level.

Therefore, a complete VIL system needs to enhance the simulation for both object list level and raw data level, and the following section introduces the augmented reality design methods for object list level sensor and raw data level sensor through BUS, GMSL, and ETH. To perform real sensor simulation, it is necessary to prepare a bus system such as CAN, CAN FD, FlexRay, LIN, or Ethernet to exchange signals and communicate with the car network. Furthermore, the sensor model must be connected to the tested device via an interface to receive data injections for simulation tests, and high-performance FPGAs can synchronize the raw sensor data, target list, and/or object list inputs to the sensor ECU.

2.2. AR based BUS Sensor

The ideal ground truth/probabilistic sensor model is a technology-independent model primarily used for object list injection, i.e., for detecting three-dimensional/two-dimensional sensors such as traffic lights, traffic signs, road objects, lanes, obstacles, pedestrians, etc. This type of model is used to check whether an object can be detected within a set range.

In sensor simulation experiments, this type of sensor model provides ideal data that can be arbitrarily added to the probability of real sensor events. For example, superimposing typical measurement noise of real radar for augmentation. The simulation returns a list of classified objects (vehicles, pedestrians, cyclists, traffic signs, etc.) along with their coordinates and motion data (distance, relative speed, relative acceleration, relative azimuth, and elevation angle).

2.3. AR based Camera

An AR-based camera can overlay virtual entities, such as virtual pedestrian, obstacles, and oncoming vehicles, rendered by a virtual rendering engine onto the real-world scene ahead, while ensuring that the test vehicle actually drives on proving ground. The actual road for this system is generally a dynamic square or an open road. When the actual vehicle runs on a dynamic square, the lane lines and objects in the simulation scenario need to be extracted at the mean time. When the real vehicle runs on an open road, the real road scenario needs to be collected, transformed, and imported, typically in the OpenDRIVE format, and the virtual camera model needs to be calibrated to ensure consistency with the inner and outer parameters of the real camera. This ensures that the virtual road surface in the camera's view overlaps with the real road surface's location, enabling virtual objects to be extracted from the simulation scenario and placed accurately in the real camera's FOV. The GPS uses the RTK-GPS (real-time kinematic - GPS) method, which improves accuracy by using correction signals sent out from benchmark points in addition to satellite signals. The graphics rendering system does not need to display the entire scene or analyze a significant amount of positioning data and scene information through algorithms to ensure that virtual objects can be precisely positioned in the real scenario. Instead, only precise modeling of the camera model is needed to ensure a corresponding relationship between the target positions in the twin scenes, thus ensuring the real-time performance of the entire system. As shown in Figure 3, the system generally includes the following three basic steps:

- obtaining real scenario information.
- generating virtual objects.
- merging video and injecting.

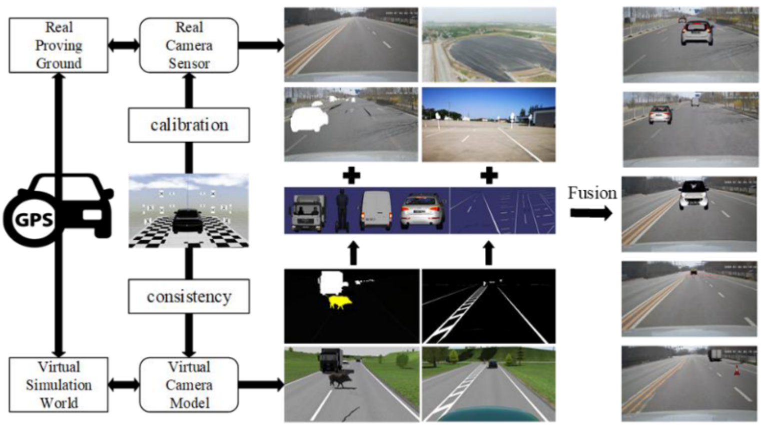


Figure 3. AR-based camera fusion method.

