When do humans in VR take over Autonomous car in off-road conditions? An IRB.

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***Abstract*—As autonomous vehicles become more prevalent, their performance in complex off-road conditions remains a critical area of research. Off-road environments present unique challenges, including unpredictable terrain, obstacles, and environmental factors such as weather and wildlife, which can exceed the capabilities of current autonomous systems. This study investigates human decision making in off-road scenarios, focusing on the conditions under which individuals override autonomous systems and resume manual control. Using the CARLA driving simulator integrated with virtual reality (VR) technology, participants were immersed in realistic off-road environments designed to mimic real-world conditions. The study analyzes key factors influencing human intervention, including terrain complexity, vehicle behavior, and environmental dynamics. By systematically observing these interactions, we aim to identify patterns in decision making and the specific triggers that lead to human takeovers. The research also compares human reactions in VR simulations with expected behaviors in real-world scenarios, bridging the gap between experimental and practical applications. The insights gained from this study will contribute to the development of autonomous systems that are better equipped to handle off-road conditions by incorporating adaptive features and enhanced user interfaces. This work ultimately seeks to improve the reliability and safety of autonomous vehicles in non-ideal environments.**

***Index Terms*—Autonomous Vehicles, Off-Road Driving, Human-Computer Interaction, Virtual Reality Simulation, Decision-Making Analysis**

I. INTRODUCTION

Recent advancements in deep neural networks have revolutionized the landscape of self-driving cars, enabling systems to process and interpret complex data with remarkable accuracy [1]. These networks excel at analyzing inputs such as images, identifying patterns, and extracting meaningful insights to facilitate decision-making. Research in autonomous driving typically follows two primary methodologies: modular systems and end-to-end approaches. Modular systems divide the driving process into distinct stages, including perception, planning, and control, each handled by specialized components [2]. The perception module, often powered by neural networks, interprets environmental data, while the planner adheres to rule-based frameworks to map out actions, and the controller executes precise vehicle maneuvers [3]. Conversely, end-to-end approaches bypass this segmentation, generating motion commands directly from sensory inputs through imitation learning or reinforcement learning [4]. These diverse strategies underline the complexity of creating autonomous systems capable of adapting to real-world challenges, particularly in non-ideal settings such as off-road driving, where environmental unpredictability demands robust and adaptive solutions [5]. This study delves into the intricacies of human decision-making in off-road scenarios, aiming to enhance the integration of human and machine intelligence in autonomous vehicle systems.

Autonomous vehicles excel in structured environments like highways or urban streets, where the rules are predictable and standardized. However, in unstructured scenarios such as off-road terrains, these systems often struggle to maintain reliability. The challenge lies in the ability to generalize across diverse and adverse conditions, including varied terrains, unpredictable obstacles, and fluctuating weather [6], [7]. Effective generalization is critical for ensuring safety, as autonomous systems must identify and focus on valuable features within sensory inputs while disregarding noise or irrelevant data. Furthermore, adversarial attacks [8], which subtly modify input data to mislead predictions, pose significant risks to the reliability of these systems. Such vulnerabilities underscore the need for rigorous testing through simulations and adversarial scenarios to evaluate robustness [9]. Researchers are also exploring the transferability of training models from simulation to real-world conditions, a task requiring exceptional adaptability due to the inherent differences between virtual environments and reality. Addressing these challenges is essential for advancing autonomous vehicle performance in unstructured environments [10].

The motivation behind this study stems from the growing reliance on autonomous vehicles and their potential to revolutionize transportation. While autonomous systems have shown great promise in structured environments, their performance in unpredictable, off-road conditions remains underexplored [11]. Off-road driving, with its complex terrains, obstacles, and environmental variables, poses unique challenges that require a higher level of adaptability and decision-making [12]. The novelty of this report lies in its focus on human intervention in these off-road scenarios. By using a virtual reality (VR) simulation [13] environment powered by the CARLA driving simulator, we can investigate when and why humans decide to take over control from an autonomous system. This approach offers a valuable opportunity to explore the intersection of human behavior and autonomous decision-making in situations

Code available on https://github.com/Abhijeet399 where machine learning models may struggle [14]. Through this research, we aim to identify critical factors that influence the decision to override an autonomous vehicle, such as terrain complexity, vehicle behavior, and environmental conditions [15]. The insights gathered could inform the design of future autonomous systems, ensuring they are better equipped to handle non-ideal driving conditions and seamlessly integrate human control when necessary.

