DOCTORAL THESIS

Digital Twin Based Computational Methods for XR Applications

Saleh Ragheb Saleh Alsaleh

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for any academic degree.

/Saleh Ragheb Saleh Alsaleh/ ________________________________

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Digitaalkaksikute põhised arvutuslikud meetodid XR rakenduste jaoks

SALEH RAGHEB SALEH ALSALEH

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Abstract

This thesis delves into the challenges and opportunities associated with integrating Extended Reality (XR) technologies into practical control engineering education and training. The research is motivated by the gap in effectively incorporating XR into mainstream computational platforms and workflows, despite its increasing accessibility and potential benefits. The thesis specifically targets the field of control engineering, recognizing its complexity, diversity, and technological readiness, making it an ideal candidate for adopting XR solutions to enhance educational and operational outcomes.

The primary aim of the thesis is to foster the widespread adoption of XR as a computational platform within practical control engineering, achieved through a three-pillar strategy. This includes integrating XR into existing workflows via a unified modular framework, introducing data-driven decision-making methodologies for designing XR applications, and integrating AI methods to enable rapid prototyping of these applications. The contributions of the thesis encompass the development of a conceptual framework for integrating XR into control engineering education, the creation and assessment of XR applications for control systems, and the proposal of innovative methods for data-driven analysis and AI-driven decision-making in XR environments.

The thesis is structured into seven chapters, each addressing different facets of the research. Chapter 2 provides a comprehensive review of the literature related to control engineering laboratories and the potential of DT and XR technologies. Chapter 3 introduces the "Reimagine Lab" framework, combining DT and XR to enhance traditional laboratory experiences. Chapter 4 showcases the practical application of the "Reimagine Lab" framework through detailed case studies. Chapter 5 presents research findings from a usability study of a lab-scale gantry crane in an XR environment. Chapter 6 explores a data-driven approach to enhancing user engagement in virtual environments (VEs), using machine learning to analyze and classify user interactions. Finally, Chapter 7 advances the framework by integrating AI-enhanced DTs, focusing on training DTs through a reinforcement learning algorithm for specific tasks.

In conclusion, the thesis addresses the challenges of integrating XR technologies into established systems and workflows. By focusing on practical control engineering education and training, the research offers a comprehensive approach to enhancing learning and operational efficiency through the innovative use of XR, data-driven decision-making, and AI methodologies.

Kokkuvõte

Käesolevas doktoritöös käsitletakse probleeme ja võimalusi, mis on seotud laiendreaalsuse (XR) tehnoloogiate integreerimisega praktilisse juhtimistehnika valdkonna haridusse ja koolitusse. Uurimistöö ajendiks on lüngad XR-i tõhusas integreerimises üldkasutatavatesse arvutusplatvormidesse ja töövoogudesse, hoolimata XR-i kättesaadavuse ja potentsiaalse kasu kasvust. Doktoritöö on suunatud konkreetselt juhtimistehnika valdkonnale selle kogu keerukuses, mitmekesisuses ja tehnoloogilises valmisolekus, mis on ideaalseks kandidaadiks XR lahenduste kasutuselevõtuks, et parandada haridus- ja töötulemusi. Doktoritöö peamine eesmärk on edendada XR-i kui arvutusplatvormi laialdast kasutuselevõttu praktilistes juhtimissüsteemides, mis saavutatakse kolme samba strateegia abil. Strateegia hõlmab XR-i integreerimist olemasolevatesse töövoogudesse ühtse modulaarse raamistiku kaudu, andmepõhiste otsustusmeetodite kasutuselevõttu XR-i rakenduste kavandamiseks ning tehisintellekti meetodite integreerimist, et võimaldada nende rakenduste kiiret prototüüpimist. Doktoritöö panus haarab kontseptuaalse raamistiku väljatöötamist XR-i integreerimiseks juhtimissüsteemide õppetöösse, XR-i rakenduste loomist ja hindamist juhtimissüsteemides kasutamiseks ning uuenduslike meetodite väljapakkumist andmepõhiseks analüüsiks ja tehisintellektipõhiseks otsuste tegemiseks XR-i keskkonnas. Doktoritöö sisaldab seitse peatükki, millest igaüks käsitleb uurimistöö erinevaid tahke. Teises peatükis antakse põhjalik ülevaade juhtimissüsteemide laboritega seotud kirjandusest ning digitaalkaksikute (DT) ja XR tehnoloogiate potentsiaalist. Kolmandas peatükis tutvustatakse "Reimagine Lab" raamistikku, mis ühendab DT ja XR tehnoloogiaid, et parandada traditsioonilisi laborikogemusi. Neljandas peatükis tutvustatakse "Reimagine Lab" raamistiku praktilist rakendamist üksikasjalike juhtumiuuringute abil. Viiendas peatükis esitatakse uurimistulemused, mis on saadud laborimõõtmelise portaalkraana kasutatavusuuringust XR keskkonnas. Kuuendas peatükis uuritakse andmepõhist lähenemisviisi kasutajate kaasatuse suurendamiseks virtuaalkeskkondades, kasutades masinõpet kasutajate interaktsioonide analüüsimiseks ja klassifitseerimiseks. Seitsmendas peatükis arendatakse väljapakutud raamistikku edasi, integreerides tehisintellekti täiustatud DT-d, keskendudes DT-de treenimisele kinnitusega õppimise algoritmi abil konkreetsete ülesannete jaoks. Kokkuvõttes käsitletakse doktoritöö väljakutseid, mis kaasnevad XR tehnoloogiate integreerimisega väljakujunenud süsteemidesse ja töövoogudesse. Keskendudes praktilisele juhtimistehnika õppele ja koolitusele, pakub uurimus terviklikku lähenemisviisi õppimise ja tegevuse tõhususe suurendamiseks XR-i, andmepõhise otsustusprotsessi ja tehisintellekti meetodite uuendusliku kasutamise abil.

List of Publications

P1. S. Alsaleh, A. Tepljakov, A. Köse, J. Belikov, and E. Petlenkov, "Reimagine lab: Bridging the gap between hands-on, virtual and remote control engineering laboratories using digital twins and extended reality," IEEE Access, vol. 10, pp. 89 924–89 943, 2022.

P2. S. Alsaleh, A. Tepljakov, M. Tamre, and E. Petlenkov, "Towards artificial intelligence driven immersive environments in virtual reality for industrial applications," in 2021 44th International Conference on Telecom- munications and Signal Processing (TSP), 2021, pp. 340–345.

P3. S. Alsaleh, A. Tepljakov, M. Tamre, V. Kuts, and E. Petlenkov, "Digital twin simulations based reinforcement learning for navigation and control of a wheel-on-leg mobile robot," in ASME International Mechanical Engineering Congress and Exposition, vol. 86649.

Other related publications

P4. A. Köse, A. Tepljakov, S. Alsaleh, and E. Petlenkov, "Self assessment tool to bridge the gap between XR technology, SMEs, and HEIs," in International Conference on Extended Reality. Springer, 2022, pp. 296–311.

P5. K. Nosrati, S. Alsaleh, A. Tepljakov, E. Petlenkov, A. Onile, V. Škiparev, and J. Belikov, "Extended reality in power distribution grid: applications and future trends," in 27th International Conference on Electricity Dis- tribution (CIRED 2023), vol. 2023, 2023, pp. 3615–3619.

P6. A. Köse, A. Tepljakov, S. Alsaleh, and E. Petlenkov, The Experience of A Self-Assessment Tool for Enhancing XR Technology Adoption in SMEs and HEIs across Europe. Springer Nature Switzerland, 2023, pp. 184–197.

Author's Contribution to the Publications

P1. I was the main author; conceptualized the "ReImagine" framework, implemented the proposed solution, planed and assisted in carrying out the experiments, performed the analysis of the results and wrote the overwhelming portion of the manuscript.

P2. I was the main author; defined the research problem ,designed and implemented the VR data reply and annotation tool, processed and labeled the data, analyzed the resultes and wrote the manuscript.

P3. I was the main author; defined the research problem, proposed to formulate the problem as a reinforcement learning task, implemented the proposed solution, planed and carried out the experiments, analyzed the results and wrote the manuscript.

Abbreviations

AR	Augmented reality
CS	Control system
DDPG	Deterministic policy gradients
DT	Digital twins
HMD	Head-mounted display
IIVE	Intelligent immersive virtual environments
MDP	Markov decision process
PID	Proportional integral derivative
PPO	Proximal policy optimization
SUS	System usability study
VE	Virtual environment
VR	Virtual reality
XR	Extended Reality

Chapter 1

Introduction

1.1 Motivation and Problem Statement

With the continuous advancements in information technology augmenting the capabilities of XR hardware, such as Head-Mounted Devices (HMDs), XR is progressively becoming more attainable and widespread. Yet, despite the success of specific XR use cases, the technology has not yet achieved its full potential as a mainstream computational platform. A significant impediment to XR's broad adoption is the lack of integration into prevailing systems and workflows. Although specific XR applications in certain sectors have shown promise, transitioning from isolated instances to a comprehensive, sustainable incorporation within existing infrastructures remains a significant challenge. It is crucial to identify and establish a foundational framework to facilitate the seamless integration of XR applications, ensuring their sustainable and effective implementation across each sector.

Moreover, as XR is an emerging technology, professionals face intrinsic challenges in designing applications, crafting interaction modalities, and developing visualization interfaces that cater to a heterogeneous user base with varied backgrounds and expertise levels. These challenges are further magnified by the spatial nature of XR interactions, which demand extensive development cycles for XR applications, presenting an additional barrier to their widespread adoption.

In addressing these challenges, this work proposes a focused approach, beginning with the selection of a specific industry or domain. After careful consideration, practical control engineering education and training has been chosen as the focal point for applying methodologies to navigate the challenges presented by XR technologies. This decision is underpinned by several compelling reasons:

Firstly, the diversity and complexity of systems within control engineering are unparalleled. This field deals with a wide range of complex systems, from simple household appliances to intricate industrial machinery, making it indispensable across various sectors such as manufacturing, automotive, and healthcare. The diversity and complexity of these systems suggest that methods successfully employed in control engineering have the potential to be adapted and applied to other sectors.

Secondly, the technological readiness of the sector is a significant factor. Educators and professionals in control engineering are typically at the forefront of technological advancements, often leading the charge in adopting innovative tools to enhance learning and operational efficiency. The technical acumen of these individuals, combined with their openness to new technologies, positions the sector as an ideal candidate for the integration of XR solutions. XR technologies, renowned for their ability to simulate complex systems and provide immersive, hands-on learning experiences, are well-equipped to tackle the existing challenges in control engineering education.

The aim of this research is to identify and address the challenges that limit the widespread acceptance and integration of technologies. The central question is how can XR specialists, position XR as a core component of established systems not just a mere technological novelty?

1.1.1 Digital Twins as the Foundation for XR Integration in Control Education

In today's rapidly evolving industrial landscape, the emergence of Industry 4.0 [1] has brought in its wake a wave of transformative technologies. This paradigm shift necessitates a broader understanding of the changing nature of industry and the impact of new technologies that fall under the Industry 4.0 umbrella. One such technology is *Digital Twins* (DT) [2].

The novel developments in the Industry 4.0 era also include the emergence of intelligent systems, including intelligent control systems. Meanwhile, one of the most significant advantages of utilizing DT is their ability to design and optimize control systems. These control systems act as intelligent regulators that guide various industrial processes towards desired states, such as maximizing energy efficiency and minimizing waste. Through the accurate representation and analysis of physical systems in the virtual world, control engineers can identify inefficiencies and tailor controllers to address specific challenges, leading to substantial improvements in energy consumption and overall system performance [3].

The adoption of Industry 4.0 technologies, driven by DT and advanced control systems, has transformative effects across various sectors. For instance, in manufacturing, control engineering allows for real-time monitoring and optimization of production lines, reducing energy consumption, and optimizing resource utilization. In smart buildings, automated control systems integrated with DT can adjust heating, cooling, and lighting based on real-time data, thus minimizing energy waste while ensuring occupant comfort. The implications of control engineering in energy efficiency extend far beyond industrial and building sectors. Transportation systems, such as smart traffic management, electric vehicle charging optimization, and intelligent public transportation networks, all benefit from advanced control strategies. These applications lead to reduced greenhouse gas emissions, lower fuel consumption, and improved traffic flow, contributing to a more sustainable and environmentally friendly society.

A new era in control technology in the scope of Industry 4.0 and beyond also necessitates the availability of highly trained control engineers familiar with the latest technological advancements. For this reason, the current approach to control education must be updated accordingly. The changing nature of industry, driven by the advent of Industry 4.0, necessitates a comprehensive understanding of DT and their role in facilitating industrial growth. Control engineering assumes a central position within this evolving landscape, emphasizing the need for proficient control system operation to optimize energy utilization and achieve desired outcomes. By merging mathematical theory with practical applications, control engineering education equips future engineers with the skills to navigate the complexities of this interdisciplinary field [4].

Control courses —as they are conventionally taught in educational institutions— have their roots in mathematical theory and at the same time they require from the students an intuitive understanding of different concepts, which allows the students to relate the acquired knowledge to actual practical applications of control theory. That is why control engineering instructors persistently highlight the importance of practical hands-on experience in successful control engineering education from the early stages of learning [5]. Surveys conducted among control educators and industrial partners indicate that teaching concepts and the implications of control engineering should take precedence before delving into the intricate mathematical calculations behind them [6].

Many pedagogical tools, such as course projects, internships, and laboratory experiments, can be used to develop the practical hands-on expertise required by control courses. Practical laboratory work "control laboratory" has become a typical component of automated control courses because it aims to [7]:

- Connect theory to what is implemented and observed in the laboratory.
- Identify differences between models and physical systems.
- Design and verify controllers that meet specifications.
- Collect and visualize data.

These laboratories have traditionally relied on working with laboratory-scale control objects to demonstrate dynamic phenomena that can be observed in full-scale, industrial counterparts of these control objects. These experimental sets are computer-interfaced, allowing students to create and tune controllers while also observing how the system performs under these new settings. For example, in [8] the laboratories included experiments with a coupled tanks system, inverted pendulum and rotary table. These systems were used to demonstrate to the students the use of modeling, simulation and control design.

Physical laboratories are expensive to create and operate. They take up a lot of room in the lab and are made up of specialist hardware, which adds to the complexity of the necessary infrastructure. Furthermore, as the number of students grows, managing the infrastructure and organizing physical laboratories becomes increasingly difficult. To put it another way, this infrastructure does not scale well. Thus, educators have created various alternative modes of technology-enabled laboratories to address issues associated with traditional physical hands-on laboratories by leveraging recent advances in information and communication technologies. Laboratory modes can be categorized based on the nature of the experimental resources (real or simulated) and the location of these resources (local or remote) as follows [9]:

1. Local access-Real resource. It represents the traditional practical laboratory and take-home laboratory kits where the student is in front of a computer connected to the real plant to carry out the experiment using DT and Reinforcement Learning.

2. Remote access-Real resource. It represents remote real experiment where the students access the real plant equipment laboratory through the internet. The user operates and controls a real plant through an experimentation interface in a remote way. This approach is named remote laboratory.

3. Local access-Simulated resource. It represents the virtual experiment where the whole environment is software and the experimentation interface works on a simulated, virtual and physically nonexistent resource. This approach is named locally hosted virtual laboratory.

4. Remote access-Simulated resource. It represents Remote virtual experiment where the students access the remote virtual environment through the internet where the software and the experimentation interface works on a simulated, virtual and physically nonexistent resources. This approach is named cloud hosted virtual laboratory.

There is an ongoing debate on the effectiveness of different laboratory modes. A comparative analysis of the different laboratory modes has shown that when these laboratory modes are developed their efficiency is measured by their ability to achieve different learning objectives [10]. Remote laboratories, for example, are more suited for conceptual understanding, but virtual laboratories are ideal for developing design abilities. This makes selecting a single laboratory mode challenging.

Another significant issue to examine is how the specific laboratory mode affects students' interactions with laboratory objects, teachers, and other students. The results of studies of students' interactions in face-to-face and remote hands-on laboratories have revealed a lack of systemic analysis of students' interactions in alternative technology laboratory modes. Before comprehensively comprehending the implications of employing such laboratory modes, it is essential to have improved tools for examining students' interactions [11]. Although hands-on physical laboratories have obvious drawbacks associated with cost and space requirements, remote and virtual laboratories also possess their own limitations:

- In remote laboratories, students report a lack of personal engagement because of the separation between them and the experimental objects [12, 13].

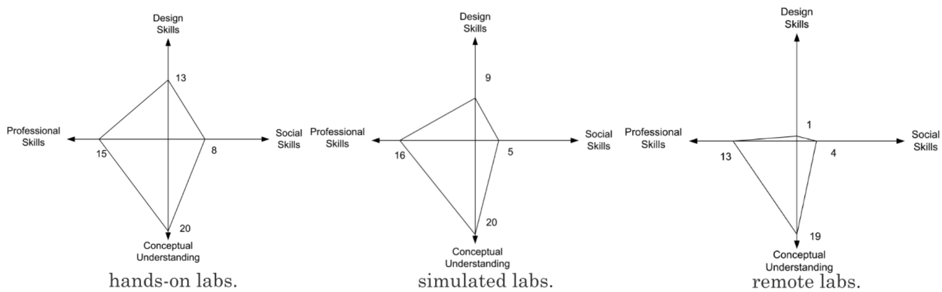
- Virtual laboratories creates further increases the separation as the virtual system does not physically exist and the relationship is not clear between the physical and VE.

- The usability of virtual laboratories is questioned as it is not the focus point when designing virtual laboratories [14].

In addition to the learning objectives of control engineering courses, engineering students should develop not only professional abilities, but also soft skills in order to meet the needs of industry and the accreditation criteria imposed on university study programs. In this situation, the working patterns that occur in hands-on laboratories are more suited to cultivate such abilities than those that occur in distant and virtual laboratories. [15]. Figure 1.1 shows the diffrent educational goals of hands-on, virtual, and remote laboratories.

Regardless of the ongoing debate a hybrid approach combining several laboratory modes has emerged that allowed for the modes to complement each other. For example, virtual and remote laboratories concerned with the same control object can be used [16]:

- The virtual mode is applied during the control design stage when no interaction with the real system is strictly necessary.



hands-on labs. simulated labs. remote labs.

Figure 1.1: Educational goals of hands-on, virtual, and remote laboratories [10].

- The remote mode is applied for observing the behaviors introduced by the real system and deepening the understanding of related concepts.

In light of these considerations, it becomes apparent that the pursuit of the ultimate laboratory mode may not be the most productive approach. Instead, a more practical and innovative solution would involve devising a method to integrate and harness the benefits of various laboratory modes within a single laboratory activity. This requirement for integration presents the optimal opportunity for the XR application on top of an underlying DT framework.

1.2 Author's Aims and Objectives

To summarize, this thesis aims to promote widespread adoption of XR as computational platform within practical control engineering education and training. It endeavors to achieve this goal through a three-pillar strategy, commencing with the integration of XR into existing workflows using a unified modular framework. Subsequently, the thesis introduces methodologies facilitating data-driven decision-making for the design of XR applications. Finally, it explores the integration of AI methods to enable rapid prototyping.

Towards achieving these aims the thesis is compromised of the flowing objectives as presented in Figure 1.2 :

- To identify and conceptualize a framework for integrating XR into practical control engineering education and training (Chapters 2-3).

- To demonstrate the proposed approach through the development of applications for various control objects (Chapter 4).

- To conduct a study to measure VR experiment usability, comparing traditional and VR experiments to assess VR's effectiveness in control systems courses (Chapter 5).