In other words, the graphics system first calculates the affine transformation that maps virtual object coordinates to the camera view plane based on the camera's position information and the positioning markers in the real scene. Then, it draws the virtual objects on the view plane based on the affine transformation matrix and, finally, directly injects the merged video into the domain controller through injection devices. In an AR-based camera system, imaging devices, tracking and positioning technology, and interaction technology are the fundamental technical support for implementing a graphics system, from camera image input to composite video injection, with a delay time of approximately 100ms.

2.4. AR based Lidar

Ray tracing technology is typically used to detect objects by tracing the reflection paths of radar signals, lidar signals, or electromagnetic waves. This involves sending a beam of light into a three-dimensional scene and capturing their reflections. In this process, physical effects such as multipath transmission can be integrated into the modeling process. The final critical step is to perform accurate physical simulation of the propagation of radar waves or near-infrared laser beams to ensure the accuracy and reality of the data. A large amount of data including reflection points, angles, distances, doppler velocity, diffuse scattering, and multipath propagation is collected and processed, then the distance between the vehicle and obstacles is calculated, and the surrounding environment is displayed in a certain way, such as point clouds. Through the above method, simulation of real sensors can be achieved, and engineers can validate sensor models by reproducing the behaviors of sensor paths.

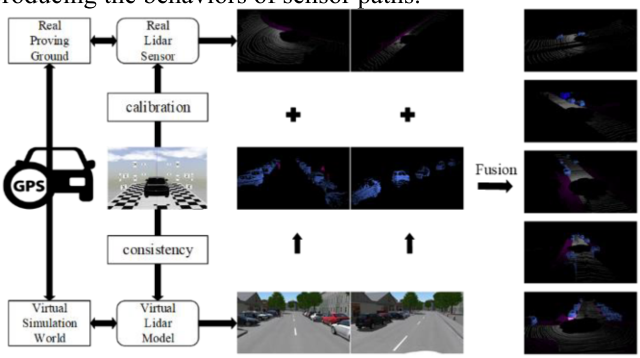


Figure 4. AR-based Lidar fusion method

Since the experiments were conducted on open roads or squares, it is assumed that there are no objects in the road location where the real sensor collects data. As shown in Figure 4, the method proposed in this paper for AR-based Lidar includes the following steps: First, receiving raw point cloud data captured by the real lidar on the vehicle, and then positioning the available space in the original point cloud data according to the virtual point cloud target positions. Second, placing an obstacle model in the available space, and simulating the point cloud data by modeling the lidar sensor of the obstacle model and adding it to the original point cloud data to obtain an augmented point cloud data. Additionally, the following steps are also included: calculating the points in the original point cloud data that are occluded and placing the obstacle model at the occluded points, and deleting the occluded points from the point cloud data. These occluded points refer to the points in the original point cloud data that are obstructed or occluded by other objects, which may affect the perception and decision-making of autonomous vehicles. By identifying and deleting these occluded points, the surrounding environment of the autonomous vehicle can be simulated more accurately, and the accuracy and safety of the autonomous vehicle in perception and decision-making can be improved.

3. Experiment

AR based VIL testing is conducted in the test field with sufficient unobstructed test space. The driver and co-driver sit inside the physical vehicle, while the test device is placed in the trunk. During testing, the vehicle drives on the test field road, and the co-driver initiates the test scenario, where virtual sensor data is fused with real sensors and input into ADAS/AD control units. For example, test scenarios may include obstacles, pedestrians at intersections or on roads, etc., which cannot be fully tested in the real world due to the high risk of dangerous collisions or the difficulty in analyzing collision-related indicators (collision points, collision speed). The generation of test scenarios is derived from industry-recognized testing standards such as the Euro-NCAP[17] test system and dedicated test cases used to validate special functions. AEB (Autonomous Emergency Braking) and other related scenarios are used to test currently implemented ADAS solutions. This study has already validated ADAS in the laboratory using multiple VTD-IPG HIL systems. The test scenarios developed for this purpose can be easily applied to vehicle VIL testing due to the high consistency of the VTD-IPG toolchain.