The methodology for this study integrates several advanced tools to create a comprehensive VR-based simulation of autonomous driving in off-road conditions. The primary tool used is Unreal Engine [21], which allows for the creation and editing of high-quality 3D off-road terrain maps. This engine facilitates the development of detailed environments where the driving scenarios will take place. The project is deployed to participants through a VR headset, enabling full immersion in the simulated environment. The CARLA Driving Simulator [16] is employed to simulate the behavior of the autonomous vehicle within the off-road terrain [17]. CARLA is a high-fidelity, open-source simulator specifically designed for autonomous driving research, making it ideal for testing vehicle behavior and decision-making in complex conditions [18]. The simulated off-road conditions include varying terrain complexities, such as hills, rocks, and uneven surfaces, which influence the vehicle's handling. Additionally, factors such as vehicle behavior, including braking, steering, and acceleration, are modeled to assess how these impact human decisions to take over control [19]. Environmental conditions, like lighting and weather variations, are also incorporated to simulate realistic driving scenarios. The goal is to study how participants interact with the vehicle and decide when to override the autonomous system, based on these challenging conditions [29].

II. Related work

A. End-to-End driving

An end-to-end driving system simplifies decision making by steering without needing complicated step-by-step data processing [22]. This leads to quick and straightforward choices. An approach used is Conditional Imitative Learning (CIL), which tackles a key challenge in IL: the difficulty of controlling the learning agent, making traditional learning methods difficult to apply [23]. Instead, the CIL relies on straightforward commands to guide agents to turn at specific intersections. In a study [24], researchers created an autonomous system that helps avoid obstacles in off-road situations. They used data from human drivers to train the agents, who learned to adapt to different conditions to ensure they could perform well across various scenarios. However, their training relied on just a small number of sets. In addition, agents who participate in online IL have shown good results in real-world tests. Although off-road environments are part of the discussion, the main focus here is on how well the system can generalize.

Another work [25] introduced an end-to-end approach for race driving, testing it on a range of road types, graphics, and physical models. They demonstrated that their method works well on tracks the system has never seen before. However, their experiments used the World Rally Championship 6 (WRC6), which is not meant for research and is not open source, making it less suitable for generalization standard tests. Multimodal inputs can enhance end-to-end driving performance [26]. Researchers trained their driving agent using various forms of visual data, including RGB and depth images, along with other measurements. This shows that using multiple types of information is vital for driving simulators [27]. Moreover, understanding uncertainty in driving—by predicting potential outcomes—has also been explored. This approach helps assess how reliable the driving agent's decisions are, which is crucial for ensuring safety in autonomous driving.

B. Simulation and Human Interaction in Autonomous Driving

The field of autonomous driving in off-road and complex environments has gained significant research attention in recent years. Several studies have focused on the robustness and adaptability of autonomous vehicles under challenging conditions. [16] utilized the CARLA simulator to explore high-fidelity urban and off-road environments, emphasizing the role of machine learning in enhancing decision-making processes. Similarly, [18] introduced the application of deep reinforcement learning for safe and efficient driving in unstructured settings, addressing the need for generalization to adverse terrains. Research by [23] highlighted the vulnerability of autonomous systems to adversarial attacks and demonstrated methods to test system robustness against such threats. Studies like [28] investigated the integration of Virtual Reality (VR) in autonomous driving simulations, providing insights into driver behavior and intervention dynamics. [29] further demonstrated the utility of VR in studying human interaction with autonomous systems in simulated environments, focusing on off-road scenarios with varying terrain complexities. These foundational works underscore the importance of combining simulation tools, machine learning, and human behavior studies to improve the safety and reliability of autonomous vehicles in diverse driving conditions.