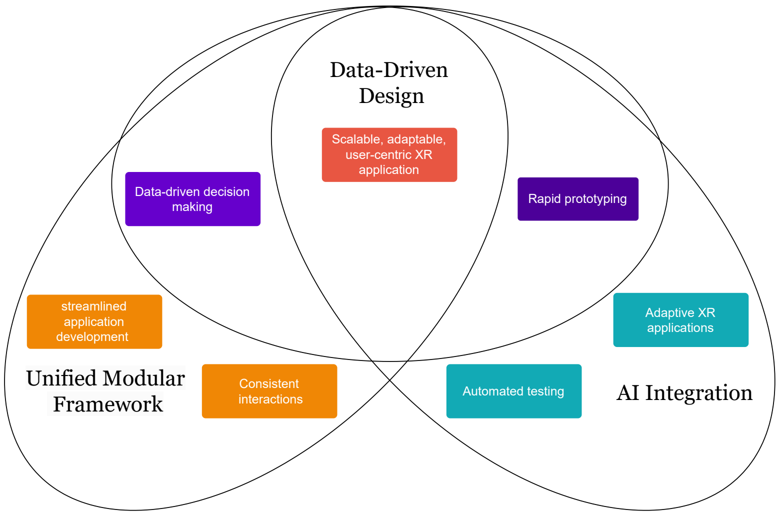


Figure 1.2: Overview of the objectives of this thesis, highlighting the integration of DT, XR, and AI Technologies for the advancement of practical engineering education

- To propose and implement methods and tools for data-driven analysis and decision-making in designing XR environments (Chapter 6).
- To propose and implement AI-driven DTs as "intelligent agents" in virtual environments(Chapter 7).

1.3 Thesis Outline

Each chapter opens with a brief overview of the material covered. Each chapter of the thesis concludes with a section offering insights into and remarks about the results provided in that chapter. Finally, the final chapter includes general concluding remarks as well as items for future investigation. Each chapter is summarized in the sections that follow.

Chapter 2

This chapter serves as an in-depth examination of the fundamental elements that underpin this thesis, commencing with an extensive review of the literature pertaining to practical control engineering laboratories and their technology-enabled alternatives, emphasizing the potential for integrating

DT and XR to bridge these modalities. . It then delves into a thorough overview of DT . Finally, it presents a analysis literature focused on enhancing interaction within virtual environments.

Chapter 3

This chapter introduces the “Reimagine Lab” framework, which is a novel approach in the domain of control laboratories, blending DT and XR to enhance traditional virtual and remote laboratory experiences. The framework’s foundation is established through two primary components: the transformation of data-driven mathematical models into DT, and the adoption of XR for improved interaction and visualization. This chapter details how the “Reimagine Lab” framework synergizes DT and XR to efficiently create new-generation virtual and remote laboratory modalities. It elaborates on the advantages of this framework in both remote and virtual laboratory settings, particularly its ability to facilitate shared experiments with hands-on laboratories. The chapter concludes by summarizing the key insights and outcomes of implementing the “Reimagine Lab” framework.

Chapter 4

This chapter is dedicated to demonstrating the practical application of the “Reimagine lab” framework through two distinct use cases, each focusing on creating a DT for a lab-scale object. It includes detailed case studies on a lab-scale multi tank system to demonstrate the “shared experiment” and highlights the seamless transition between simulated and physical system modes in a mixed reality setting. The second use case of a gantry crane system, which is used to demonstrate the simulated mode and how to apply the framework to a lab-scale gantry crane in a VR setting. The gantry crane use-case is also used in the subsequent chapters to perform the usability analysis and develop the data-driven replay and annotation system. The process for each example begins with the development of a mathematical model that mirrors the real object’s behavior, laying the groundwork for its DT counterpart. Following this, a 3D visual model is constructed for each object, which serves as the basis for visualization and interaction within an XR experiment. Furthermore, the chapter outlines an educational goal for each experiment, which guides the development of interaction mechanisms.

Chapter 5

This chapter focuses on presenting the initial findings from a System Usability Scale (SUS) study conducted using a “ReImagine lab” application, specifically featuring a lab-scale gantry crane. The 3D crane DT, which users can experience in an XR environment, was previously introduced. Although the experiment concentrates solely on the virtual lab mode, it's crucial to recognize that both the DT and XR technologies are integral to all lab modes and are at the core components of the framework. The insights gained from subject-based testing aim to guide the broader applicability and effectiveness of these technologies for their designated purpose. If results indicate that DT and XR are beneficial in this specific context, these findings could have broader implications for other lab modes. The chapter is structured to first detail the planned study, then describe the questionnaire used in study, followed by presenting and discussing the study's findings. It concludes by summarizing the key outcomes and implications of the research.

Chapter 6

In this chapter, we delve into a data-driven machine learning approach, guided by the "Reimagine Lab" framework, which integrates DT and XR. This framework forms the basis of our research into improving user engagement in VEs. Utilizing the detailed data from DT and the immersive qualities of XR, a replay and annotation system is employed to classify user behaviors, especially in the context of the 3D crane experiment focusing on throwing actions. This system, a product of the combined strengths of DT and XR, facilitates a deeper understanding of user interactions and aids in developing a machine learning algorithm specifically designed to classify these interactions. The chapter is structured to first discuss the interplay between interaction and immersion, followed by detailing the data-driven interaction process and introducing the replay system. It then describes the experimental setup, presents and analyzes the results, and concludes with the key findings and implications of the study.

Chapter 7

This chapter advances the Reimagine Lab framework by incorporating AI-enhanced DTs, termed "intelligent agents". Central to this approach is the application of a reinforcement learning algorithm tailored for training DTs to execute designated tasks proficiently. In this context, mobile robots are selectively used to illustrate the effectiveness of the proposed approach. The chapter is structured to initially propose the integration of AI with DT by defining the problem within the reinforcement learning paradigm. followed by a detailed explanation of the proposed DT and reinforcement learning framework, including the implementation of the hybrid mobile robot as a DT. It then outlines the three tasks used for evaluating the robot's capabilities, presents and discusses the results of the experiments, and concludes with key insights derived from these findings.

Chapter 2

Background

In the following chapter, we introduce the reader to fundamental concepts central to this thesis. The chapter begins with an extensive review of the literature pertaining to practical control engineering laboratories and their technology-enabled alternatives, emphasizing the potential for integrating DT and XR to bridge these modalities. Next, an overview of DT and XR is presented focusing on immersion in virtual reality environments and its promised effect is presented.

The chapter is organized as follows: Section 2.1 presents control engineering laboratories and their alternatives. Section 2.2 presents the evolution of data-driven mathematical models into DT. Section 2.3 provides a compilation of previous work on the use of DT and XR in practical educational settings. Finally, Section 2.4 covers the immersion in VR environments and its promised effect.

2.1 Laboratories in Control Engineering and Their Alternatives

Experts in control engineering understand the the importance of practical demonstrations and learning through conducting relevant experiments in the transfer of knowledge to control engineering students [5]. On the other hand, the traditional method of teaching control engineering involves directing the students to learn the subject matter through memorization and recitation techniques which may cause inefficiency of developing their critical thinking, problem solving and decision making skills [17]. Due to the multidisciplinary nature of control engineering applications, the majority of courses dedicated to control and real-time systems are highly conceptional. Moreover, those courses are usually mathematics-intensive and as such could remain distant and abstract without developing in the student an intuitive understanding of the problem. Thereby they may fail to enlighten students with the realities of different types of control system implementation [9]. Furthermore, it is not reasonable to assert that skill and knowledge levels pertaining to subjects related to control engineering are equal among students. Those factors may likewise result in a less fruitful classroom experience [9].

One of the best approaches is to present the theory in a directed fashion with the instructor going through experiments [18]. Unlike classroom education, laboratory sessions are usually held with several groups of students which makes it possible to divide students according to their knowledge background and time schedule. Through laboratory experiments, students can understand the state dynamics in real-life control systems sufficiently and validate their theoretical knowledge with prototypes in control systems (CS) laboratories [9]. As a matter of fact, the motivation of students in the control engineering learning process is directly related to the opportunity to interact with laboratory equipment. The interactivity in CS laboratories encourages students to play a more active role and to get involved in the CS learning process [19]. In addition, laboratory objectives are useful in analyzing what students can likely achieve in a laboratory [7]. Furthermore, experiments held in a laboratory environment may provide a significant educational advantage: students who are enrolled to practical experiments are able to investigate the resulting dynamics immediately. Thus, they become aware of some physical phenomena that are inconvenient to perceive from only a theoretical point of view taught in the classroom [19].

Laboratory sessions are therefore an essential part of education in engineering. The theoretical material should be solidified with real-life laboratory experiments. Nowadays, however, providing practical experiments is restricted by several major matters such as the growing number of students each year, considerable cost of necessary laboratory equipment to accommodate the needs of the students, maintenance costs, as well as limited time of laboratory personnel [11].

Researchers have proposed various methods and applications to alleviate these long-standing difficulties and provide simpler means for the students to engage with laboratory experiments [20, 21, 22]. Proposed solutions have been observed to meet different criteria such as cost, time efficiency, interactivity and the achievement of learning outcomes. The use of such laboratory counterparts has shifted from being an optional alternative to a necessity due to the recent social distancing and restrictions caused by the COVID pandemic [23, 24, 25, 26, 27]

Educators have devised many alternative types of technology-enabled laboratories to address the challenges associated with traditional physical hands-on laboratories by harnessing current advancements in information and communication technologies. As indicated in Table 2.1, the authors of [9] have classified these several laboratory modes depending on the nature of the experimental resources (actual or simulated) and the location of these resources (local or remote). This taxonomy will inform the majority of future discussion.

2.1.1 Virtual Laboratories

Unlike hands-on laboratories, virtual or simulated laboratories are based on software simulations of physical phenomena. They allow students to explore a specific topic in an offline manner with the ability to pause and restart the application. This laboratory mode serves as a low cost alternative to hands-on laboratories. Replacing the the hands-on laboratories with a virtual alternative not only eliminates the need of developing, assembling and deploying physical laboratory assets, but also allows to significantly reduce costs related to the maintenance and operation of these assets. Researchers have explored the use of different technologies for deploying many different modes of virtual laboratories. For instance, these laboratories can be implemented as software applications based on relevant mathematical models and deployed to

- the local user machine, or
- to a cloud infrastructure from which they are accessible using the Internet.

Cloud-hosted virtual laboratories allow access at a very large scale and low computational requirements on the students end [28]. The flexible nature of virtual laboratories allows changing the models and running the experiments in non-real-time manner which makes them ideal for fulfilling the learning objective of control design in control engineering education [18]. While the space and cost factors in hands-on laboratories limit the scale and complexity of the experiments/plants, the advances in ICT has allowed for modeling and deploying complex simulated/virtual real world control plants [29]. All of this has made virtual laboratories a critical part in massive open online courses as an easy-access and cost-efficient way of online learning [30].

2.1.2 Remote Laboratories

Remote laboratories comprise real-life equipment accessed remotely over the Internet through a digital interface. This laboratory mode offers students the means to access the laboratories and relevant equipment without the necessity of close physical proximity to the equipment. Remote laboratories' main advantage is flexibility: the students can access the remote laboratories at any convenient time and from any physical place, provided an Internet-enabled device is available that is capable of handling the interactions with the equipment via the digital interface. Furthermore, remote access allows the students to have a safe experience in safety critical plants [31]. While hands-on laboratories require additional physical space to accommodate the the students as well as additional interfacing hardware, remote laboratories offer a lower cost alternative where multiple low cost experimental platforms can be stored in a smaller space [32]. The accessibility of remote laboratories make it more suitable for teaching concepts in control engineering as the students have more freedom and flexibility in accessing the experiment [33]. As remote laboratories remove the physical location limitations, they facilitate the sharing of resources across different education institutions in what is called *laboratory Federations* which make it possible to distribute the cost of hosting remote laboratories between those institutions and provide students with access to a wider variety of laboratory experiments based on different equipment [34].

2.1.3 At-home Laboratory Kits

Take-home kits are small-scale, compact and portable sets of devices and accessories that can be easily assembled, disassembled, and transported to allow the students to preform laboratory experiments at home. For example, a DC motor control experiment kit was created to allow students to learn from home during the COVID health pandemic [22]. This kit is aimed to give students any time/any place access to the experiment, so they could perform various tasks, collect data, and analyse the results to get a better understanding the of concepts presented in online lectures. In fact, long before the COVID pandemic, researchers have prompted the use of home laboratory kits as a cost effective alternative to hands-on laboratories enabled by the combination of widespread personal computers owing decent computational power, and low cost micro-controllers for real-time control. In [35], home laboratory kits comprising a mass-spring-damper system and an analog filter were used to assist in teaching of undergraduate level control course. Another approach pertains to the introduction of build-it-yourself home laboratory kits that attempts to bring the hands-on laboratory experience to the students home [27]. In this work, a bifilar pendulum that students can build on their own from low cost materials was introduced. This kit can be used to investigate different physical phenomena related to vibration to students. Take-home laboratories have also been used to overcome the lack of hands-on experiments in Massive Open Online Courses. In [36], a student group trial aimed at studying the effect of using laboratory-home kits in MOOCs resulted in the conclusion that such low cost laboratory kits provide a viable way to complement the MOOC experience.

Having reviewed the various laboratory modes, Now, our attention shifts to the novel research items that are expected to integrate all of these disconnected modes in a highly flexible and efficient manner.

2.2 Evolution of Data-Driven Mathematical Models into DT

The concept of DT is a relatively new paradigm that leverages advancements in information technology to create a higher level of representation for physical objects and processes.

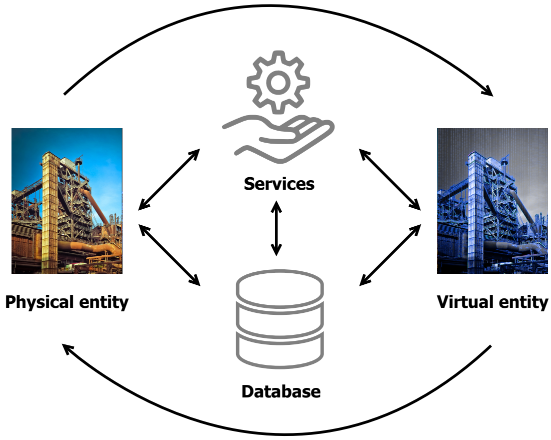


Figure 2.1: Illustration of the Digital Twin concept as the five-dimensional model including the (1) physical entity; (2) virtual entity; (3) connections between nodes; (4) storage/database; (5) services layer according to [2].

Shown in Figure 2.1, the DT concept is depicted as a novel paradigm that enhances the representation of physical objects by capitalizing on recent advancements in information technology.

Consistent with the definition of a DT, the model used to power it is of paramount importance. An ideal model for a DT should possess two key traits: firstly, it must enable an accurate duplication of the behavior exhibited by the original object, which in the DT paradigm is also referred to as "simulation capacity" of the DT, and secondly, it should facilitate the updating of its model parameters using the data received from the actual object.

Modeling in control engineering involves creating mathematical representations of the desired physical system. These models allow engineers to gain insights into the system's behavior, perform analytical evaluations, and develop virtual simulations. The models are based on the principles of system dynamics, wherein the evolution of internal variables (states) under external stimuli (inputs) is computed to accurately depict the system's dynamics.

There are several modeling approaches, each with its advantages and use cases. Figure 2.2 depicts the most popular "box" models that are considered when developing modeling approaches:

- *White box* modeling (also known as *First Principles* modeling). The structure of the model is known and the model is derived from physical laws.

- *Grey box* modeling. Some of the model is derived from physical laws. The model includes some aspects that are approximated in a way that prevents direct physical interpretation while yet being useful for modeling.

- *Black box* modeling. There is no a prior knowledge of the system's physical structure. As a result, the model is developed by fitting experimental data to an arbitrary mathematical model type and structure. Although it may be less useful if the structure of the systems under research is understood, this data-driven technique is widely used.

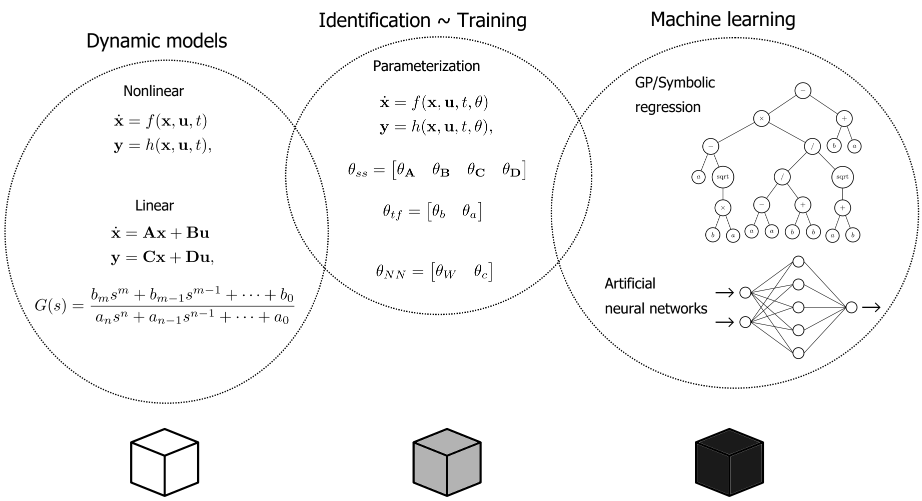


Figure 2.2: The most popular "box" models approaches [P1].

Looking closely at the creation of dynamic system model, a state space representation of a dynamic model employing a system of differential equations is as follows

$$\begin{aligned} \dot{\mathbf{x}} &= f(\mathbf{x}, \mathbf{u}, t) \\ \mathbf{y} &= h(\mathbf{x}, \mathbf{u}, t), \end{aligned} \tag{2.1}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the state vector, $\mathbf{u} \in \mathbb{R}^m$ is the input vector, $\mathbf{y} \in \mathbb{R}^p$ is the output vector, t is the time argument, and $f(\cdot)$ and $h(\cdot)$ are nonlinear functions. For convenience, linear, time-invariant approximations of (2.1) are often used and are of the form

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \\ \mathbf{y} &= \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u},\end{aligned} \tag{2.2}$$

where $\mathbf{A} \in \mathbb{R}^{n\times n}$, $\mathbf{B} \in \mathbb{R}^{n\times m}$, $\mathbf{C} \in \mathbb{R}^{p\times n}$, and $\mathbf{D} \in \mathbb{R}^{p\times m}$ are state, input, output, and direct transmission matrices with numerical entries, respectively [37]. The transfer function notion can be used for linear, time-invariant systems with a single input and single output. Shown below is the equivalent dynamics equation in the Laplace domain.

$$G(s) = \frac{b_m s^m + b_{m-1}s^{m-1} + \cdots + b_0}{a_n s^n + a_{n-1}s^{n-1} + \cdots + a_0}, \tag{2.3}$$

where s is the Laplace operator, a_i and b_j are real numbers, and n is the order of the model. For the system in (2.3) must be proper, i.e., the condition $n \geqslant m$ must be satisfied for it to be practically realizable

Data from actual plants must be gathered for grey and black box models. The sensors of the actual control object are sampled in the current work to gather data. A data acquisition device connects the devices to the desktop computer. The model identification process is carried out after data gathering and reprocessing. For that purpose, the general model in (2.1) is parameterized as

$$\begin{aligned}\dot{\mathbf{x}} &= f(\mathbf{x}, \mathbf{u}, t, \theta) \\ \mathbf{y} &= h(\mathbf{x}, \mathbf{u}, t, \theta),\end{aligned} \tag{2.4}$$

where θ is a set of model parameters to be identified. For the linear models in (2.2) and (2.3), the parameter sets are

$$\theta_{ss} = \begin{bmatrix}\theta_{\mathbf{A}} & \theta_{\mathbf{B}} & \theta_{\mathbf{C}} & \theta_{\mathbf{D}}\end{bmatrix} \tag{2.5}$$

and

$$\theta_{tf} = \begin{bmatrix}\theta_b & \theta_a\end{bmatrix}, \tag{2.6}$$

respectively. Time identification is employed such that the output error criterion (residual norm)

$$F = \sum_{i=1}^{n} \varepsilon_i^2 = \|\varepsilon\|_2^2 \tag{2.7}$$

is minimized, where $\varepsilon_i = y_i - \hat{y}_i$ is the residual (simulation error), y_i is the true system output and $\hat{y}_i$ is the predicted output for collected samples $i = 1, 2, \ldots, N$. Figure 2.3 shows a typical time series chart for studying control system dynamics.

