1. Introduction

1.1. Autonomous Vehicles

Transportation has played an important role in the human history, evolving from the invention of the rotary wheel to the modern road cars. The invention of fuel engines in the last century marked a significant revolution, impacting faster goods transportation and extending to civilian life with the introduction of road cars. This period also witnessed the development of proper road infrastructures to accommodate the advancements in vehicle performance.

The fourth industrial revolution mark a start of new era where intelligent systems-controlled machines are developed which reduces the manual errors and enhancing performance. The automotive industry is also undergone this transformation with various intelligent driver assistance systems like Advanced Driver Assistance Systems (ADAS) which not only reducing human effort in driving but also ensuring safety. Engineers and scientists globally are working to enhance the capabilities of intelligent systems, aiming for complete autonomous driving, eliminating the need for human guidance.

The concept of autonomous driving dates back to 1926, with the development of a radio-controlled car in New York City. In 1960s, the Transport and Road Research Laboratory in the United Kingdom laid magnetic cables beneath the road, serving as a path detection tool for self-driving cars and tested its performance. Later, in 1995 Mercedes Benz achieved a significant milestone with the development of first self-sufficient autonomous vehicle, a retrofitted Mercedes S class equipped with efficient cameras and exclusive processors for parallel computing. This vehicle reached a maximum speed of 175 kmph, covering 1500 kms from Munich, Germany, to Copenhagen, Denmark, performing various manoeuvres in traffic without human assistance. In the late 2000s, carmakers like Toyota and Volvo, along with tech companies such as Google and Waymo, developed their prototypes of Autonomous Vehicles (AVs).

The parallel advancements in the field of Artificial Intelligence and efficient hardware accelerated research in self-driving technology. Notably, improvements in cameras and GPUs facilitated fast and efficient processing, while intelligent algorithms like neural networks laid the foundation for Autonomous Vehicles (AVs). In 2014, Tesla Motors launched Model S, a semi-autonomous driving car. This vehicle featured a various assistance feature, including lane detection, autonomous braking and parking, and speed limit recognition using computer vision. Tesla's entry into functional semi-autonomous driving represented a notable advancement in the field. During the same year, the Society of Automotive Engineers (SAE) had drafted a 6-level taxonomy for autonomous driving. This framework provided a standardized and structured classification system for assessing the level of autonomy in vehicles. Recognizing the growing impact of autonomous driving, several countries, including the United States of America, the United Kingdom, and Japan, made decisions to formulate laws addressing autonomous driving in the next few years. Various leading car manufacturers, including Mercedes Benz, BMW, and Volvo, have introduced their commercial fully or semi-autonomous production vehicles. They are continually enhancing their automation levels, as classified by the Society of Automotive Engineers (SAE). For instance, in 2022, Mercedes Benz achieved SAE Level 3 automation with its S-Class and EQS models, equipped with advanced driving technologies like an automated lane-keeping system. However, Tesla Motors has been a leader in this field, showcasing superior performance.

The SAE J3016 classifies autonomous vehicles into six levels, ranging from fully manual driving to fully automated systems [1].

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| Level 0 | No driving automation | This level involves no driving assistance system, and the entire driving process is manually controlled. |
| Level 1 | Driver assistance | Vehicles at this level feature a single automated system under the driver's supervision. |
| Level 2 | Partial driving automation | Multiple automated systems, such as automated steering and braking, work simultaneously under the driver's attention. The driver must be ready to take control at any moment. |
| Level 3 | Conditional driving automation | This level involves a system with an intelligent algorithm capable of making decisions like overtaking navigation. However, human attention is still required. |
| Level 4 | High driving automation | At this level, the vehicle can make optimistic decisions in the event of a failure, reducing the need for human interaction. This level is often suitable for confined areas or regions |
| Level 5 | Full driving automation | Here, the vehicle can perform all driving tasks without human interaction, comparable to an experienced human driver. |

Table1: Levels of driving automation defined in SAE J3016

Driverless vehicles find applications not only in passenger cars but also across various areas like shuttling people on campuses, moving goods in warehouses, and in military operations. Especially in industries, these automated machines could transport goods across the premises which save time and minimize human error. However, ensuring their safety of operation is crucial especially when it comes to road cars. Governments worldwide are creating regulations for autonomous mobility. Moreover, vehicle manufacturers are enhancing hardware and software while conducting extensive testing to ensure safety and prevent failures.