III. Method

A. Participant Recruitment and Demographics

The success of this study depends significantly on the diversity of participants, which is why we will recruit 30–50 participants from varied backgrounds. This group size allows for meaningful statistical analysis while also ensuring that results are not influenced by a small, homogeneous sample. The participants will be aged between 20 and 50 years, ensuring a balance of youthful energy and experience in driving. The driving experience will vary, with some participants having novice experience and others possessing advanced driving skills. This variation helps to understand how people with different levels of driving experience respond to autonomous systems under stressful conditions. Additionally, participants' experience with virtual reality (VR) systems will be considered, as prior exposure to VR can influence the ease with

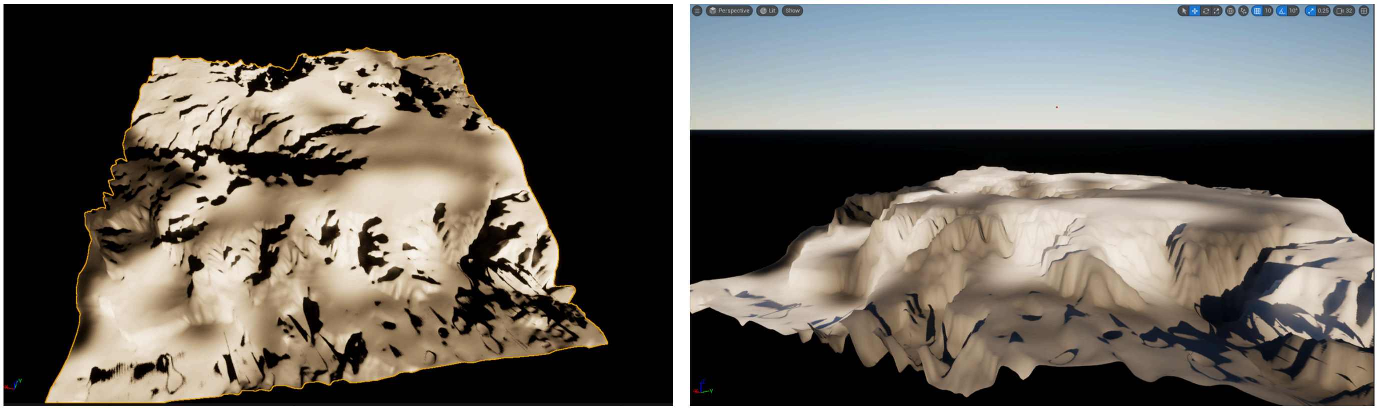

Fig. 1. Top view and side view of the off-terrain map that'll be used for the survey in which the participants of the study will decide to overtake or not the autonomous car in CARLA and Unreal Engine.

which they engage with the experiment. Participants will complete a detailed questionnaire about their driving history and familiarity with VR to establish baseline information. This will help identify any correlations between prior experience and how participants interact with the autonomous vehicle system.

B. Experimental Setup

The experimental setup centers around the use of the CARLA driving simulator, a high-fidelity simulation tool specifically designed for autonomous driving research. CARLA allows for the creation of various real-world and synthetic driving environments, including complex off-road scenarios. This feature is crucial to replicating off-road driving conditions where autonomous vehicles are often tested. Participants will be immersed in these environments through a VR headset, which provides a more realistic experience compared to traditional screens. Initially, the autonomous system will drive the vehicle, but participants have the freedom to take control of the vehicle whenever they choose. This method will help study human intervention behavior, such as whether participants trust the system to handle specific situations or whether they feel the need to take over control, especially in complex or risky conditions. The ability to take control at any point ensures that the participants are acting as they would in a real-world scenario where they might need to intervene during an autonomous vehicle's operation.

C. Data Collection

The data collected during the simulation will provide insight into how humans interact with autonomous systems, particularly in off-road conditions. Several key data points will be tracked:

- **Takeover Events**: Each time a participant assumes control of the vehicle, he/she will click a clicker in his/her hand. This is vital to understanding at what point participants feel the need to override the autonomous system.
- **Reasons for Takeover**: Following each takeover, participants will be asked why they decided to take control. This could be due to a variety of factors, such as lack of trust in the system, poor vehicle performance, or an unexpected environmental factor. Understanding the reasons for takeovers will provide insight into where and why the system might fail to perform adequately under certain conditions.
- **Reaction Metrics**: Reaction time is an important factor in understanding how quickly participants assess and respond to perceived risks in the environment. Additionally, biometric measurements such as heart rate variability or sweat responses can be recorded to assess stress levels and engagement, providing a deeper layer of insight into how participants emotionally and physiologically react to different driving conditions.
- **Behavioral Observations**: Observing behavioral patterns, such as hesitation or confidence, will help understand how participants interact with the autonomous system. For example, if a participant hesitates before taking control, it may suggest a lack of trust in the vehicle's ability to handle the situation. On the other hand, a confident takeover could indicate a better understanding or trust in their ability to control the vehicle when needed.
- **Post-Simulation Survey**: After completing the simulation, participants will fill out a detailed survey about their perceptions of the autonomous system and the decision-making process. This will gather subjective data on the participants' trust in the system, their satisfaction with their decisions, and their opinions on how well the system performed.

D. Current Progress

- **3D Map for Off-Road Simulation**: Successfully developed a basic off-road terrain map using Unreal Engine. The terrain includes key features like uneven surfaces, slopes, and natural obstacles (e.g., rocks, trees) to simulate realistic off-road driving conditions. This provides a foundation for testing autonomous vehicles in a variety of challenging terrains. The 3D map can in Figure 1.

- **Navigating the Autonomous Car in Off-Road Terrain**: Successfully integrated CARLA with a custom off-road terrain. The autonomous vehicle has been programmed to handle basic driving tasks like steering, braking, and accelerating over uneven terrain. The system is able to adjust the vehicle's speed and trajectory in response to obstacles, terrain complexity, and environmental factors such as dirt roads and rough surfaces. The navigation in a desired map can be seen here.(Video)
- **Connecting CARLA and Unreal Engine to Load a Desired Map**: Successfully established a workflow to link CARLA with Unreal Engine, allowing the loading and simulation of custom 3D maps. This setup enables the CARLA simulator to visualize and interact with various off-road terrains, including the successful deployment of a racetrack terrain for testing vehicle control in structured settings. The process ensures smooth integration and enables future simulations with diverse environments. The navigation in a desired map can be seen here.(Video)

IV. Hypothesis

Several key factors influence a driver's decision to take control from an autonomous vehicle in off-road conditions. Terrain complexity plays a major role, with types of terrain such as rocky, muddy, or steep inclines challenging the vehicle's ability to navigate effectively. More complex terrain often leads to hesitation or the need for human intervention to maintain safety and control. Vehicle behavior is another critical factor, where unexpected actions like sudden deceleration or the vehicle's inability to navigate accurately may prompt the driver to take over. For instance, if the autonomous vehicle fails to recognize an obstacle or executes an incorrect maneuver, the human driver might intervene to prevent a collision. Environmental factors, such as obstacles, changing weather conditions, or reduced visibility, can also significantly impact control decisions. For example, if the vehicle encounters a dense fog or an unforeseen obstruction, the driver might feel the need to take over to ensure safe navigation. These factors collectively determine when and why a human might override the autonomous system to prevent potential accidents or failures in complex and unpredictable off-road conditions.

A. *Expectations*

- More Frequent Control Takeover: Participants are expected to take control of the autonomous vehicle more often in complex or unpredictable conditions.
- Terrain Difficulty: As terrain complexity increases (e.g., rocky, muddy, or steep inclines), participants are likely to feel less confident in the vehicle's ability to navigate, prompting more frequent intervention.
- Vehicle Performance Triggers: Poor vehicle performance, such as improper navigation or sudden deceleration, will likely trigger human intervention.
- Stress Levels: Stress levels are anticipated to rise in more challenging terrains, with higher terrain complexity possibly leading to increased physiological stress markers.
- Influence on Decision-Making: Elevated stress could influence participants' decision-making, making them more cautious or hesitant when deciding whether to take control.
- Insights for Autonomous Vehicle Development: These findings will help understand human factors influencing control decisions and inform the design of safer, more reliable autonomous systems for off-road conditions.