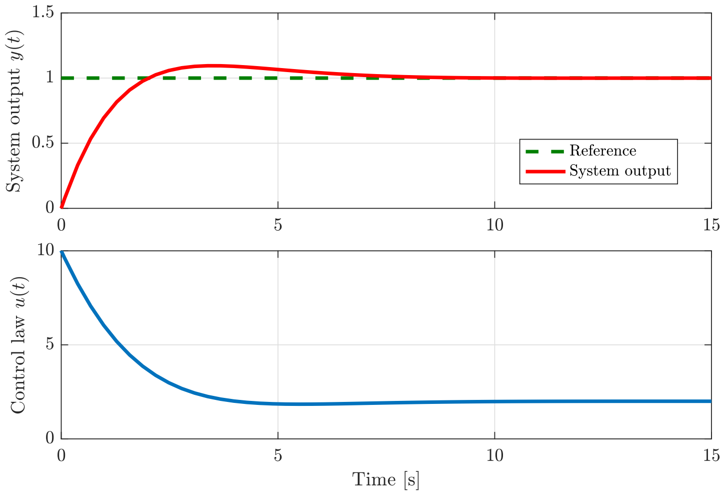


Figure 2.3: Typical time series chart for studying control system dynamics, here for a single input, single output system. Top: tracking performance analysis through step response evaluation. Bottom: control law dynamics analysis (system input generated by a controller) [P1].

In case of a multi-input, multi-output system, A weighted sum is utilized as the cost function, and the residuals from modeling individual outputs are scaled in accordance with the size of the modeled physical variable. The Trust Region Reflective algorithm [38, 39], the Levenberg-Marquardt algorithm [40, 41], and the Nelder-Mead direct search method [42] are some of the optimization methods used to estimate the parameters of the model. The latter well-suited to optimize a function whose derivatives are unknown or non-existent. Because state space model identification requires estimating a significant number of parameters, the parameter set $\theta_{\mathbf{D}}$ can be disregarded because the relevant matrix is often a zero matrix., i.e., $\mathbf{D} = \mathbf{0}$.The subspace estimation method is also utilized to address the issue of initial parameter estimate [43].

Not all studied control objects are stable. Hence, a closed loop system with a stabilizing controller (compensator) must be constructed in order to produce significant results. In order to illustrate several connected topics, the controller should also be given laboratory instruction. The traditional negative unity feedback control loop is taken into consideration in this work.

$$H(s) = \frac{C(s)G(s)}{1 + C(s)G(s)} \tag{2.8}$$

comprised of a plant represented $G(s)$ and a controller represented by $C(s)$. The aim of control engineering is to develop a control system, which in case of the present work amounts to solving the tracking problem — the measured output of a given system must converge to the desired prescribed value we refer to as the set point. Thus, the control system's goal is to modify the plant input u through the controller in order to reduce the error e , or the difference between the desired output$r$ (reference value) and the actual output of the plant y, i.e., the output tracking problem is taken into consideration. A proportional-integral-derivative (PID) controller is frequently employed in real-world industrial applications [44, 45, 46]. In this work, the parallel form of the PID controller is employed, which takes the following form::

$$C(s) = K_p + K_i s^{-1} + K_d s \tag{2.9}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively. These parameters must be properly tuned for each control loop that composes the full system.

The parameters of the models created using the approaches outlined above will not be static and will co-evolve with changes in the real systems in the case of DT synchronization with those systems. As a result, parameter estimation and controller parameter transfer will be ongoing processes. The unique physical lab asset will provide useful data as it is used, which will be kept on the server and used to get the most recent mathematical models. To summarize The following steps are involved in developing a data-driven mathematical model for the DT:

- Relevant data are first collected from the real plant.
- second, one of the outlined box models is used with system identification.
- Finally, the DT can use the model of the dynamics. The model is periodically updated in a process referred to as synchronization of the real system and the DT.

2.3 Use of DT and XR in Laboratories

In control engineering, hands-on laboratories are frequently supplemented with mathematical models and simulations that, on the one hand, give the theoretical underpinnings for modeling the specific control object and, on the other, enable students to construct control systems based on these models. The models are frequently based on approximations that result in unmodeled dynamics; for instance, the parameters of the researched systems are believed to be time-invariant, when in reality the values are prone to change. Hence, upgrading these models and simulations necessitates manual labor and specialized knowledge, which increases the expense of establishing, operating, and maintaining laboratories.

On the other side, the Industry 4.0 revolution started to stress the utilization of data as the foundation for enhancing process and operations across all industries. For instance, Industry 4.0 builds on top of a data-driven architecture by employing models that may leverage data from real systems to synchronize the virtual representation of these systems with their real-world counterparts, resulting in the notion of DT. The most frequently referenced definition of a DT is [47]. Note that the quote is taken from a NASA-published paper, hence the use of the term "flying twin," but the applications of DT are not confined to the aerospace industry. Moving forward, Industry 5.0 integrates this data-driven approach with a renewed focus on human collaboration, sustainability, and societal contributions, further advancing the synergy between digital advancements and human ingenuity in the industrial domain.

A DT is defined as comprehensive multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that utilizes the best available physical models, sensor updates, fleet history, etc., to replicate the life of its flying twin.

As a developing technology, the DT notion has multiple meanings in the literature, and academics are experimenting with its applications in various industries.

This work adhere to the "Digital Twin Consortium's" definition: "A digital twin is a virtual representation of real-world things and processes, synchronized with a predetermined frequency and degree of accuracy" [48]. Regarding the dynamical modeling aspect of a DT, the work refers to [49], in which the DT is stated as consisting of three primary components:

- a replica of the object,
- an evolving collection of facts about the thing,
- a mechanism for dynamically updating or modifying the model based on the data.

The authors of [50] highlight the benefits of going from simulated/virtual laboratories to DT; the authors argue that while DT of laboratories are more difficult to develop, simulated laboratories have applications mainly focused on education, while DT have applications in research as well. In [51], the authors identify two key issues that need to be addressed before the transformation from simulated laboratories to DT can occur:

- devising the control architecture;
- solving the problem of synchronization.

In [52], a web-based DT of a thermal power plant was introduced, the authors highlight the advantages of such a system in education and training, as the

DT approach allows students to gain valuable practice with operation and control of the facility which is not possible in the real plant due to safety issues, nor is it feasible in hands-on laboratories as they lack the required scale and complexity.

In [53, 54], the DT concept was introduced to students as part of the mechatronics course, as it involves the application of identification, modelling, and analysis, controller design and validation. The same DT are later used to compensate for the lack of availability of real laboratories for remote operations. DT have been also widely used in applications where students safety might be an issue. The authors of [55] showed how the connection of DT and VR can be used to create a safe working environment for students in robotics applications. The authors of [56] showed how the use of virtual and augmented reality (AR) in remote and simulated laboratories can be used to enable collaboration using avatars. The study showed that this approach requires integration into an e-learning system to ensure success in the learning process. The use of AR to enhance remote laboratories have a shown to increase students performance, as it allows students to experience the laboratory in a way that was not possible with traditional hands-on laboratory [57]. Immersive virtual technology has gained a lot of interest as a tool for higher education. This technology has wide adoption and uses especially in engineering and computer science. However, these adoptions are mostly in the experimentation phase and focused more on usability and performance. Only a few have drawn the line between the design and theories of learning or discussed how it is going to be adopted in the curriculum. A review of VR enabled laboratories has suggested that a blended/hybrid approach could be an ideal solution, where the hands-on laboratories can be introduced to address the issue of belief, and later on, more versatile and cost-effective laboratory modes can be used, such as remote and virtual laboratories. The hybrid approach must take into account the student differences in terms of grade level, cognitive skills and psychological development [58]. A VR experience that enables a higher level of interaction is introduced for investigating electrical connections in [59]. The system allows for faster iterations while performing experiments compared to hands-on laboratories. The authors argue that this will lead to students' better understating of the basic principles on which the experiments are based upon. The visualization capabilities of XR (and AR in particular) afford many opportunities for enhancing the ways complex systems can be monitored and controlled. This is especially important in the context of Industry 4.0 and the Internet of Things. If these opportunities are seized early in control engineering education through integration of XR technologies into hands-on experiences, these experiences can naturally lead the students through the landscape of Industry 4.0 and prepare them for actual industrial applications where XR is used as a part of human-machine interfaces.

2.4 Enhancing Interactions in Virtual Environments

A key aspect of VR is its immersive quality, often referred to as 'presence,' which is categorized into two distinct illusions [60]:

1. *The place illusion*: The user is feeling that he or she is moved into another place;

2. *The plausibility illusion*: the user's satisfaction with the environment in response to his or her interaction with it.

The plausibility illusions particularly intriguing because it encompasses the interface devices, such as controllers, and the algorithms that enhance user interaction within the VR environment. A preferred interaction method within the VE is using natural gestures, akin to how one quickly adapts to smartphone usage [61].This method forgoes the need for familiarizing oneself with physical devices like the HTC Vive controller. Despite its advantages, this approach has its challenges, especially in providing physical feedback, which is usually offered by tangible controllers. Innovations like the Myo Armband [62] have been introduced to address this gap, yet they still face challenges in maintaining user immersion, as discussed by [63]. An alternative strategy involves multimodal input techniques. For instance, the "gaze and pinch" technique. [64] which integrates gaze tracking with hand gestures for a more versatile interaction with VE objects. The believability of interactions also hinges on the algorithms that govern the VE's response to user actions. Traditional handcrafted, rule-based algorithms struggle to adapt to a diverse user base. In contrast, recent trends show a growing reliance on data-driven approaches for recognizing and classifying human behavior patterns in VEs. For example, [65] utilized eye gaze data to determine movement direction in collaborative robot environments. Additionally the authors of [66] reported on a system capable of semantic extraction and real-time data analysis for activity classification in VEs. Similarly, the authors of [67] proposed a deep learning framework for continuous human behavior monitoring, applicable in fields like sports, rehabilitation, and smart home environments.

Table 2.1: Laboratory Modes Classification

Laboratory mode	Resource nature	Resource location	Description
Traditional practical laboratory	Real resources	Local access	It represents the traditional practical laboratory and take-home laboratory kits where the student is in front of a computer connected to the real plant to carry out the experiment
Remote laboratory	Real resource	Remote access	It represents remote real experiment where the students access the real plant equipment laboratory through the internet. The user operates and controls a real plant through an experimentation interface in a remote way.
Locally hosted virtual laboratory	Simulated resource	Local access	It represents the virtual experiment where the whole environment is software and the experimentation interface works on a simulated, virtual and physically nonexistent resource
Cloud hosted virtual laboratory	Simulated resource	Remote access	It represents Remote virtual experiment where the students access the remote VE through the internet where the software and the experimentation interface works on a simulated, virtual and physically nonexistent resources.

Chapter 3

Novel Unified Framework for Control Engineering Laboratories

In the subsequent chapter, the "Reimagine Lab" framework is proposed, wherein the application of DT and XR is utilized to Reimagine the traditional virtual and remote laboratory modalities, resulting in a unified and efficient new generation of control laboratories. The introduction of the framework begins by establishing its two fundamental components XR and DT. Firstly, The overall "Reimagine Lab" framework and how it combines DT and XR to streamline the creation of virtual and remote laboratories modes is detailed in Section 3.1, Next, in Section 3.2, XR is used to replace the usual 2D desktop interface to allow for a higher level of interaction and visualization necessitate by the rich DT representation. The benefits of employing the framework for both remote and virtual laboratories are discussed, along with the capability it provides to create shared experiments with hands-on laboratories in Section 3.3. Finally, conclusions for this chapter are drawn in Section 3.4.

3.1 The Integration of DT and XR: The "Reimagine Lab" Framework

As concluded by the literature review there is an ongoing debate about the efficiency of various laboratory modes. A comparison of the various laboratory modes found that the efficiency of these modes is decided by their ability to achieve specific learning objectives. While hands-on physical laboratories have challenges due to cost and space constraints, remote and virtual laboratories suffer from the following:

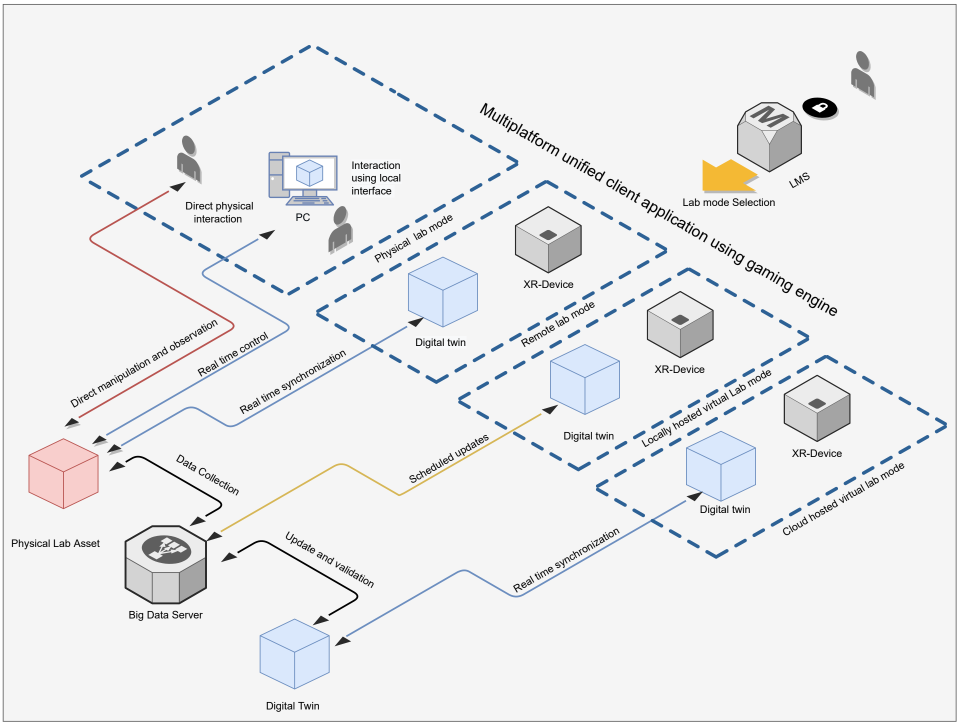


Figure 3.1: The overall schematic diagram for the ReImagine-laboratory framework [P1].

- Students express a lack of personal engagement in remote laboratories due to the separation between themselves and the experiment items [12, 13].
- Virtual laboratories are even more isolated since the virtual system does not exist in the physical world and the relationship between the physical and virtual environments is unclear.
- The usability of virtual laboratories is called into question because it is not the focal feature of their design [14].

Additionally, engineering students must develop soft skills in order to meet the needs of the industry and the accreditation standards set on university study programs. In this case, working patterns in hands-on laboratories are more suited to cultivating these skills than those in distant and virtual laboratories. [15]. A hybrid technique including many laboratory modes has emerged, allowing the modes to complement one another. For example, virtual and remote laboratories belonging to the same control object may be used [16]:

- The virtual mode is implemented at the control design phase when direct interface with the actual system is not necessarily required;

- the remote mode is utilized for studying the behaviors exhibited by the actual system and for gaining a deeper comprehension of the associated concepts.

As a result, rather than pursuing the optimal laboratory mode, one may devise a method for incorporating all modes into a single laboratory activity.

Motivated by this understanding, an architecture was proposed to facilitate the establishment of unified and compliant modes for hands-on, virtual, and remote laboratory experiments by integrating DT and XR in the following manner:

- Initially, remote laboratories are duplicated as high-frequency DT of the original laboratories.

- Secondly, locally hosted virtual laboratories are DT of the real laboratories that are frequently synchronized to assure the virtual representation's validity.

- Lastly, XR is employed to enable a higher level of interactivity and visualization provided by the DT depiction.

Illustrated in Figure 3.1, the framework overview shows how several fidelity levels of DT implementations are employed to represent the controlled physical object, while XR is used to enable the enhanced visualization and interactivity required by the DT representation. The proposed framework aims to improve usability in remote and simulated modalities to levels comparable to those seen in physical laboratories while retaining the flexibility and scalability offered by virtual and remote laboratory modalities. Additionally, the usage of XR has increased cooperation and immersion possibilities in these modalities. The "Reimagine Lab" framework indicates that DT-based laboratories not only replace old virtual and remote laboratories, but also improve traditional hands-on experimentation by providing shared or mixed experiences in conjunction with the usage of XR technology. Section 3.3 contains a detailed overview of how the framework achieves these characteristics.

Remote mode

As depicted in Figure 3.2. The framework enables remote teleoperation of the laboratory asset by replacing video streaming with local synchronization of the actual asset's digital counterpart. XR is being used to give a more intuitive and natural sort of interaction, giving users an experience comparable to that found in hands-on laboratories, by leveraging hand gestures and other techniques. Furthermore, XR fosters collaboration by creating VEs in which participants can interact with one another and the laboratory object.

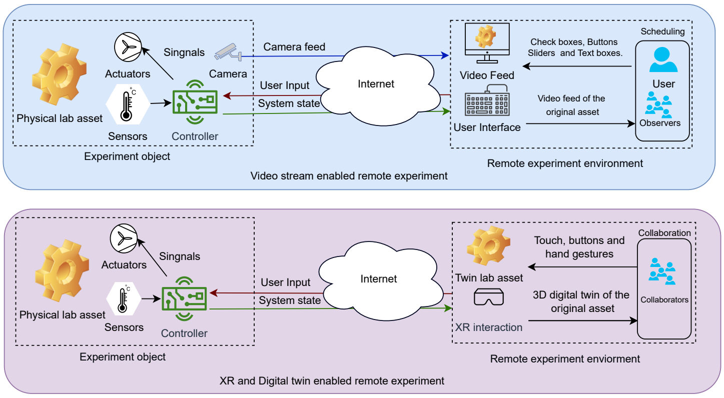


Figure 3.2: The schematic diagram for a remote laboratory and ReImagine enabled remote laboratory [P1].

Virtual mode

Figure 3.3 demonstrates how the proposed approach enables locally hosted virtual laboratories by replacing the simulated model with a DT:

- first, the bidirectional collection of data ensures that updates from the actual laboratory object are automatically applied to the DT;
- secondly, in accordance with the DT notion, data describing the uncertainty and divergence between the DT and physical twin are also accessible;
- And finally, the employment of XR technology as a means of engagement to capitalize on the wealth of data made available by the DT architecture.

The first two components are intended to boost student trust in the virtual simulation, while the incorporation of XR allows for the creation of environments that promote student interaction. Cloud-hosted VEs provide further framework benefits by allowing the use of more precise twin models. As shown in3.3. The simulation is distributed across the network, with local devices providing visual representations of the DT while computation is offloaded to the cloud.