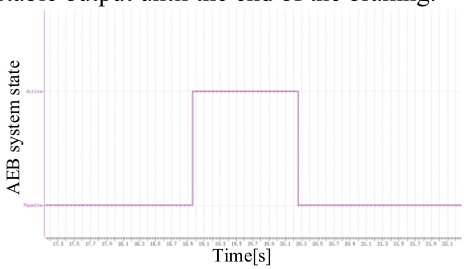
Figure 5. System hardware configuration

Due to the high power consumption of graphic workstations and real-time machines, two generators with a rated power of 1.6 KVA (as shown in Figure 5) were installed behind the vehicle. In addition, to account for the possibility of generator failure, an uninterruptible power supply (UPS) was equipped in the luggage compartment. To ensure the safety of the test personnel, a brake was installed on the passenger side similar to that of a driving instructor's car. The testing site also had uniform specifications, requiring testing to be done on concrete or asphalt roads longer than 800 m, with smooth, dry, and good adhesion road surface conditions, and the environmental temperature during testing should be between 0~45 ℃, with wind speed not affecting the normal conduct of the test and good horizontal visibility.

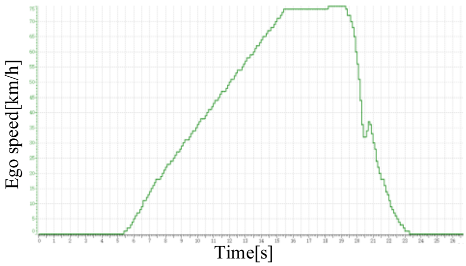
In this study, common driving scenarios were used to define AEB maneuvers. The scenario consisted of an ego vehicle and a target vehicle. The ego vehicle was traveling at a constant speed on a straight lane, while the target vehicle was stationary or suddenly decelerates. Therefore, the ego vehicle needed to decelerate to avoid colliding with the target vehicle. Ego vehicle was equipped with onboard sensors and injected with virtual sensors that can perceive the surrounding environment during driving. When the ego vehicle senses the target vehicle, it conducts a risk assessment and, if necessary, emergency braking to avoid a traffic accident. The verification experiments were conducted using the augmented reality-based proving ground vehicle-in-the-loop test platform constructed in this study.

Before starting the static test, the target vehicle should be stationary in the same lane as the test vehicle. To ensure that the test vehicle could identify obstacles within a normal range, relevant standards specifies that the distance between the centerlines of the two vehicles should be <0.5 m. In order to give the ego vehicle sufficient time to detect the target vehicle, the two vehicles should maintain a longitudinal distance >120 m before the start of the test. During the formal test, the driver drives the ego vehicle at a constant speed of (75±2) km/h in a straight line towards the stationary target vehicle. To eliminate human interference factors, relevant standard stipulates that during the test period, no adjustments can be made to the vehicle except for slight directional corrections. The AEB system should be able to detect obstacles ahead and take braking action at the appropriate stage to mitigate collisions. The test is considered over when the test vehicle comes into contact with the target vehicle or when the ego vehicle's speed is 0.

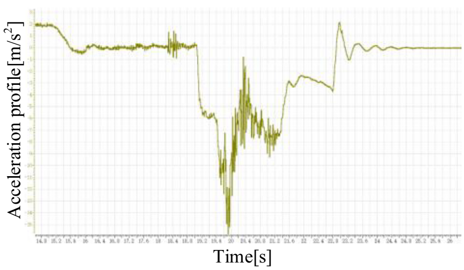
At the initial time, the preceding vehicle was stationary, and the relative distance from the ego vehicle was 150 m. The ego vehicle was located in an open test area, accelerated to a speed of (75±2) km/h, and maintained a constant speed. Data recording began when the speed stabilized. As shown in Figure 6, when the vehicle was driving normally, a=0, and the driver's normal driving was not disturbed. After the ego vehicle started braking, the relative speed curve changed smoothly, and both speeds were reduced to 0 in a timely manner. The reduction in speed curve output was smooth, and oscillation was minimal. The relative longitudinal distance curves all showed no collision with the target vehicle ($\Delta s \neq 0$). The warning system correctly issued the warning signal and braking signal, and during the braking process, the braking signal could maintain a stable output until the end of the braking.