1.2. Simulators

Simulators imitate real-world systems, replicating their dynamics and features. They come in different types: software, hardware, or a mix of both. These systems replicate various functions, interacting with users, taking inputs, and providing feedback to the users. For example, driving simulators create visual environments and hardware setup for driver training and testing, Which takes control commands from users and update their states. Simulators can be classified based on various features Some of the examples are

Based on Time

Discrete Event Simulation: Each step happens at distinct intervals, which are mapped to specific durations. Driving simulators fall into this category, where observation states change at each step. The time duration of a single time step is defined by required precision.

Continuous Simulation: In this type of simulation, time moves continuously without distinct steps, backed by differential equations. These are useful for modelling continuous events like microbe growth in biology.

Based on Stochasticity:

Stochastic Simulation: This type of simulation introduces a controlled amount of randomness within sensible limits in the parameters. It's helpful for studying systems with random noise, like analysing daily usage patterns on a social media site.

Deterministic Simulation: These systems operate using deterministic algorithms without any randomness. They're commonly applied in engineering. The outcomes of these simulations remain consistent and reproducible for a specific set of parameters.

Users can tweak these parameters to test and tune the results of the system. Usually, simulations help to find the optimal parameters and it have diverse applications, for events spanning millions of years to nanoseconds. Simulations play a vital role in result analysis, safety engineering, and design processes. They save significant time during testing and can enhance the testing outcomes. For instance, testing the driving of an autonomous car for 10,000 km in the real world demands a lot of time and resources, whereas using a simulator significantly reduces this timeframe. However, there's often a discrepancy between the real world and simulations, which might lead to errors in analysis. In fields like machine learning and robotics, it contributes a crucial role. One of the three paradigm of Machine learning is reinforcement learning where a virtual agent within a simulator takes diverse actions under various conditions and learns from the feedback provided. In robotics, algorithm which drives the robots are trained using simulation for tasks like localization, pick and place, faulty detection…

1.3 Problem Statement

1.3.1 Lack of system of comparison

In the growing domain of autonomous vehicle research, simulator plays a significant role in the process of development such as algorithm training, performance evaluation across diverse environments and comparison of method. There are numerous simulators, varying in types and functionalities, available in the community for direct or indirect use in research works. In addition, the domain of self-driving vehicle research itself is broad, includes distinct applications such as indoor robots, industrial autonomous vehicles (AVs), on-road vehicles, and semi-autonomous vehicles. Each application requires a unique simulator tailored to its specific requirements.

The challenge arises due to the diversity among these simulators and their requirements, each comes with its own set of advantages, features, and limitations. Consequently, comparing and selecting the most suitable simulator becomes a complex task. For instance, a simulator might perform well in numerous aspects, yet fail to simulate a crucial sensor required by a user, making it unsuitable for that specific application. Conversely, another simulator might lack certain features but could be better suited for the user.

The aim of this thesis is to establish a concrete set of metrics for comparison purposes. The proposed metric will be generic and adaptable to individual user preferences. Users will have the flexibility to adjust the importance of criteria based on their requirements and they are universally applicable across all types of autonomous vehicle simulators. Through this systematic approach, users could able to assign personalized ratings to simulators, facilitating informed decision-making in selecting the most suitable simulator according to their preferences and needs.

1.3.2 Simulators Based on Generative AI

Generative AI had gained momentum in recent years, continuously improving its performance. This field primarily uses deep neural networks, trained on any provided data, learning its distribution. These trained models can generate novel, meaningful data samples which are not present in the training set but similar to it.

In the domain of autonomous vehicle simulators, rendering new scenarios and environments is a one of its objectives. This feature enhances its suitability for algorithm testing across diverse environments, potentially improving the model’s performance. It’s also important that these new scenarios closely resemble real-world features while being meaningful and plausible.

Sensors in Autonomous cars play a important role in understanding the real world where the vehicle navigates. These vehicles utilize data from various of sensors such as cameras, LiDAR, and radar to perceive their surroundings. The second part of this thesis aims to design and develop a simulator driven by a Generative AI model trained on real-world sensory data. The expected outcome is the generation of new, meaningful sensory data can effectively represent diverse and realistic environments. The simulator will operate on discrete time steps, ensuring that the generated data remains relative to preceding time steps.

List of figures

List of Tables

Table1: Levels of driving automation defined in SAE J3016

References

[1] https://www.sae.org/news/2019/01/sae-updates-j3016-automated-driving-graphic