Hands-on mode

As previously noted, the benefits of adopting the framework are not restricted to technology-enabled laboratories; they also assist hands-on laboratories by enabling for a variety of laboratory experiences to be combined.The use of XR and DT as shown in Figure 3.4 allows a blended learning environment in which some students interact directly with the laboratory asset

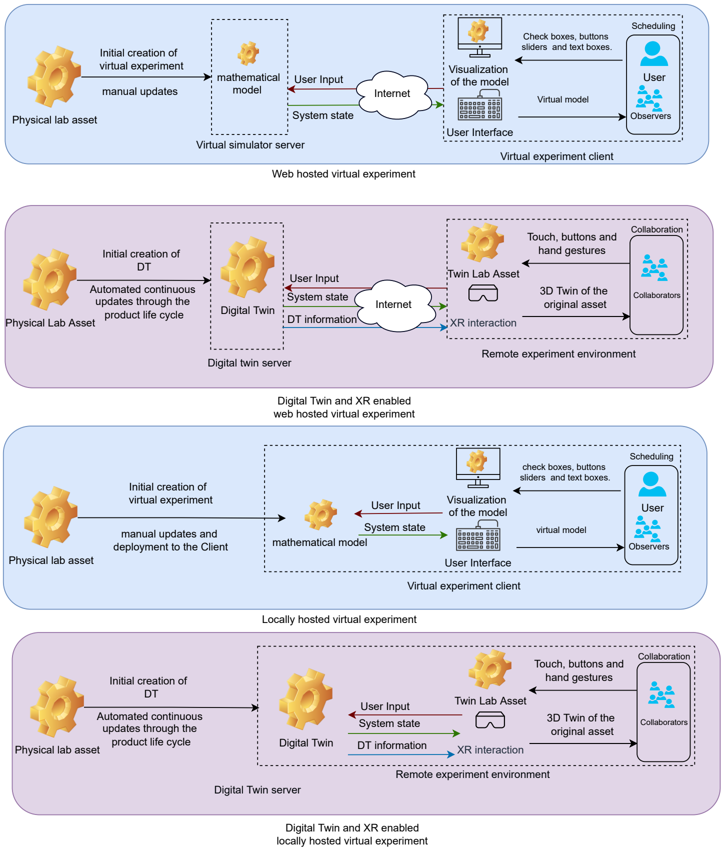


Figure 3.3: The schematic diagram for a virtual laboratory and ReImagine enabled virtual laboratory [P1].

while others interact remotely. If local students are also adopting AR to interact with laboratory object, this interaction can be bidirectional.

3.2 Utilizing XR for Enhanced Interaction and Visualization

The second essential component of the Reimagine Lab framework are XR applications which encompass the DT representation. To achieve the Reimagine Lab's goal of improving student engagement, graphical data analysis and intuitive interaction design are constructed on top of the DT's 3D model.

3.2.1 3D Models

All DT of control objects are built by first measuring the size of actual device parts or utilizing existing blueprints, and then implementing 3D models with

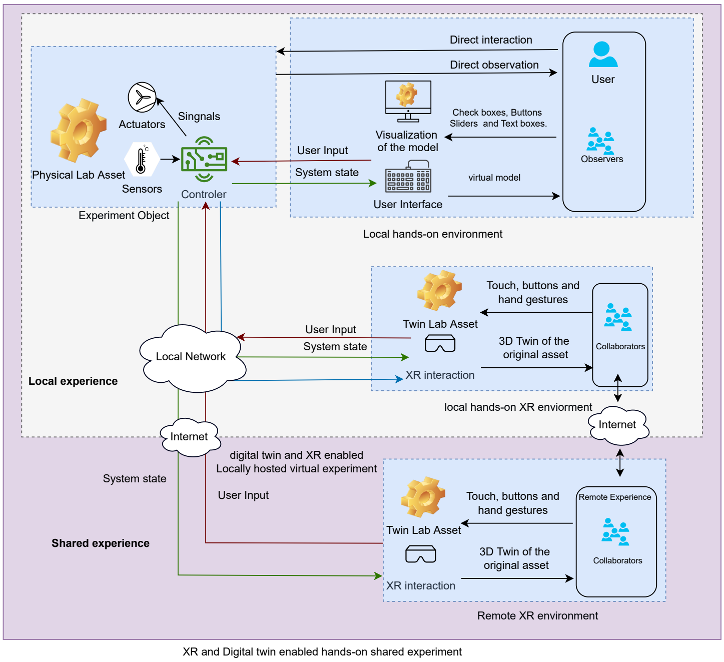


Figure 3.4: The schematic diagram for a hands-on laboratory and ReImagine enabled hands-on laboratory [P1].

CAD tools such as Blender 3D modeling software [68]. Because fast real-time rendering of objects is required for XR applications, the following critical factors must be applied while modeling all objects:

- All 3D models must be optimized, i.e., the number of polygons forming the part reduced and visualization trade-offs sought in terms of applying textures, displacement- and light maps.
- A sufficient level of detail must be ensured such that the effect of immersion is achieved [69].

The complete procedure for 3D modeling thus comprises the following steps:

1. Measuring the physical devices or using previously known blueprint data;
2. 3D modeling in Blender ensuring the sufficient level of detail is achieved;
3. Optimization: application of necessary textures, baking displacement- and light-maps;
4. Exporting the 3D model from Blender into a common 3D asset exchange format (usually FBX);

5. Importing the 3D asset into the real-time rendering engine, creation of materials that are used on the 3D model, validation in the target XR application.

If necessary, one may return to step 2 to correct any issues discovered in the real-time application.

3.2.2 Interaction Design

Interaction is the most critical part of an immersive XR environment. The fundamental purpose of the application's training aspect in the construction of DT of control systems is the design of meaningful interactions. [70]. As a result, the creation of coherent interactions is recognized as a high priority for assuring effective laboratory instruction.

This work investigate two forms of interactions that occur in the field of control systems:

1. Interactive selection of the control system tracking reference (set point);
2. Interactions with floating information panels that display valuable data concerning the setup and the state of the laboratory experiment.

In the subsequent discussion, the focus will be on the essential aspects of implementing these interactions. In terms of interface design, there are multiple options available. One approach is to utilize the physics engine provided by the target platform for implementation. However, the mathematical explanation of the procedure in this case is inherently ambiguous. Hence, the objective is to establish a sound mathematical model of the entire system, encompassing the interactions, which must be replicated in the DT. Consequently, interaction design is regarded as a mathematical problem, and all of the modeling methods outlined in Subsection 2.2 are appropriate for this purpose. Interaction mechanics are created using a variety of techniques:

- Interactions are coupled with the object dynamics, that is, the corresponding (non)linear mathematical model is augmented with corresponding inputs and states;
- Interactions are decoupled from the object dynamics, that is, a separate mathematical model is designed for the interaction. This approach is feasible only if the interaction does not affect control system performance, so its use is usually limited.
- An interaction is designed for the supporting components of the XR experience (such as using the information panels). Mathematical models of these interactions are, at first glance, not required; yet, if one considers the concept of intelligent immersive virtual environments (IIVEs), really useful intelligent mechanics can be employed as well [P2]

The performance of the model is initially compared to that of the original control object to measure interaction mechanics. Internal subject-based evaluation is then performed in XR by developers, followed by subject-based tests. If the input shows that the results are insufficient, the mechanism is revised.

3.2.3 Graphical Data Analysis

Graphical Data visualization is a very useful tool for evaluating the underlying processes [71]. As a result, one of the most important parts of learning control system dynamics is the analysis of time series charts displaying system dynamics [37]. As a result, the matching feature in the XR visualization must be implemented. That is, a real-time time series chart is required. To that purpose, the following items are taken into account:

- Due to the flexibility of presenting data in XR, the graphs can be presented to the user upon request and attached to the view port in an unobtrusive way. For example, the dynamic chart may be attached to one or both of the motion controllers and be shown upon the user pressing a preset button;

- The structure and types of charts shall depend on the particular study. In studying control systems, one is generally interested in control system tracking performance and control law behavior.

3.3 Characteristics of The "Reimagine Lab" Framework

Hands-on, remote, and virtual laboratories each have strengths, and educators have experimented with a variety of laboratory modalities in order to achieve high educational goals. Each lab mode demands specialized expertise and approaches, resulting in fragmentation and increased development and maintenance costs. The framework through the use of DT will solve fragmentation by taking a simplified and consistent approach that can be used to a wide range of control laboratory objects. Furthermore, in virtual and remote laboratory modes, the psychological separation between the student and the object is reduced by providing students with a thorough introduction to the use of DT in the creation of various laboratory modalities that assist in bridging this psychological separation.

As virtual simulated objects are elevated to be twins of the original laboratory objects the student-object engagement level is increased. Because laboratory modes are DT based on the original object, they allow for greater flexibility in laboratory mode selections. For example, students can conduct

Table 3.1: Characteristics Comparison of Different Laboratory Modes and Hybrid ReImagine Laboratories

Laboratory mode	**Usability**	**Scalability**	**Flexibility**	**Immersion**	**Collaboration**
Hands-on laboratories	High	Low	Low	High	High
Simulated laboratories	Medium	High	High	Low	Medium
Remote laboratories	Medium	Medium	Medium	Medium	Low
ReImagine laboratories	High	Medium	High	High	High

design experiments in virtual mode and then smoothly move to remote or hands-on modes to investigate the investigated phenomenon further. This transformation facilitates the selection of a laboratory mode based on available resources (physical access, connection, application) without harming the teaching experience.

The ability to produce immersion, or the sense that the user has been transferred to another location, is a significant advantage of adopting immersive VR. While immersion may be produced with a standard desktop computer, immersive VR makes it much easier. When the amount of immersion is enhanced, the student's involvement and interaction with the laboratory object improves. Furthermore while typically are few opportunities for students to acquire social skills when engage in virtual and remote laboratories, it is possible to build a shared VR experience utilizing XR in which students are portrayed as avatars within the environment and may communicate and collaborate as a group.

The use of many laboratory modes introduces differences in elements that affect system response and may result in unexpected behavior. For example, virtual laboratories are typically driven by an approximate model of the real object, which creates uncertainty. Also, communication latency has a significant impact on system response in remote laboratories. Users must be aware of these factors and their implications for the system. Implementing DT methode entails being honest about the differences between the DT model and the real system, resulting in a transparent experience.

Table 3.1 provides a comparison of the characteristics of the various laboratory modes and hybrid Reimagine laboratories.

3.4 Conclusion

This Chapter proposes and analyzes a DT and XR-enabled framework for constructing new generation of control system laboratory. This framework combines the use of DT and XR towards creating a unified solution for all laboratory modalities . Remote and virtual laboratories are recreated as DT of actual control objects while the inclusion of XR into the proposed digital representation enables more interaction with the object and collaboration between students and instructors. This unified solution not only transforms control system laboratories but also contributes to the advancement of both DT technology and XR applications in education and engineering.

Chapter 4

Control Engineering Use Cases with Lab-scale Equipment

In this chapter, two use cases will be presented to showcase the creation of a cohesive DT and XR application for a lab-scale object using the "Reimagine Lab" framework. First in Section 4.2, a multi-tank system is used to demonstrate the shared experiment and highlights the seamless transition between simulated and physical system modes in a mixed reality setting. Next, Section 4.3 hold the examples of a gantry crane system, which is used to demonstrate the simulated mode and how to apply the framework to a lab-scale gantry crane in a VR setting. The gantry crane use-case is also used in the subsequent chapters to perform the usability analysis and develop the data-driven replay and annotation system. The process of generating the DT for each control object is outlined in detail, starting with the development of a mathematical model that replicates the behavior of the real object, forming the basis for the DT representation. Subsequently, a 3D visual model is constructed, which will be utilized for visualization and interaction within the XR experiment. Lastly, an educational goal is defined for each experiment, upon which the interaction mechanisms are developed. Conclusions are presented in Section 4.4.

4.1 Selection of Specific Experimental Examples

The selection of specific experimental examples for showcasing the creation of cohesive DT using the "Reimagine Lab" framework was based on several key criteria. Below are the reasons why these specific experiments were selected:

1. Multi tank system (Section 4.2): The Multi Tank System consists of interconnected tanks with varying cross-sectional shapes, introducing nonlinear dynamics. The system features a variable speed pump for fluid transfer and adjustable valves for flow control, simulating real industrial liquid storage challenges. Control strategies such as PID, adaptive, and fuzzy logic are implemented to maintain stable liquid levels. This system is chosen as the initial example with an educational focus on PID controller tuning. Students initially engage with a simulated model of the system, enhanced with XR and DT visualizations in a Mixed Reality setting. Once the initial controller tuning is complete, students can seamlessly transition to operating the actual system. This transition exemplifies the proposed framework's approach, offering a shared experience that bridges simulated and hands-on laboratory activities through the use of XR.

2. Overhead Gantry Crane (Section 4.3): The overhead gantry crane is a nonlinear electromechanical system with complex dynamic behavior and challenging control problems. Its real-life industrial counterpart is used in various industries and seaports for transporting large and heavy containers, making it an essential object for efficient and safe cargo handling. The overhead gantry crane's selection as an experimental example demonstrates the framework's versatility in handling real-world industrial control applications with multiple degrees of freedom, offering insights into designing control strategies for optimizing transport efficiency and stability.

In addition to their technical attributes, these experiments were also chosen because they were created by the Inteco company, ensuring standardized and well-documented models. Their availability as laboratory models enhances their accessibility for research and educational purposes. The diversity of the selected experiments, including the different types of systems and their complexities, allows the "Reimagine" framework to showcase its adaptability to a wide range of control problems.

4.2 Multi Tank System

The Multitank System is a laboratory apparatus designed for the study and application of control systems. It includes multiple tanks with varying cross sections - some spherical and others conical, introducing nonlinear elements into the system. This setup utilizes a variable speed pump to transfer liquid between tanks, with gravity aiding in the outflow. Tank valves, adjustable to control flow resistance, help manage the outflow characteristics The system serves to explore and implement various control methods, including PID, adaptive, and fuzzy logic controls. Control is executed through adjustments in pump operation and valve settings, aiming to stabilize liquid levels within the tanks. This setup mirrors industrial storage tank control problems, emphasizing the need for precise liquid level control.

The laboratory model of the Multi Tank System considered in this work is depicted in Figure 4.1a. The Multitank System consists of several interconnected tanks with variable cross sections, a variable speed pump, adjustable drain valves, a water reservoir, level sensors. A schematic drawing depicting this configuration is borrowed from the manual, provided by INTECO [72], and depicted Figure 4.2.

3D model of the MLS

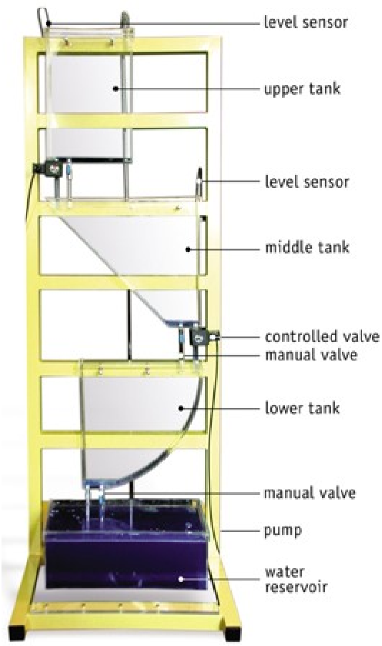
Similar to the 3D crane object, the 3D asset that represents the real life system was prepared in Blender. However in this case only the water level in each tank is considered for animations. Once the asset is transferred to Unreal Engine, the asset is reconstructed where the a water level component is attached to each water tank. The 3D model of the Multi tank sysytem is developed by recreating the following major components:

- The yellow frame;
- The water tanks and reservoir;
- The water level sensors;
- The pump;

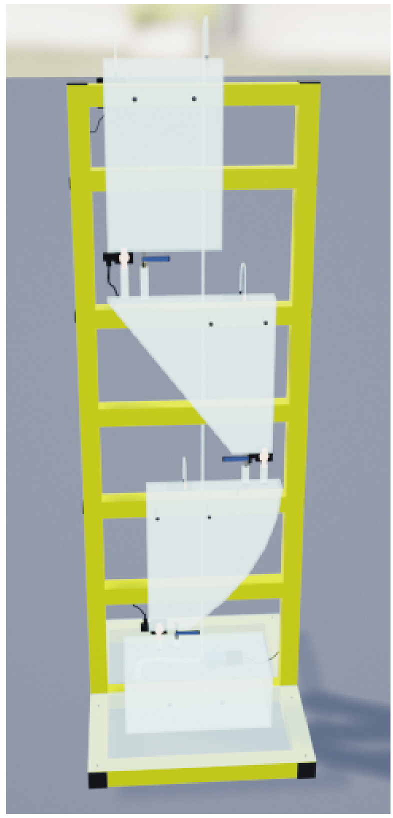
Thus, all critical components and the frame have been faithfully recreated, while the wires, and power switches are ignored. The resulting model is shown in Figure 4.1b.

Mathematical model of the MLS

The model of a Multi Tank system is borrowed from the manual, provided by [72] The differential equations, describing dynamics of the Tank system,



(a) Real-life Multi Tank System system, courtesy of the Center for Intelligent Systems at Talltech [72].



(b) 3D Model of the Multi Tank System system.

Figure 4.1: Multi Tank System control object in real life and the corresponding computer graphics version [72].

can be derived, assuming the laminar outflow rate of an ideal fluid from a tank, by means of mass balance as . The resulting model is a nonlinear model with three states that has the following form

$$
\begin{aligned}
\dot{x}_1 &= \frac{1}{aw}(u - C_1 x_1^{\alpha 1}) \\
\dot{x}_2 &= \frac{H_{2max}}{cwh + bwx_2}(C_1 x_1^{\alpha 1} - C_2 x_2^{\alpha 2}) \\
\dot{x}_3 &= \frac{1}{w\sqrt{R^2 - (R - x_3)^2}}(C_2 x_2^{\alpha 2} - C_3 x_3^{\alpha 3}).
\end{aligned} \tag{4.1}
$$

where a, b, c, w, H_{2max}, R are geometrical parameters of the tanks shown in figure 4.2, $x_i$is the fluid level of the $i$the tank, C_i is the resistance of the output orifice of the ith tank, $\alpha_i$is the flow coefficient for the ith tank.

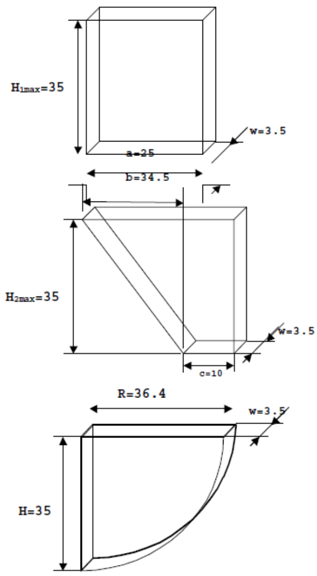


Figure 4.2: A schematic drawing of the Multi Tank System

Finally, q is the inflow of the upper tank which is the pump capacity that depends on the normalized control input $v \in [0, 1]$.

We assume that a classical PI controller will be used to control a given plant; in particular, we consider the parallel form of the PI controller which operates on the negative unity feedback-produced error signal

$$e(t) = y_{SP} - y_{real} \tag{4.2}$$

wherey_{SP} is the set point and y_{real} is the controlled plant output, to produce a control law $u(t)$ that in the time domain has the form

$$u(t) \quad = \quad K_p e(t) + K_i \int_0^{\tau} e(t) d, \tag{4.3}$$

where K_p is the proportional gain, and K_i is the integral gain. In industrial applications, K_p and K_i are the usual "tuning knobs"—appropriate values of these gains ensure stable and efficient operation of the control system. Unfortunately, there are numerous instances where the PI controller's tuning is far from ideal. Therefore, mastering the process of adjusting these gains to produce sufficient control performance is crucial for control engineering practice in order to enhance tracking performance, safety, efficiency, and dependability of control systems as well as to minimize energy waste that results from the control law's improper behavior.