V. Discussion

A. *Expected Contribution to Autonomous Vehicle Design*

This study provides crucial insights into the interaction between humans and autonomous vehicles in off-road conditions, particularly focusing on when human intervention is necessary. By examining the thresholds for human intervention in complex and unpredictable environments, the research helps identify the conditions under which an autonomous vehicle's decision-making system may fail or become unreliable [30]. These findings will contribute to the design of more reliable autonomous systems that are capable of recognizing when they need assistance or intervention from the driver [31]. Furthermore, understanding the triggers for manual control, such as terrain complexity or unexpected vehicle behavior, will inform how these systems can be optimized to handle off-road scenarios with greater autonomy while still allowing for seamless human intervention when necessary [32]. Ultimately, this study aims to contribute to the development of safer autonomous vehicles, ensuring that future designs account for human behavior and decision-making processes in off-road environments [34]. By integrating these human factors into system design, autonomous vehicles can become more resilient and adaptive to real-world challenges, enhancing their safety and reliability for diverse terrains and unpredictable conditions [33].

The findings of this study could significantly enhance our understanding of human behavior in the context of autonomous vehicles [36], particularly in off-road environments. One key takeaway from this research is the importance of developing autonomous systems that are adaptable to varying terrains, especially those that are less predictable, like rocky or muddy conditions. Given that human intervention is likely to occur more frequently in such environments, it is essential to refine autonomous driving algorithms to better handle complex terrains without triggering unnecessary takeovers [35]. The study also highlights the need for improving human-vehicle communication, ensuring that users can easily assess the vehicle's performance and make informed decisions about when to intervene. Moreover, stress and decision-making under challenging conditions are crucial factors to consider [37]. If the system can detect heightened stress or uncertainty in the driver, it could prompt proactive measures, such as alerting the driver or even taking over control in critical situations. Ultimately, the study's contribution to autonomous vehicle design is not just about improving vehicle performance in isolation, but also about understanding the dynamic between human operators and autonomous systems to create a more integrated, effective, and safe driving experience in unpredictable environments [38].

Following the completion of this study, the next steps will focus on enhancing and refining the off-road terrain simulation, providing more realism and interactivity. Key future work includes:

- **Connecting All Modules into an End-to-End Pipeline**: Integrating the 3D off-road terrain, autonomous vehicle navigation, and the VR setup to create a seamless, fully-functional system for real-time testing. This integration will streamline data collection and improve the consistency of results when analyzing human decision-making in complex environments (Park et al., 2021; He et al., 2023).
- **Enhancing Visuals for Realism**: To increase immersion and improve the accuracy of participant reactions, more advanced visuals will be added to the 3D terrain map, including enhanced textures, dynamic lighting, and realistic environmental factors like weather effects (Li et al., 2023). This improvement will help simulate real-world conditions more closely, ensuring that participants' decision-making is tested under more authentic scenarios (Mizutani et al., 2022).
- **Waypoint Navigation for Autonomous Vehicles**: Developing and incorporating waypoints for the autonomous vehicle will enable more controlled navigation through the complex terrain. This will allow the vehicle to follow predetermined paths that vary in complexity, simulating real-world off-road driving more effectively. Waypoint-based navigation will also provide a clear structure for evaluating vehicle performance and the need for human intervention (Jain et al., 2021).

These steps will contribute significantly to refining the simulation and advancing autonomous vehicle technology for off-road conditions. They will also facilitate deeper insights into the critical points where human intervention is necessary, helping to design safer, more reliable autonomous systems.

VI. Conclusion

This study explores human intervention in autonomous driving, specifically in off-road environments, where the complexity of the terrain and vehicle behavior presents unique challenges. By analyzing when and why participants take control of an autonomous vehicle, the research aims to provide valuable insights into the design of future autonomous systems. The findings will contribute to the development of more adaptive and human-centered autonomous vehicles, particularly in non-ideal conditions like off-road driving.

Understanding the decision-making process of human operators, especially in the context of varying terrain difficulties, environmental factors, and vehicle performance, is critical for improving the safety and reliability of autonomous driving systems. The results will inform future designs, ensuring that vehicles can effectively navigate complex environments while also accommodating human intervention when necessary. Ultimately, this study aims to enhance the safety and usability of autonomous systems by accounting for human behavior in dynamic, off-road scenarios, paving the way for more robust and resilient autonomous vehicles in diverse environments.

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