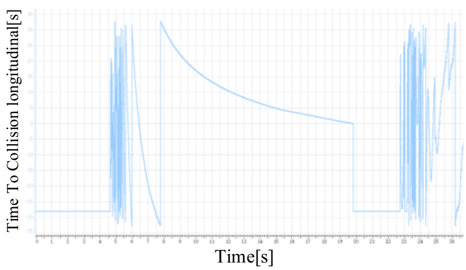
(a). AEB system state



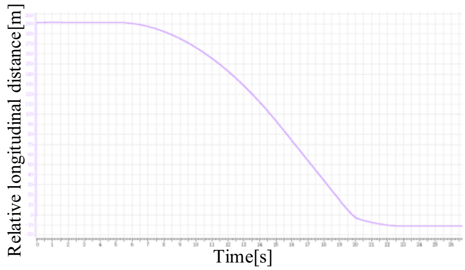
(b). Ego speed



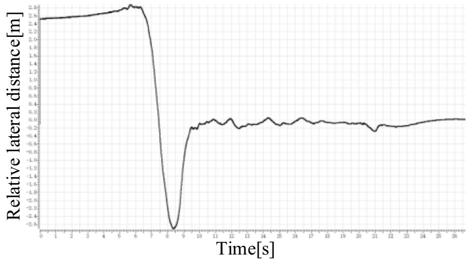
(c). Acceleration profile



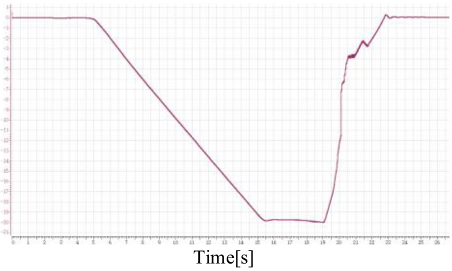
(d). Time to collision longitudinal



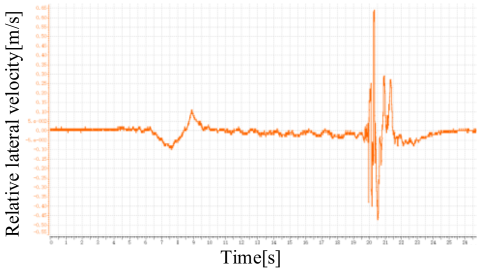
(e). Relative longitudinal distance



(f). Relative lateral distance



(g). Relative longitudinal velocity



(h). Relative lateral velocity

Figure 6. Analysis of AEB test results

The AEB test results based on AR based VIL have a high similarity to the results of real road tests. These results confirm that the AR based VIL simulation platform we proposed has great potential to replace real road tests, at least in terms of AEB testing.

4. Conclusions

The use of augmented reality testing shows great potential in accelerating the testing process and reducing the cost of testing for autonomous driving vehicles. Testers can create a scenario library containing all test cases generated by computers and conduct risk-free, non-damaging, injury-free, and endless repeat experiments to help developers improve hardware and software component functionality. The AR-based testing process helps ensure manufacturers, suppliers, and consumers that rapidly developing autonomous driving vehicles will be reliable, safe, and trustworthy.

In this paper, in order to construct a new paradigm for autonomous driving testing that is safer and more realistic, we established an augmented reality-based proving ground vehicle-in-the-loop test platform. We further showed how to use this AR system to enhance perception capabilities and verify autonomous driving safety. We believe that the proposed AR-based VIL paradigm will influence a large number of research works in the fields of autonomous driving, robotics, and intelligent transportation.

Through research and simulated implementation based on our platform, we draw the following conclusions:

- In theory, the augmented reality-based proving ground vehicle-in-the-loop test platform is feasible for autonomous driving vehicle testing, but there may be engineering problems in the construction of the actual testing platform.

- The AR based VIL platform can not only provide a rich testing environment, hazardous scenarios, and complex scenes that are difficult to reproduce for replicability testing, but also can access the motion state of physical vehicles traveling on real roads.

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