Educational objective and interaction design

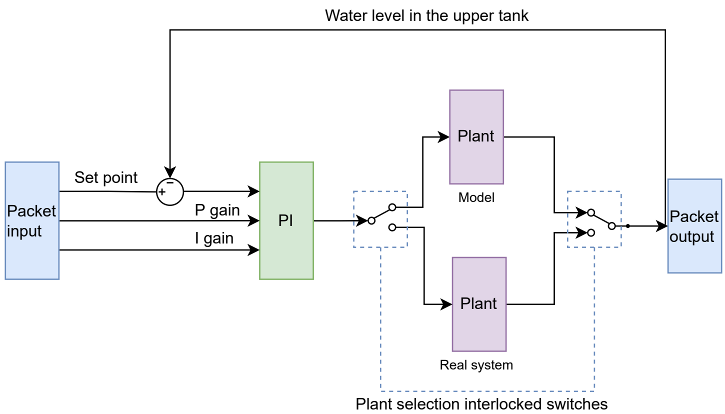


Figure 4.3: The schematic diagram for the multi tank system control experiment.

Next, the educational objective is outlined. This part is implemented in MATLAB/Simulink environment as a control loop. The schematic diagram that represents the whole configuration is shown in Figure 4.3. This experiment focuses on PI controller tuning in an instructional manner. In a Mixed Reality environment, students first interact with a simulated model of the system that is supplemented with XR and DT representations. After finishing up the basic controller tweaking, students can easily move on to controlling the real system as shown in Figure 4.4. This transition serves as an excellent example of the methodology of the proposed framework, providing a shared experience that uses XR to connect simulated and practical laboratory activities.

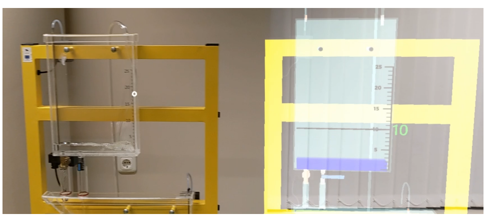
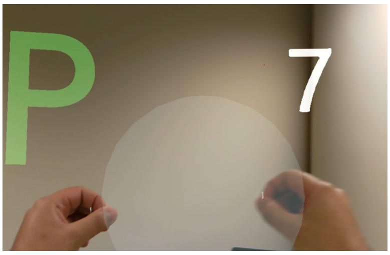


Figure 4.4: Screenshot from the XR-based multi tank application: The user has switched over to controlling the real device, and the digital twin can be used to visualize the system's performance and change the desired set point.

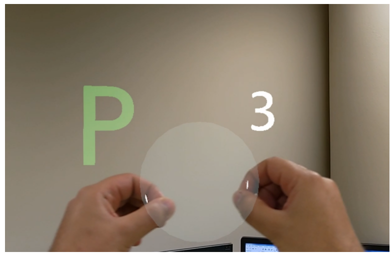
The following three interaction mechanics have been implemented for the experiment with the multi tank system:

- Interaction with the PI tuning spheres: changing the PI gains by resizing the corresponding spheres as shown in Figure 4.5a and 4.5b;

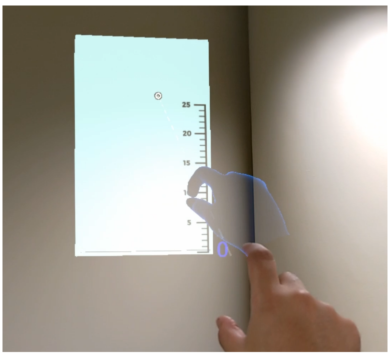
- Interaction with control object variables: changing the set-point—the desired water level in the upper tank—as shown in Figure 4.5c ;
- Interaction with plot widgets: such as grabbing and moving them to a new location or or resizing the figures using both hands as shown in Figure 4.5d.



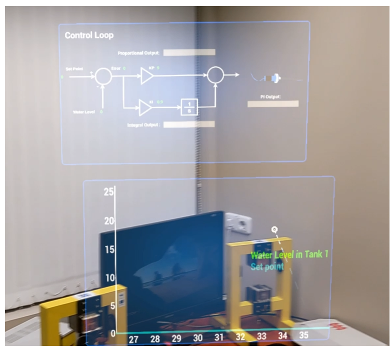
(a) Interaction with the PI tuning spheres: First, the spheres are grasped using both hands to initiate the resizing.



(b) Interaction with the PI tuning spheres: Next, the sphere is resized by bringing the hands closer together or moving them further apart from each other.



(c) Interaction with control object variables: The desired set point is changed by directly aiming at the upper water tank of the digital twin and confirming the new set point using the pinch gesture.



(d) Interaction with plot widgets involves moving them to a new location or resizing the figures using both hands.

Figure 4.5: Multi Tank System interaction mechanics.

4.3 Overhead Gantry Crane

In the context of the suggested framework, a case study of constructing a coherent DT of a lab-scale model of an overhead crane is described below. The initial real-life control object was created by the Inteco company and is known colloquially as the “3D crane” due to the number of degrees of freedom needed in manipulating the cargo [72].

The 3D Crane is a nonlinear electromechanical system that possesses a complex dynamic behavior and creates challenging control problems [72, 73]. The 3D Crane is a nonlinear electromechanical system with complex dynamic behavior and difficult control problems.This laboratory model’s industrial counterpart is used in a variety of industries and seaports to transport large and heavy containers and other payloads. To ensure efficiency and productivity, the crane must transport the payload to its destination as quickly as possible. However, a specific motion profile must be used so that the control actions leading to the payload’s acceleration and deceleration ensure secure and sway-free transportation. [74]. The system’s characteristics enable the use of various control strategies [73, 75, 76]. As a result, it is very appealing as an educational tool in the control systems laboratory.

Figure 4.6adepicts the current control object. It is made up of a frame with a moving rail to which a moving cart is attached. A rotating spool connects the payload to the cart. As a result, three degrees of freedom are obtained. DC motors drive the rail, cart, and payload spool, and their positions are determined by incremental encoder sensors. In addition, the cart has two encoders that measure the swing angle of the attached payload.

3D model of the overhead crane

Following the discussion above, the 3D model of the crane is developed. The following major components are recreated:

- The yellow frame;
- The moving rail;
- The moving cart with the moving spool;
- The payload itself attached to its cable.

As a result, all critical mechanical components and the frame were faithfully recreated, while the wires, DC motors, encoders, pulleys, and belts were left out. Initial experiments confirmed that as long as the recreated components have the correct scale and behave exactly as expected, the 3D model will be convincing enough to induce immersion. The resulting model is depicted in Figure 4.6b.

Mathematical model of the 3D crane

(a) Real-life 3D crane control object, courtesy of the Center for Intelligent Systems at Talltech.

(b) 3D Model of the 3D crane control object.

Figure 4.6: 3D crane control object in real life and the corresponding computer graphics version.

The discussion below pertains to obtaining a single snapshot of the physical twin dynamics using the methods described in Section. 2.2. The model shall be updated periodically based on the data generated during the operation of the physical overhead crane.

in what follows we detail the identification procedure 3D crane system and give detailed description of the input and output signals used for the identification.

The approximate model of the 3D crane was obtained by identification three sub models:

- A transfer function describing the motion of the rail.
- A transfer function describing the motion of the cart.
- A state space model describing the dynamics of the payload swing angles α and β.

The first step in the system identification procedure is collecting the data. The 3D crane is interfaced using Simulink model which was used to drive the crane. Figure 4.7 shows the Simulink model used to collect and store the data.

$$F = \sum_{i=1}^{n} \varepsilon_i^2 = ||\,\varepsilon||_2^2 \tag{4.4}$$

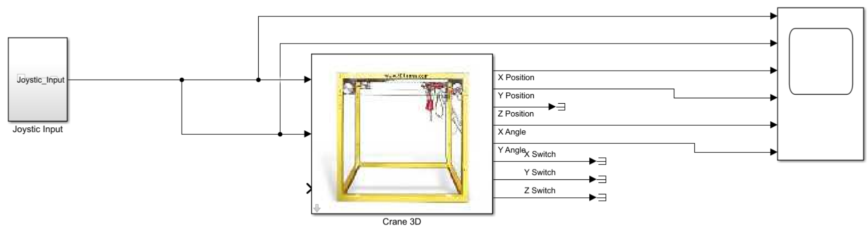


Figure 4.7: The Simulink model used to collect the data.

where $\varepsilon_i = y_i - \widehat{y}_i$ is the residual (simulation error), y_i is the true system output and $\widehat{y}_i$is the predicted output for collected samples $i = 1, 2, \ldots N$. In case of a multi-input, multi-output system, the residuals resulting from modeling individual outputs are scaled according to the magnitude of the modeled physical variable and a weighted sum is used as the cost function. Trust region reflective algorithm is used for the purpose of estimating the parameters of the model.

The input signals u_x , u_y and output signals x , y , α , β were collected for the identification procure. We exited the system with the input from joystick controller to get coherent response of the system. Figure 4.8 shows the input signal used when colleting the data for the system identification procedure. The rail and cart position output is shown in Figure 4.9 and the payload rotation angles α *and* β are shown in Figure 4.10.

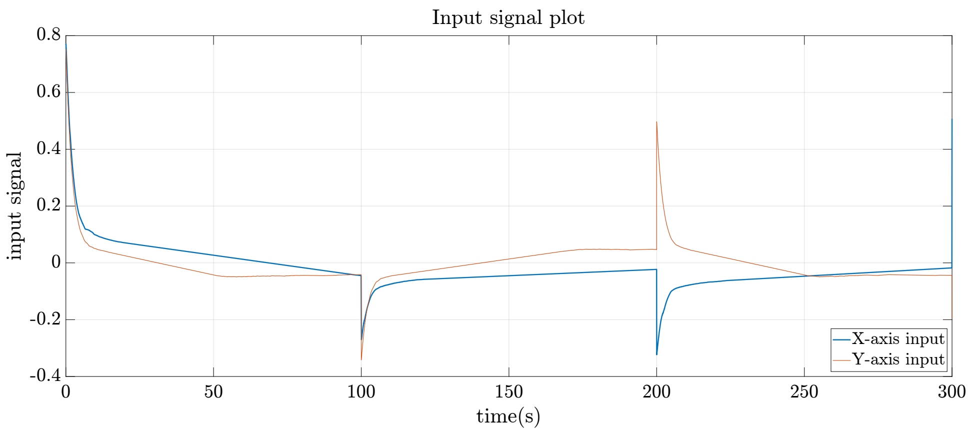


Figure 4.8: The input signal used when collecting the data for the system identification procedure.

This model identification procedure is used to estimate the parameters

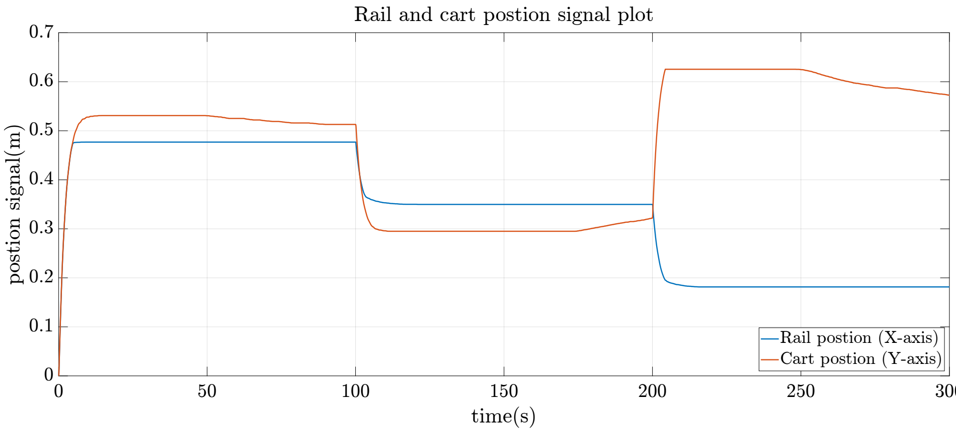


Figure 4.9: Rail and cart output signal used in the system identification procedure.

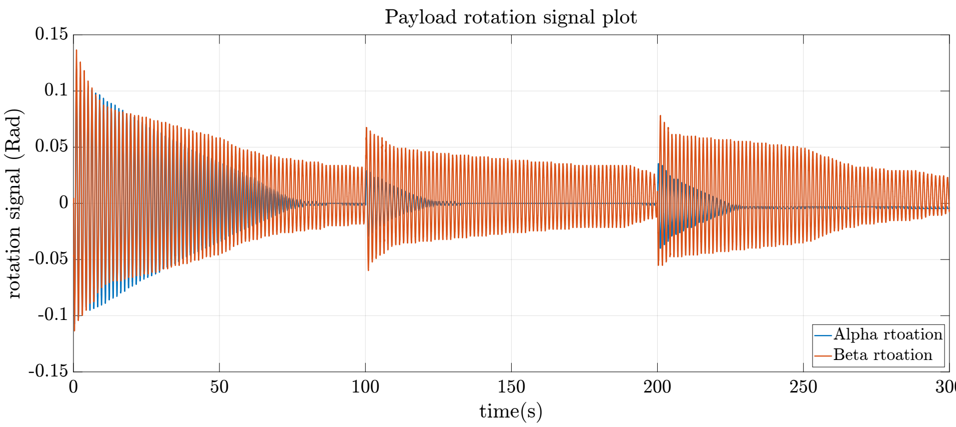


Figure 4.10: Payload rotation output signal plot used in the system identification procedure.

of the transfer functions and the state space model.

The parameters for the transfer function of the rail motion are estimated as:

$$G_x(s) = \frac{1}{s}\frac{0.30651}{0.035073s + 1} \tag{4.5}$$

And the parameters for the transfer function of the cart motion are estimated as:

$$G_y(s) = \frac{1}{s}\frac{0.33821}{0.041963s + 1} \tag{4.6}$$

As for the payload dynamics of the payload swing angles α and β the State space matrices parameters are estimated as:

$$\theta_{ss} = [\theta_A \quad \theta_B \quad \theta_C \quad \theta_D] \,, \tag{4.7}$$

$$A = \begin{bmatrix} -0.4377 & 3.513 & 0.5393 & -1.9075 \\ -3.804 & 0.2155 & -1.5478 & -0.8172 \\ -0.0913 & 1.3392 & -0.0178 & 4.3422 \\ 1.1336 & 0.0534 & -3.0303 & 0.1400 \end{bmatrix}, \tag{4.8}$$

$$B = \begin{bmatrix} 0.56505 & 0.21808 \\ -1.1166 & -6.7447 \\ -0.13395 & -2.3007 \\ 4.8125 & -3.1489 \end{bmatrix}, \tag{4.9}$$

$$C = \begin{bmatrix} -0.0123 & 0.02454 & -0.00524 & -0.03695 \\ -0.04552 & 0.09786 & 0.03010 & -0.02335 \end{bmatrix}, \tag{4.10}$$

$$D = \begin{bmatrix} -0.0011281 & 0.0013873 \\ 0.0011836 & 0.0012102 \end{bmatrix}. \tag{4.11}$$

It is of course possible to represent the above linear approximation as a single state space formulation:

$$A = \begin{bmatrix} -28.5120 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -23.8305 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.4377 & 3.513 & 0.5393 & -1.9075 \\ 0 & 0 & 0 & 0 & -3.804 & 0.2155 & -1.5478 & -0.8172 \\ 0 & 0 & 0 & 0 & -0.0913 & 1.3392 & -0.0178 & 4.3422 \\ 0 & 0 & 0 & 0 & 1.1336 & 0.0534 & -3.0303 & 0.1400 \end{bmatrix}, \tag{4.12}$$

$$B = \begin{bmatrix} 1.0 & 0 \\ 0 & 0 \\ 0 & 1.0 \\ 0 & 0 \\ 0.56505 & 0.21808 \\ -1.1166 & -6.7447 \\ -0.13395 & -2.3007 \\ 4.8125 & -3.1489 \end{bmatrix}, \tag{4.13}$$

$$C = \begin{bmatrix} 0 & 8.7392 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 8.0597 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.0123 & 0.02454 & -0.00524 & -0.03695 \\ 0 & 0 & 0 & 0 & -0.04552 & 0.09786 & 0.03010 & -0.02335 \end{bmatrix}, \tag{4.14}$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ -0.0011281 & 0.0013873 \\ 0.0011836 & 0.0012102 \end{bmatrix}. \tag{4.15}$$

The last stage involves confirming whether the resultant estimated model effectively captures the swinging characteristics of the payload. This assessment serves to underscore the significance of employing feedback control to counteract and eradicate payload swinging. To validate the model, a comparison is drawn between its behavior and the response of the original physical system. This ensures that the essential dynamics are faithfully replicated within the DT model.

As shown in Figure 4.11, certain discrepancies can be observed between the model and the real system. Taking a closer look at the data specifically by plotting the difference between the model and actual system we get an actual measure of the error.

Nevertheless, when observing the DT of the 3D crane within the XR environment, these modeling errors typically do not disrupt the immersive experience. The crane's dynamics are still perceived as plausible by users. The model's accuracy largely hinges on the learning objectives of the control experiment. For instance, if the aim is not to showcase the mathematical

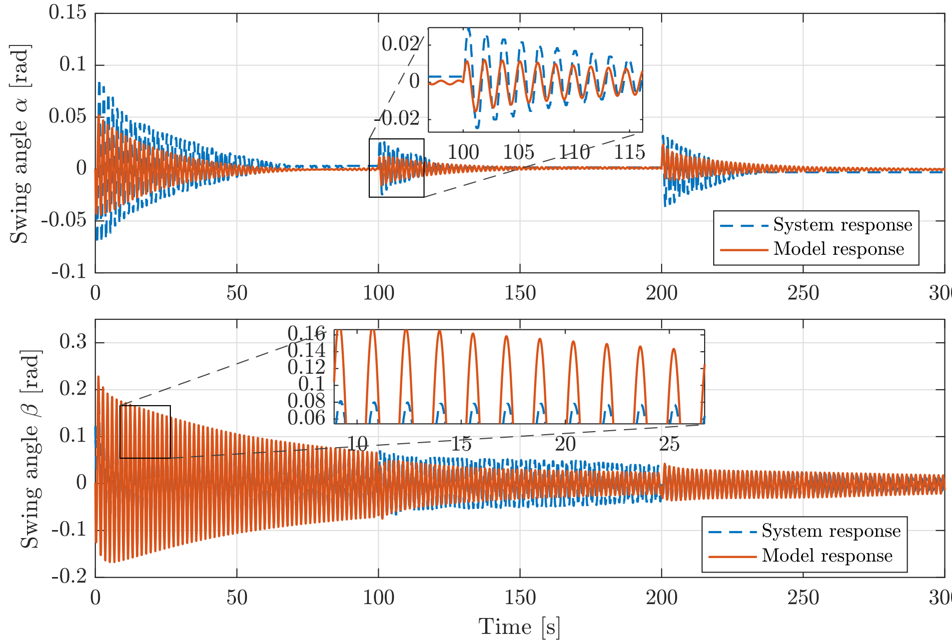


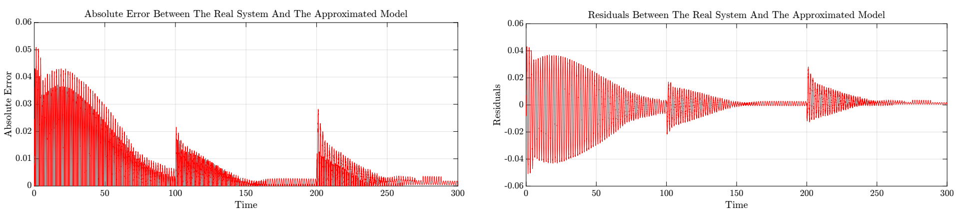
Figure 4.11: Validation results of the reduced state space model for the swing angle dynamics of the 3D crane [P1].

model's precision but to illustrate high-level control concepts, the accuracy achieved by the previously estimated model suffices. Examining MAE, MSE, and RMSE in Table 4.1, it becomes evident that the disparity between the real system and the approximated model is exceptionally small. Furthermore, as illustrated in Figure 4.12, when we measure the residuals and absolute errors between the responses of the real system and the approximated model, we can confirm that the most significant deviations occur during periods of intense crane payload oscillations, i.e., when the crane is uncontrolled. On the other hand, the crane exhibits more precise responses when it is under control. This is acceptable behavior in the context of the proposed experiment because the proposed model successfully accounts for both the uncontrolled case, where it is important to demonstrate the swining of the payload, and the controlled case, where it is important to demonstrate accurate tracking of the set point. The proposed model effectively fulfills both of these criteria, therefore confirming the positive validation of this model.

When planning experiments that necessitate a more accurate representation, a more refined modeling approach becomes essential. Instead of opting for the black box method, as illustrated in Figure 4.13, which yields a linear approximation for a fixed crane line length, the gray box approach is preferable. This involves incorporating a nonlinear model of the system, resulting in a more precise representation. The model can also integrate the state

Table 4.1: Fit Accuracy Metrics for Model

Metric	**Description**	**Value**
MAE (Mean Absolute Error)	The average of the absolute differences between the predicted and observed values.	$\approx 7.33 \times 10^{-3}$
MSE (Mean Squared Error)	The average of the squares of the differences between the predicted and observed values.	$\approx 1.44 \times 10^{-4}$
RMSE (Root Mean Squared Error)	The square root of MSE, measuring the differences between values predicted by a model and those observed.	$\approx 1.20 \times 10^{-2}$



(a) Absolute Error

(b) Residuals

Figure 4.12: Residuals And Absolute Error Between The Real System And The Approximated Model of The 3D Crane.

variable corresponding to the line length. This refined approach enables the design and execution of experiments, such as controller tuning, within both the real environment and the DT context.

Educational objective and interaction design

The experimental configuration is depicted in Figure 4.14. The primary control loop is concerned with the payload's position in the (x, y)-plane. The goal is to move the payload as quickly as possible from one location to another. The secondary loop compensates for payload swing and can be turned on and off; the goal of the experiment is to evaluate the performance of the control loop in both of these scenarios. Figure 4.15 shows a screenshot

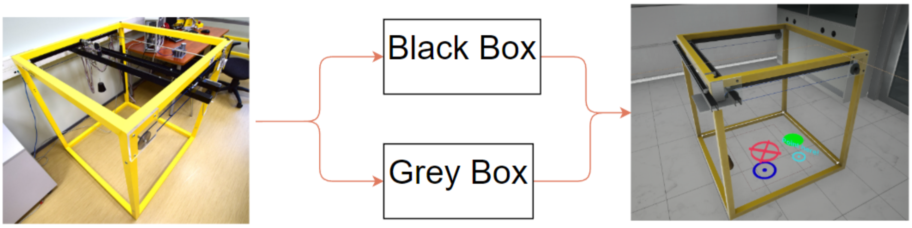


Figure 4.13: Schematic diagram showing the use of different modeling approaches for DT models [P1].

from the application. Because the user is pointing the motion controller away from the reference cube, the set point remains unchanged but is displayed on the floor in the form of a cross-hair.

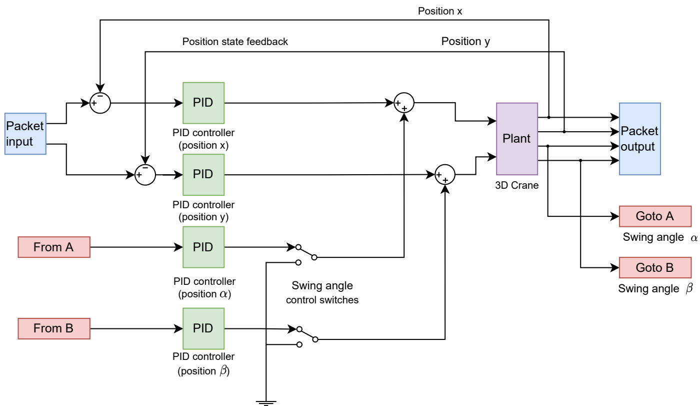


Figure 4.14: The schematic diagram for the 3D crane control experiment [P1].

In this case, the charting facility is used to compare the performance of the control loop with and without swing compensation enabled. Figure 4.16 shows an example of a result depicting the situation when swing compensation is enabled. It can be seen that introducing control actions that cause oscillations in caret position effectively dampens the swing. Better tuning of PID controllers, which is part of the control laboratory assignment, can improve performance.

The following two interaction mechanics have been implemented for the experiment with the 3D crane:

- Interaction with control object variables: changing the set-point—the desired location of the crane's payload—and changing the crane's control model;

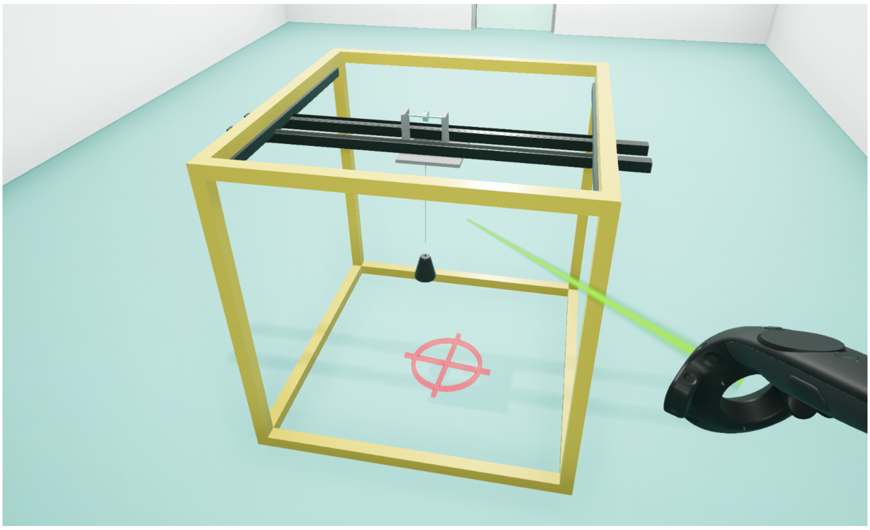


Figure 4.15: Screenshot from the VR based 3D Crane application. The user is pointing the motion controller to an area outside of the reference box, so the cross-hair appears only to show the current set point [P1].

- Interaction with plot widgets, such as moving them to predefined locations, grabbing and moving them to a new location, or grabbing and throwing them anywhere in the VE.

4.4 Conclusion

In this chapter, we have demonstrated several examples of how to use the "Reimagine" framework to XR application of control laboratories. The examples have shown that a similar work flow may be used to acquire the mathematical model and 3D visualized model for the representation of the DT across different control objects. On the other hand the design of the interaction mechanism is largely dependent on the desired education object and may change for various aims, even for the same control object. While this may first imply that more handmade effort is required for each experience, it turns out that the interface designed for educational aims is reusable across different control objects. This chapter showed that the proposed framework. which seamlessly integrates DT and XR, goes beyond theory to practical application. Through its successful implementation on diverse control objects, it not only transforms control system laboratories but also serves as a pioneering example of how DT technology and XR applications can contribute to education and engineering fields.

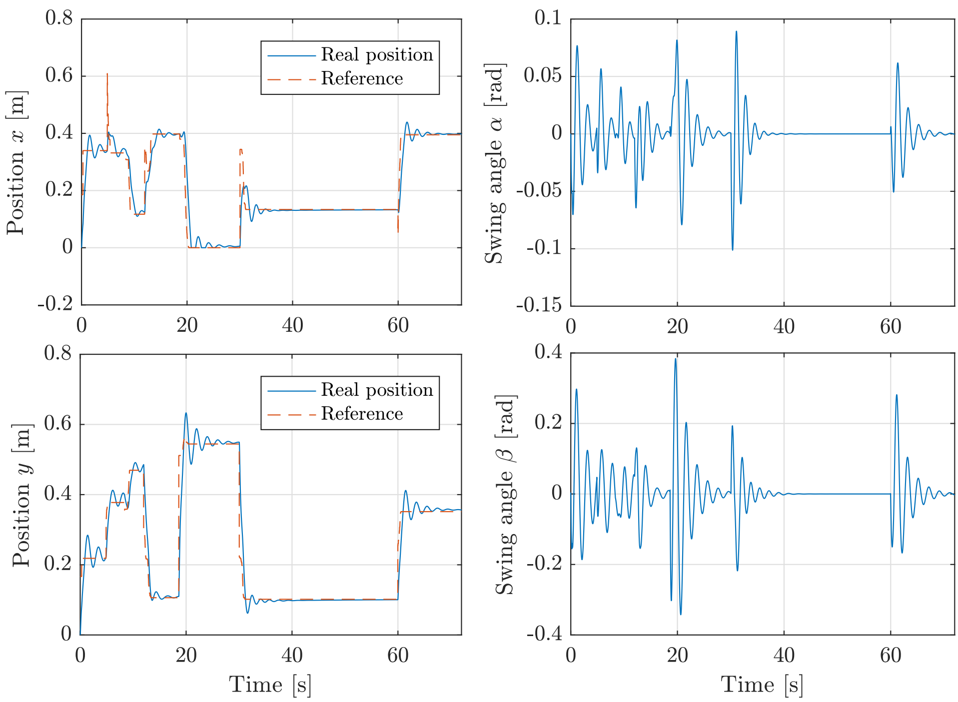


Figure 4.16: Experimental chart showing the performance of the control system with payload swing compensation enabled [P1].

Chapter 5

System Usability Study for the Framework

This chapter present the initial findings derived from conducting research using a "ReImagine laboratory" application featuring a lab-scale gantry crane. The 3D crane DT which was demonstrated in Sec 4.3 can be experienced in an XR environment. While the experiment exclusively explores the virtual lab mode, it is important to note that both the DT and XR technologies are fundamental to all lab modes and are central to this research. Therefore, the insights derived from subject-based testing are expected to shed light on the broader applicability and usability of these technologies for their intended purpose. If the findings suggest that DT and XR are effective in this specific application, the implications can be extended to other lab modes. This chapter is arranged as follows: Section 5.1 details the planned study, Section 5.2 describes the questionnaire used in the SUS study, and the study's findings are presented and discussed in Section 5.3. Finally, in Section 5.4, the conclusions are drawn.

5.1 Design of the Experiment

The experiment was designed primarily to conduct a SUS, aiming to assess and compare the effectiveness of two distinct learning environments. The focus was on a traditional laboratory experiment and a similar VR experiment, both centered around the implementation of an automated control system for a laboratory-scale gantry crane. The traditional experiment made use of an interactive Simulink environment coupled with an augmented 3D model of the crane. Conversely, the VR experiment utilized a DT of the crane, created in Unreal Engine and controlled via a mathematical model developed in MATLAB. This comparative approach was intended to yield valuable insights into the usability and effectiveness of VR technology in enhancing the learning experience in control systems courses.

The experiment is broken down into three parts. First, the course instructor creates a presentation that introduces the participant to the experiment and the 3D crane control object. The second section is a traditional control course experiment carried out on a desktop computer, in which a Simulink model of the 3D crane and swing compensation PID controller is provided. The Simulink interface depicted in Figure 5.1 is exhibited on one screen, while the second shows graphs displaying the model's real-time response and a 3D representation of the crane moving in real-time based on data received from the Simulink model depicted in Figure 5.2. The third section consists of a similar control course experiment carried out in a VR lab environment. It includes the 3D crane control object, an Inteco-produced lab-scale simplified model of a gantry crane that was created as a VR DT, as well as two interactive plot widgets, the first of which displays real-time data illustrating the dynamics of the 3D crane, and the other graph, which explains the control object parameters. Figure 5.3 demonstrates the various components of the VR lab.

The desktop experiment was conducted using a laptop computer connected to two monitors. The Simulink model was displayed on the first screen, while the second screen showed a 3D model of the crane created with Unreal Engine. Table 5.1 displays the Desktop PC's Component configuration. For the VR environment, an HTC VIVE Pro Eye VR headset was utilized. The headset incorporates precision eye tracking sensors and dual-OLED displays with a combined resolution of 2880x1600 pixels. The detailed specification of the headset is provided in Table 5.2.Additionally, two HTC Vive Controllers were employed to track the location of the user's hands and capture input commands. To establish a tracking area, two sensors were installed, covering an approximate measurement of 3 by 2 meters. The VE was hosted by a PC, to which the headset was connected. Table 5.1 demonstrates the VR PC's component configuration.

Table 5.1: Hardware Comparison for VR and Desktop Experiments

Component	**VR experiment**	**Desktop experiment**
CPU	Intel i7-6700K @4.00GHZ	Intel i7-7700HQ @2.80GHZ
Graphics card	NVIDIA Geforce GTX 1080 - 8.0 GB GPU memory	NVIDIA Geforce GTX 1070 with Max-Q Design - 8.0 GB GPU
RAM	32GB	16GB

Table 5.2: HTC Vive Pro Eye VR Headset Technical Specifications

Specification	**Details**
Headset	HTC Vive Pro Eye
Display Resolution	2880×1600
Refresh Rate	90 Hz
Field of View	110 degrees

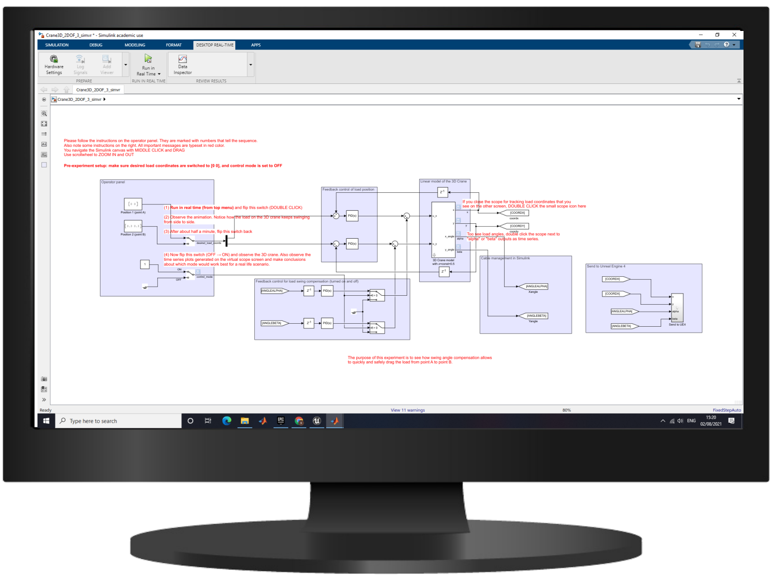


Figure 5.1: Simulink model of the 3D crane and swing compensation PID controller [P1].

Our study included 37 participants (20 male, 17 female, average age of 25.0 years old). Table 5.3 summarizes the distribution of participants according to several key variables.

The instructions given to all test takers are described below. The three components of the study are all held in the same room. Following a brief introduction to the three primary duties that the participant will undertake, they are directed to the desktop computer where the presentation is delivered. Participants are instructed to go through the slides and ask questions if any of them are unclear.

When the subject confirms that they have completed the slides, they are given the second phase of the experiment and the following instructions:

1. Select run in real time (from top menu) and flip the first switch (DOU-

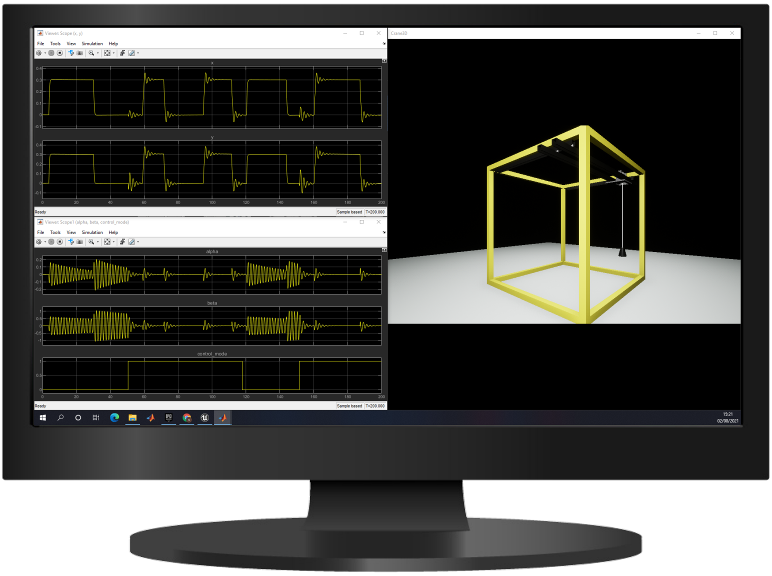


Figure 5.2: Charts that display the real-time response of the model and a 3D model of the crane that is moving in real-time based on data received from the Simulink model graphs that display the real-time response of the model and a 3D model of the crane that is moving in real-time based on data received from the Simulink model [P1].

BLE CLICK);

2. Observe the animation. Notice how the load on the 3D crane keeps swinging from side to side;

3. After about half a minute, flip the first switch back;

4. Now flip the second switch (OFF / ON) and observe the 3D crane. Also observe the time series plots generated on the virtual scope screen and make conclusions about which mode would work best for a real life scenario.

When the second half of the experiment is completed, the subject is directed to a location in the same room as the VR HMD.

In the third stage of the experiment, a series of procedures are performed to introduce the VR controllers and HMD, as well as to perform eye calibration, which allows the participant's gaze direction to be captured:

1. An introduction to the VR headset and controllers is given;

2. The headset is put on and adjusted such that the display is centred in the view;

3. The controllerssetup are located and picked up;

Table 5.3: Distribution Table of Participants

Variables	**Description**	**Frequency**
Gender	Male	20 ($\approx$ 54.1%)
	Female	17 ($\approx$ 45.9%)
Dominant hand	Right Hand	35 ($\approx$ 94.6%)
	Left Hand	2 ($\approx$ 5.4%)
Study status	Current Student	23 ($\approx$ 62.2%)
	Not a current Student	14 ($\approx$ 37.8%)
Confidence level using VR	Not confident	20 ($\approx$ 54.1%)
	Neutral	5 ($\approx$ 13.5%)
	Confident	12 ($\approx$ 32.4%)
General IT skills and knowledge confidence level	Not confident	5 ($\approx$ 13.5%)
	Neutral	10 ($\approx$ 27.0%)
	Confident	22 ($\approx$ 59.5%)
Confidence level with the topic of Control systems	Not confident	19 ($\approx$ 51.4%)
	Neutral	7 ($\approx$ 18.9%)
	Confident	11 ($\approx$ 29.7%)

4. The eye-tracker is calibrated:
   (a) The headset is adjusted vertically so that the display is centred on the eyes;
   (b) The lens distance is adjusted based on participants eyes;
   (c) The participants are asked to follow a set of dots using only their eyes.
5. The operator starts the experiment.

The participant's first objective during the experiment is to walk to a preset position near to the control object. The specific spot is clearly marked in the VE. When the participants arrive at the designated site, they may choose from the following options:

Figure 5.3: VE used in the experiment [P1].

- Interact of the control object (change the set-point—i.e., the desired location of the crane's payload,—and change the control mode of the crane);
- Interact with the plot widgets (move them to the predefined locations, grab and move them to a new location, or grab and throw them anywhere in the VE).

5.2 Questionnaire and System Usability Scale

After completing the final phase of the experiment, participants were asked to complete a questionnaire comprising 10 SUS questions for the Desktop trial and 10 SUS questions for the VE experiment, as well as three extra questions concerning their degree of confidence in VR, IT, and Control systems. The system usability measure consists of ten items, each with five values ranging from strongly agree to strongly disagree. The following is an example questionnaire:

1. "I think that I would like to use this system frequently."
2. "I found the system unnecessarily complex."
3. "I thought the system was easy to use."
4. "I think that I would need the support of a technical person to be able to use this system."

5. “I found the various functions in this system were well integrated.”
6. “I thought there was too much inconsistency in this system.”
7. “I would imagine that most people would learn to use this system very quickly.”
8. “I found the system very cumbersome to use.”
9. “I felt very confident using the system.”
10. “I needed to learn a lot of things before I could get going with this system.”

5.3 Results

The SUS elements are classified as either positive or negative. Even objects are bad, while odd items are good. To obtain the real score of the SUS results, subtract 1 for each of the user replies for the five odd components, then subtract the user answer from 5 for the even components, and then multiply all of the components by 2.5 to obtain a score ranging from 0 to 100. Figure 5.5 presents the System Usability Scale (SUS) results, where the average scores for each individual question are illustrated for all participants. This comprehensive comparison encompasses both the Desktop and VR experiments, providing a clear view of user experience metrics across different platforms. Figure 5.5 depicts the quartile distribution of the SUS score for all participants in both experiments. The average SUS score for all PC participants was 70 with a standard deviation (SD) of 20.8279, while the average SUS score for all VR participants was 85 (SD=10.2977).

This demonstrates that the suggested solution is more usable than the desktop experiment. Furthermore, the smaller SD indicates that there was more consensus on the effectiveness of the technology in the VR trial. Further investigation was carried out to see how the self-reported participant distribution affected the utility of both studies. First, as illustrated in Figure 5.6,The system usability scale results revealed that users who reported being confident in using VR got the highest average usability score. This research indicates that as users gain trust in VR and get more comfortable with it, the system's usability will improve. These findings lend support to the utilization of VR experiments in a larger context across the control systems course.

Next, an investigation was conducted to determine whether individuals with greater confidence in their general IT abilities were more inclined to choose VR. In the case of the VR solution, it was observed that participants

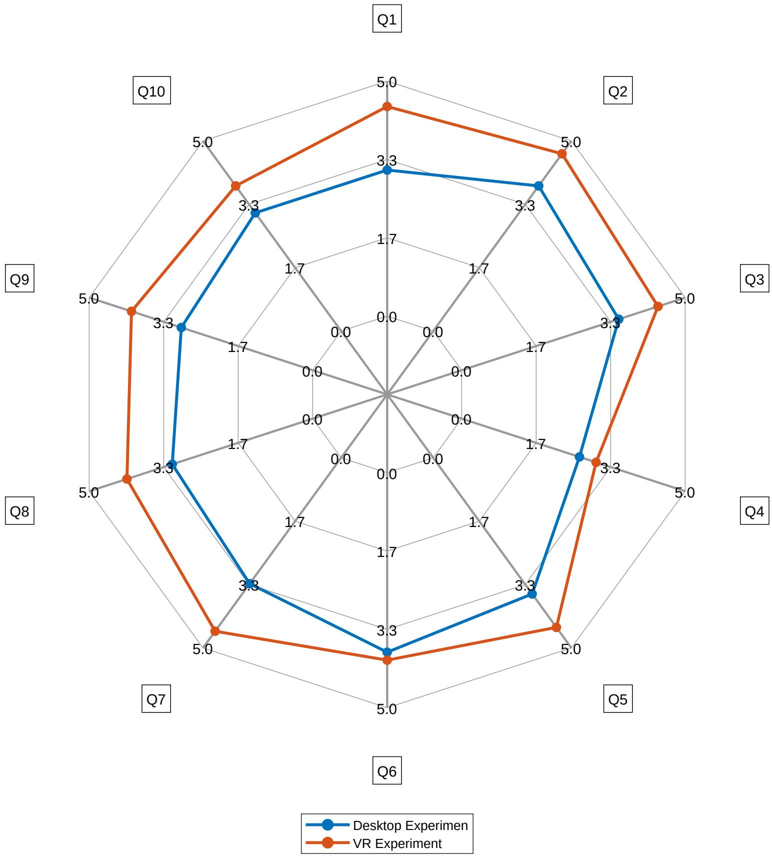


Figure 5.4: System Usability Scale Results Displaying Average Scores for Each Individual Question Across All Participants in Both Desktop and VR Experiments.

with higher levels of confidence in general IT abilities and knowledge obtained higher average SUS scores, as illustrated in Figure 5.7, whereas the average score for the Desktop experiment did not alter significantly.

Lastly, an examination was undertaken to ascertain whether the participants' level of trust in the specific research material had an impact on the SUS findings, particularly in the context of control systems. The outcomes of the system usability scale were categorized according to the participants' self-assessed level of trust in control systems, as depicted in Figure 5.8. Participants who rated neutral confidence in control methods offered the highest usability score in both the desktop and VR studies. Participants assessed the VR experiment as easier to use than the desktop trial in general. While the small sample size limits any inferences drawn from this study, the findings underline the need of incorporating VR into the development of more realistic rich experiments for control object DT.

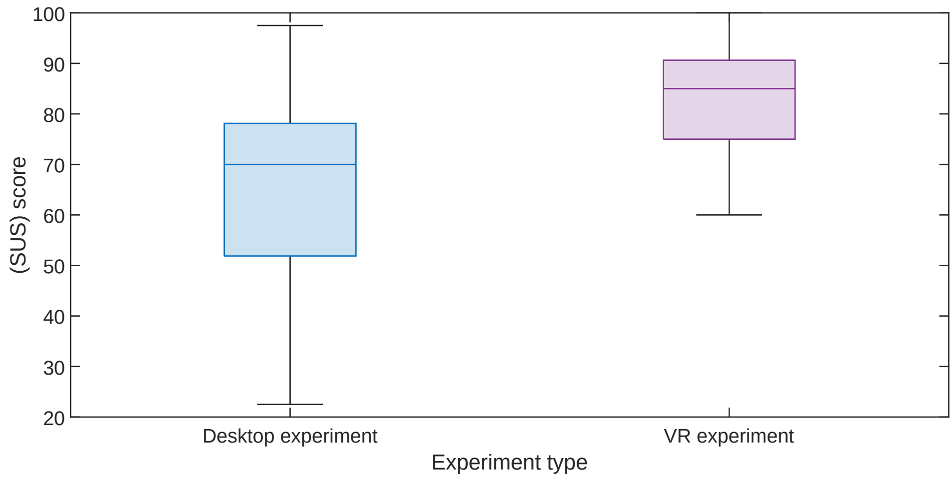


Figure 5.5: System usability scale results for all participants in the Desktop and VR experiments [P1].

5.4 Conclusion

In this chapter, we conducted a SUS study to assess the usability of the 3D crane DT experienced in an XR environment, specifically focusing on the virtual lab mode. The DT and XR technologies form the foundation of all lab modes and represent a significant contribution to the current work. Therefore, understanding their general usability for the intended application is essential to establish their effectiveness across all other lab modes. Based on the analysis of the study's results, it is evident that the DT and XR technologies demonstrated promising usability for the intended application in the virtual lab mode. The participant's feedback indicated positive experiences and effective interactions with the system, suggesting that these technologies hold significant potential for various other lab modes. In this chapter We showed that our framework's practical application extends to a usability case study, where we systematically evaluated the impact of VR in control systems education. This research not only complements the transformation of control system laboratories but also advances the understanding of how XR technologies, such as VR, can significantly improve the educational experience in engineering and beyond.

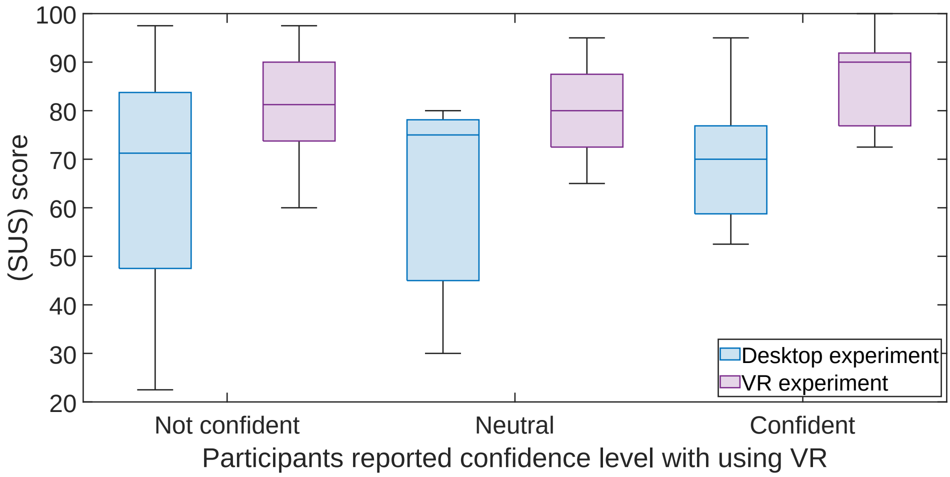


Figure 5.6: System usability scale results based on participants self-evaluated confidence using VR [P1].

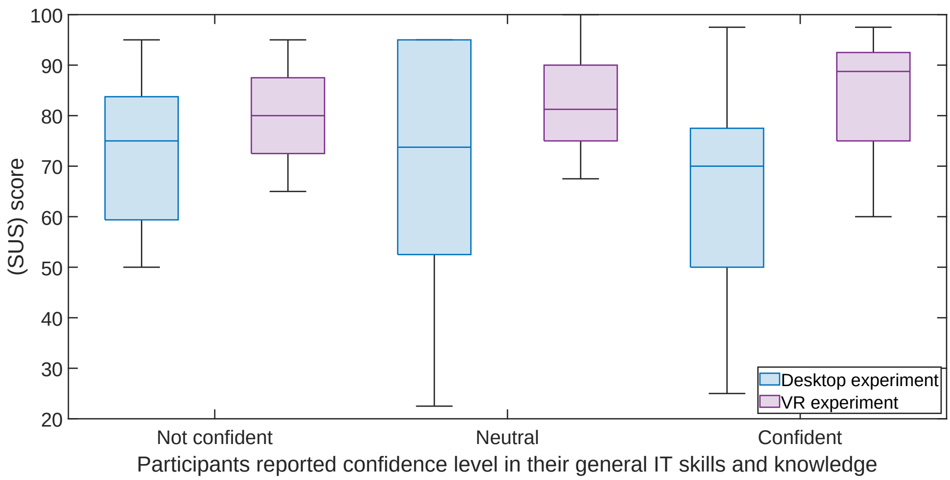


Figure 5.7: System usability scale results based on participants self-evaluated confidence in general IT skills and knowledge [P1].

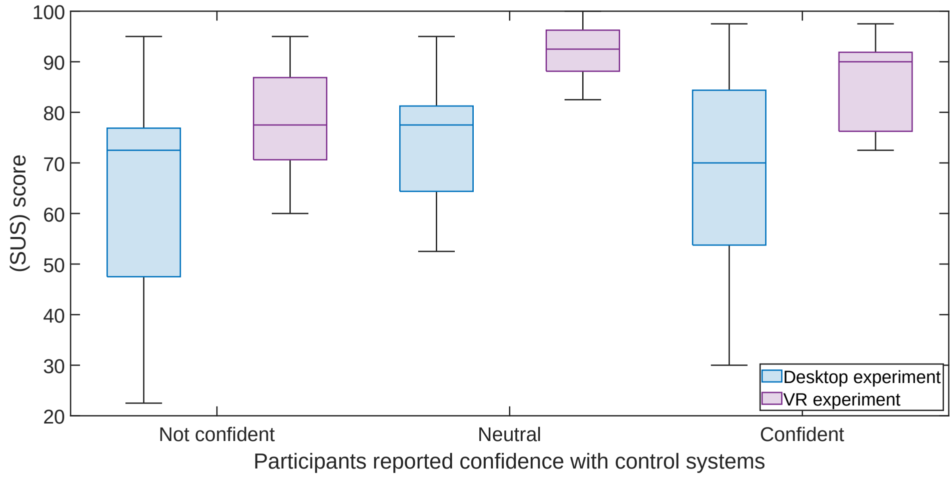


Figure 5.8: System usability scale results based on participants self-evaluated confidence with control systems [P1].

Chapter 6

Data-Driven XR Design Methods and Tools

In this chapter, we explore a data-driven machine learning approach, anchored within the principles of the "Reimagine Lab" framework. This framework, with its foundation in DT and XR, serves as a foundation for our investigations into enhancing user engagement in virtual settings.

Leveraging the detailed data representation from DT and the immersive visualization from XR, we employ a data-driven replay and annotation system. This system plays a pivotal role in classifying user behaviors, drawing its strengths from the synergies of DT and XR as proposed in the "Reimagine Lab" framework. Our studies centered around the 3D crane experiment, with a particular emphasis on the throwing action. Using the insights derived from this use case of the "Reimagine Lab" framework, we utilized the replay system to better understand these throw attempts. This led to the development of a machine learning classification algorithm fine-tuned to classify user interactions.

The Chapter organized as follows. In Section 6.1, the relationship between interaction and immersion is discussed. Next in Section, 6.2 the proposed data driven interactions procedure is detailed and the replay system is introduced. The results are presented and analyzed in Section 6.3. Finally, in Section 6.4, conclusions are drawn.

6.1 Interaction and immersion

One remarkable feature of VR is its capacity to create a sensation known as "immersion", wherein the user, while experiencing the VE, genuinely feels as though they have been transported into an entirely different reality. This immersive experience provides valuable learning opportunities, as it closely mimics real-world scenarios, allowing users to interact with the environment authentically, with the added benefit that artificial components in such an environment can be easily synthesized, something not achievable in the physical world.

The quality of immersion of the VR environment or presence divided into two parts [60]:

1. *The place illusion*: The user is feeling that they are moved into another place;

2. *The plausibility illusion*: the user's satisfaction with the environment in response to their interaction with it.

This chapter centers its attention on the latter aspect, specifically the concept of plausibility illusion. This particular focus is intriguing due to its reliance on interface devices (controllers) and the algorithms that govern the extent of user interaction within the environment. Within this chapter, we delve into a potential solution for addressing this unique challenge. To be more precise, we explore a scenario where the VE is endowed with rudimentary intelligence, enabling it to anticipate the user's actions. This anticipation is achieved through signal processing and classification applied to the data collected from biometric and human motion data, thereby facilitating a seamless assistance to the user in carrying out those actions.

6.2 Data Driven Interactions

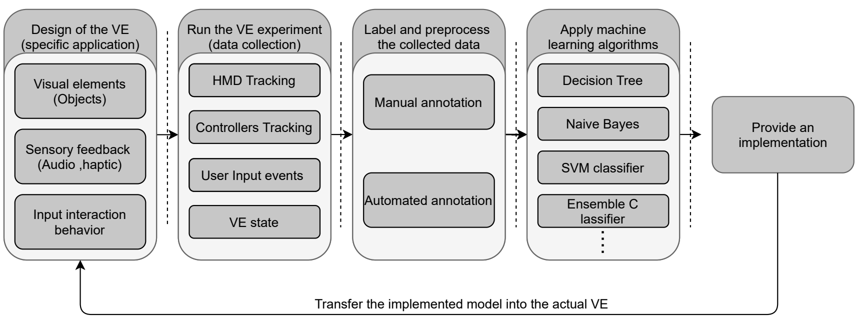


Figure 6.1: Diagram of the data driven procedure for the implementation of assistive features in a VE [P2].

Figure 6.1 illustrates the proposed process for constructing a Data-driven VE. This process initiates with the design of the VE. While VEs may vary considerably across different applications and industries, they typically consist of three core components:

- visual elements, which are graphical representations of the objects and the environment,

- sensory feedback that is used increases the effect of immersion for the user,
- the algorithms that determine the environment's responses to the user interaction (input).

The next phase in the procedure is data collection. To comprehensively capture the user's behavior, it is essential to record all the input data that the user imparts to the VE. This encompasses tracking data from both the HMD and controllers, as well as the input events generated by pressing buttons on the controllers.

Subsequently, the third step involves labeling and data processing. This task is efficiently carried out using the proposed replay and annotation system, as elaborated in Subsection 6.2.1.

Through the utilization of this system, we are able to pinpoint and label undesired interactions or behaviors within the VE. Moreover, this system serves as a valuable tool for providing developers with insights into user actions within the VE.

In the final phase, we employ machine learning algorithms to train classifiers capable of more accurately predicting intended human behavior. This training process utilizes the annotated data obtained from the replay and annotation system. A wide spectrum of algorithms is available for this purpose. For instance, we can opt for a naive Bayes classifier, which is a straightforward probabilistic model assuming independence among different features. Alternatively, support vector machines and decision trees, among other methods, can also be applied effectively.

Once we have achieved a model with a satisfactory level of accuracy, it can be integrated into our original VE as an alternative to the initial rule-based algorithm that led to undesirable interaction behaviors.

6.2.1 Replay and annotation system

Figure 6.2 depicts the proposed VR data replay and annotation approach designed for the analysis and classification of data collected within VR environments. Through this interactive visual interface, developers gain the capability to employ this data-driven replay system for the following purposes:

- Replay the participant's behaviour in the experiment;
- Annotate the user behaviour and actions in the experiment;
- Test alternative algorithms for the user interaction with the environment without the need to record new data;
- Automate post-processing and annotation of the data.

setup

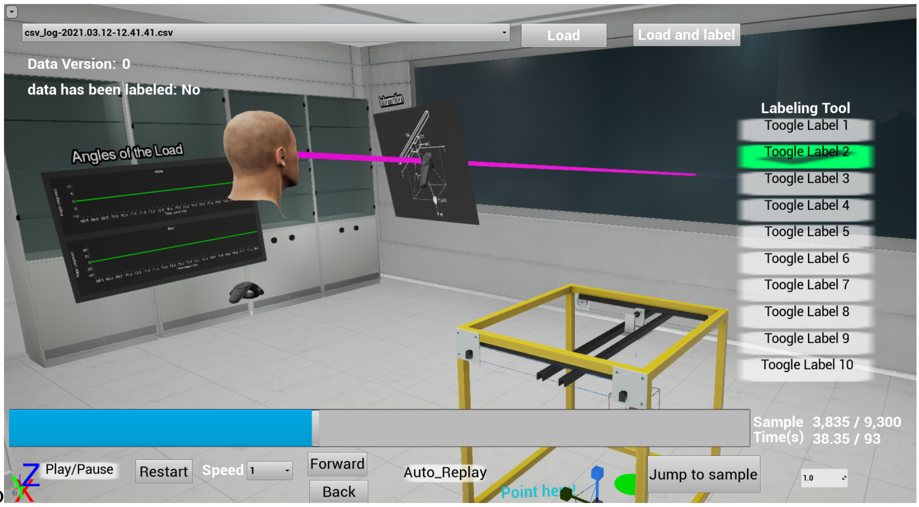


Figure 6.2: VR data replay and annotation system [P2].

6.3 Results And Analysis

Within this section, we present two instances exemplifying the workflow of the system. We pinpoint situations where undesired outcomes arise due to user interactions during the experiment. Moreover, we illustrate the system's capability to employ a data-driven approach, which allows for the development of alternative and more precise interaction algorithms.

6.3.1 Grabbing Actions

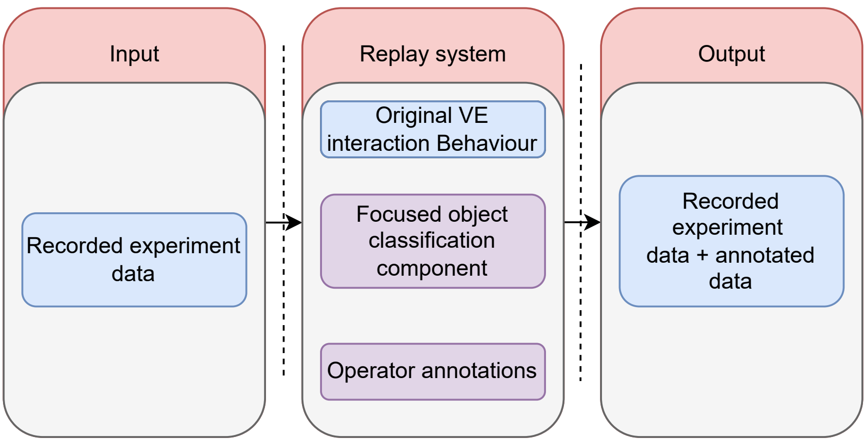
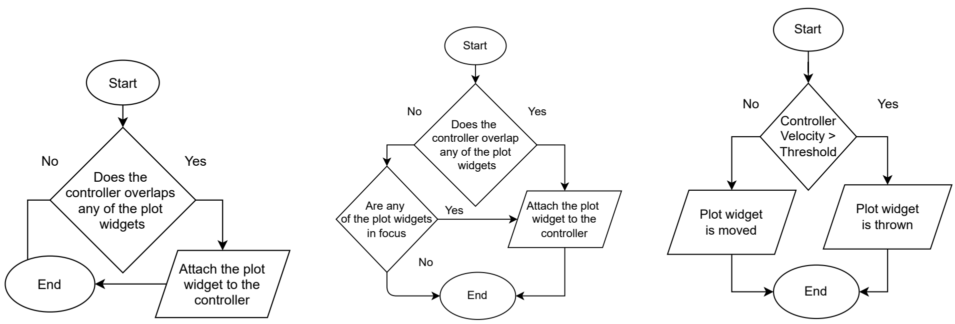


Figure 6.3: Replay system workflow for data annotation [P2].

In this subsection, we will present the first example of utilizing the replay system to enhance the interaction within the VE. This improvement is achieved through the insights obtained from the collected data and by employing the replay system for annotating and categorizing user actions and objects.

Throughout the experiment, it became evident that participants encountered difficulties when attempting to grasp objects within the VR environment. Subsequent analysis of the collected data confirmed these observations. Among the 26 participants, a total of 421 attempts were made to grab objects, with 180 of these attempts resulting in failure.($\approx 42.8\%$). Certain attempts may be considered as random occurrences where users were not intentionally trying to grab objects. To validate this observation, we employed the replay and annotation system, which confirmed that users were indeed encountering difficulties with the grabbing action. Initially, it is imperative to examine the rule-based algorithm governing the interaction with the interactive plot widgets, as depicted in Figure 6.4a.



(a) Original rule-based algorithm defining grabbing the interactive plot widgets interaction.

(b) Improved rule-based algorithm defining grabbing the interactive plot widgets interaction.

(c) Original rule-based algorithm defining moving/throwing the interactive plot widgets interaction
.

Figure 6.4: Different algorithms for interactions in a VE [P2].

Numerous factors may have contributed to the undesirable interaction behavior observed during the experiment. These factors include varying levels of depth perception and VR experience among participants. Leveraging the replay system, we embarked on a data-driven exploration to develop a more robust grasping implementation. This involved examining trends within user-collected data with a focus on the grabbing action.

Our analysis led us to a significant conclusion: integrating gaze data with the grabbing input event could potentially reduce the number of failed grabbing attempts.

To assess the viability of using the object that captures the user's gaze at the moment of grabbing, we conducted a new data collection process.

This involved introducing a new component into the replay system, which utilizes collision detection boxes to identify the object of interest within the environment. Subsequently, the replay system was employed to annotate and capture the gaze-focused object for each participant frame by frame. The comprehensive workflow of this annotation method, facilitated by the replay system, is illustrated in Figure 6.3.

The last phase of the process involved incorporating the user's gaze-focused object into the interaction behavior of the grabbing action, depicted in Figure 6.4b.

The new approach reduced the number of failed attempts to 84, reducing the percentage of failed attempts to ($\approx$ 20.0%). Table 6.1 demonstrates the disparity in failed grab attempts between the original and enhanced rule-based algorithms.

Though this example may appear straightforward in its application, it underscores the value of incorporating data within the iterative process of constructing immersive environments.

Table 6.1: Grabbing objects interaction algorithms comparison

Algorithm	**Total grab attempts**	**Failed grab attempts**
Original rule-based algorithm	421	180 ($\approx$ 42.8%)
Improved rule-based algorithm	421	84 ($\approx$ 20.0%)

6.3.2 Moving and Throwing Actions

Once the plot widgets have been grabbed, users have the option to either relocate them or discard them, with the latter causing the plot widgets to reappear on the virtual window frame.

Similar to the previous scenario, it was observed that some participants attempted to initiate the throwing of plot widgets. However, their attempts often failed due to issues such as a failure to release the grip button on the VR controller at the correct moment or insufficient throwing speed. These challenges highlight how differences in reaction time and user dexterity can lead to undesired interactions within the VE.

In contrast to the previous scenario, improving the throwing action's robustness in VEs is not as straightforward, as there is no single feature that can be introduced. However, upon closer examination of the movement patterns, distinctions between moving an object within the VE and throwing it become apparent.

In cases like these, machine learning classification methods can serve as a viable alternative to the original rule-based algorithm for both moving and throwing actions, as depicted in Figure 6.4c.

The Replay system was employed to annotate all instances of attempts to either throw or move the interactive plot. The comprehensive workflow of this annotation method, facilitated by the replay system, was previously illustrated in Figure 6.3. According to the data collected from the 26 participants, there were a total of 89 attempts to throw the interactive plot. Among these attempts, 23($\approx$ 25.8%) resulted in failure.

The acquired data was employed to train a classifier of the ensemble bagged trees type, enabling the prediction of whether the user intended to throw or move the interactive plot. The outcomes of utilizing this classifier in comparison to the original rule-based algorithms are presented in Table 6.2. By employing the classifier, the number of failed throw attempts was notably reduced to just 6 ($\approx$ 6.7%) of the total attempts..

Figure 6.5 shows the confusion matrix of the result of the training with 5-fold cross-validation. While the trained classifier has a high overall recognition accuracy of approximately 95% and a throw action accuracy of approximately 93%, it introduced an undesired effect of classifying eight move actions as thrown, reducing the accuracy of the move action to approximately 95%.

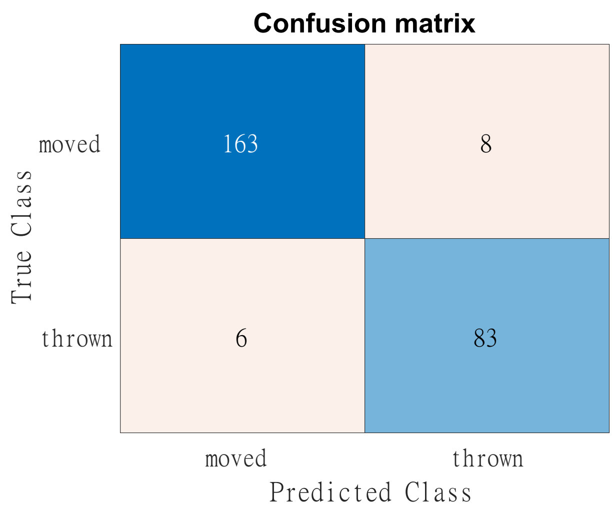


Figure 6.5: The confusion matrix of the classifier results using 5-fold cross-validation [P2].

Table 6.2: Moving-Throwing objects interaction algorithms comparison

Algorithm	**Total throw attempts**	**Failed throw attempts**
Original rule-based algorithm	89	23 ($\approx$ 25.8%)
Classifier of *ensemble bagged trees* type	89	6 ($\approx$ 6.7%)

6.3.3 Analysis

The replay and annotation system has opened up possibilities for leveraging a data-driven approach to analyze and enhance user interaction within VR. Although the two cases we examined were relatively simple, the same methodology and tools can be extended to more intricate and densely populated VR environments with more sophisticated interaction behaviors.

It is worth noting that this system facilitates the testing of alternative algorithms without the need for recording entirely new data. By replaying an experiment with a newly introduced algorithm (distinct from the one used during the original data recording), we can explore different approaches. However, it is essential to acknowledge that the introduction of this new algorithm can disrupt the continuity of user actions, as their reactions to these alternative algorithms remain unknown. Therefore, our analysis should be confined to isolated activities within the recorded experiment, rather than the entire sequence of actions.

It is crucial to recognize that VR immersion involves various factors beyond just VE interaction algorithms. Elements like haptic and visual feedback significantly influence the level of immersion in a VE. Consequently, it becomes essential to investigate the impact of introducing these alternative algorithms on other aspects of immersion. Examining the case of grabbing or moving interactions and their influence on other immersion factors reveals some limitations of substituting rule-based methods with machine learning classifiers. Machine learning models, due to their complex nature, make it challenging to provide users with a straightforward description of the model's decision-making process. For instance, while it is feasible to add a visual indicator to the VE when using the original rule-based algorithms (as shown in Figure 6.4c), indicating whether the threshold velocity has been reached, such indicators become more complex to implement with machine learning models.

6.4 Conclusion

In this chapter, we have unveiled a data-driven replay and annotation system, directly drawing from datasets procured from VR laboratory experiments. Aligning with the “Reimagine Lab” framework’s principles, we ventured deeper into the utilization of data-driven techniques and machine learning to bolster user interactions within VR settings. This engagement is realized through strategic data classification, informed by the unique insights our system offers. As a testament to our methodology’s reliability, we anchored our exploration in data assembled and annotated from the 3D crane experiment. Not only does our proposed approach highlight the potential of machine learning in crafting more intuitive interactions within VR spaces but is also a pivotal contribution to the evolution of adaptive VEs, aligned with the “Reimagine Lab” framework.

Chapter 7

Intelligent agents in virtual environments

This chapter extends the Reimagine Lab framework, introducing AI-driven DTs as “intelligent agents”. Here, mobile robots are specifically chosen to illustrate the effectiveness of the proposed approach. The field of robotics, a cornerstone of control engineering, underpins this initiative, emphasizing the creation of controllers for various systems, from basic cart-poles to sophisticated mobile robots, essential in control education. The method utilizes a reinforcement learning algorithm for training mobile robots in specific tasks.

This chapter structure is organized as follows: We begin by formulating the problem as a reinforcement learning task in Section 7.1. Next, we delve into the details of our proposed DT and reinforcement learning framework in Section 7.2, wherein we implement the hybrid mobile robot as a DT. The three tasks used to assess the robot’s abilities are outlined in Section 7.3. Following that, we present and discuss the results of our experiments in Section 7.4. Finally, we draw conclusions based on our findings in Section 7.5.

7.1 Formulating the Problem as a Reinforcement Learning Task

This section details how AI-enhanced Digital Twins (DTs), known as “intelligent agents,” are integrated into the Reimagine Lab framework, addressing the challenge of assessing DT performance. This creates a new challenge for XR specialists integrating XR and DT in the proposed “Reimagined Framework”. The proposed method defines evaluating DT performance as a reinforcement learning problem. It utilizes learning-based methods to understand and evaluate the DT’s capability to accomplish predefined tasks. This approach is showcased through a case study of a hybrid, multi-mode locomotion mobile robot. The complexity and adaptability of this robot demonstrate the feasibility and potential of the proposed method.

Mobile robots serve a wide array of purposes, ranging from planetary exploration to industrial manufacturing and package delivery. Depending on the environment, different locomotion mechanisms have been proposed for these robots. For instance, wheeled robots excel in energy efficiency and ease of control on smooth terrains like paved roads and indoor spaces, while legged robots offer superior obstacle navigation capabilities, making them suitable for rough and unstructured terrains, although with increased energy consumption and control complexity [77]. In real-world applications, mobile robots encounter a mix of rough and smooth terrains, necessitating the use of hybrid locomotion concepts. These concepts allow robots to operate in various locomotion modes, adapting to their surroundings. However, determining the optimal operational mode for these hybrid robots requires prior knowledge of each mode's limitations and capabilities. This constraint adds complexity to navigation strategies and limits their widespread application.

Inspired by the successes of deep reinforcement learning algorithms in various domains [78], such as video games, energy management systems [79], and robotics for manipulation and navigation purposes [80, 81], we propose a data-driven method to evaluate hybrid mobile robots. We achieve this by formulating the problem as a reinforcement learning task applied to a DT simulation of the mobile robot, taking advantage of industry 4.0 technology.

The proposed method involves developing a collection of testing environments for evaluating the robot's capabilities in different operation modes and with various task sets, utilizing deep reinforcement learning algorithms. A schematic representation of the approach is shown in Figure 7.1.

Specifically, we create a DT of the Hybrid Wheel-on-Leg mobile robot [82] using a general-purpose reinforcement learning simulation tool. The DT is then trained on three predefined tasks to assess the robot's abilities in its two locomotion modes for solving these tasks.

The three tasks consist of evaluating the robot's capability to reach a known target position rapidly, ascend an increasing steep slope, and climb over steps of increasing height. By conducting these tests in both operational modes, we analyze the results to determine the robot's optimal operational mode for accomplishing each set of tasks. This data-driven approach leverages the power of reinforcement learning to optimize the performance of hybrid mobile robots in diverse environments.

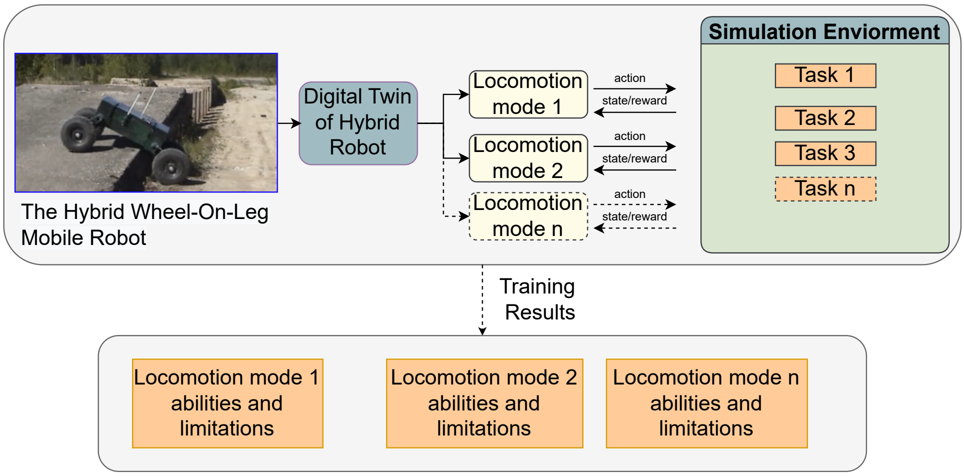


Figure 7.1: Overall reinforcement learning the DT method for evaluating hybrid mobile robot [83] locomotion modes [P3].

7.2 DT Simulation of the Hybrid Mobile Robot

The Unity Engine and the ML-agents [84] framework were used for creating the DT and reinforcement learning training. The process of creating a DT is shown in Figure 7.2 and can be summarized as follows:

1. Conversion of SolidWorks Assemblies to ".OBJ" Files: To initiate the DT creation process, the existing SolidWorks assemblies of the target robot were converted into ".OBJ" files, which are compatible with the Unity Engine. This step ensures seamless integration of the robot's physical properties and geometry into the VE.

2. Hierarchical Construction within Unity: After importing OBJ files into Unity, we establish a hierarchical system of rigid bodies, joints, and collision components to mimic the robot's overall behavior and locomotion mode. This structure reflects the robot's physical framework, enabling the simulation to capture its dynamic movements and interactions with the environment.

3. Programmable Sensor and Motor Functionality: To enable effective interaction and control of the DT, custom and built-in scripts are employed to implement programmable sensor and motor functionality. These scripts facilitate the integration of various sensors, enabling the DT to perceive the VE, and motors.

SolidWorks was used to create the original 3D model of the hybrid robot, Where the robot is composed of numerous sub assemblies for each physical component. The first step involved exporting the SolidWorks sub assemblies

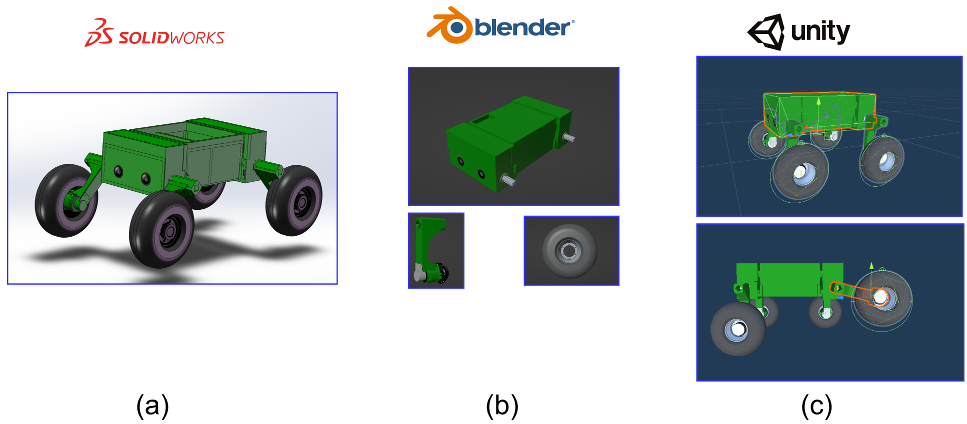


Figure 7.2: The DT creation process: (a) original SoildWorks assembly [83] (b) exported sub assemblies in Blender (c) DT in Unity 3D [P3].

for the vehicle's main body, legs, and wheels as OBJ files. Blender was used as a bridge between Unity and Soildworks to modify the OBJ files, such as reducing the number of vertices and setting an appropriate pivot points for each sub assembly, to make re-creating the vehicle easier in the following steps.

After importing the OBJ files for all of the components, the robot is modeled using a hierarchical parent-child approach, with the main body serving as the parent for all four legs that are located in relative coordinates to the main body and the wheels as child objects of the legs. If the pivot points are selected correctly, as described previously, the process is quite simple to follow.

At this point, the robot is only a visualization of a DT of the robot. To achieve physical interaction with the unity environment, component definitions must be used to define the robot's behavior, which will be simulated using the Unity 3D-physics simulation [85]. The first component is the rigid body, which was added to the robot's main body and each of its four legs. We define properties such as the mass of the body part in this component which will be used by the engine during the simulation. Each wheel was fitted with the built-in wheel collider component. This wheel component enables torque to be applied independently to each wheel while also managing the interaction with the surface. To enable the engine to detect and handle collisions, the Mesh collider component was also added to the wheels and robot's body. Finally, the legs motorized function function is applied via a coded script that rotates the legs at the pivot point where they are connected to the mobile robot's main body. The final step in this process is simulating the sensors which will be used as observations for the reinforcement learning training. First, the robot posture and velocity are extracted by accessing the internal states in the previously added rigid body components. Second an array of laser range finders competent which comes built-in with the ML-Agent Framework is used to for sensing the environment.Figure 7.3displays a visualization of the laser range finders attached to the robot.

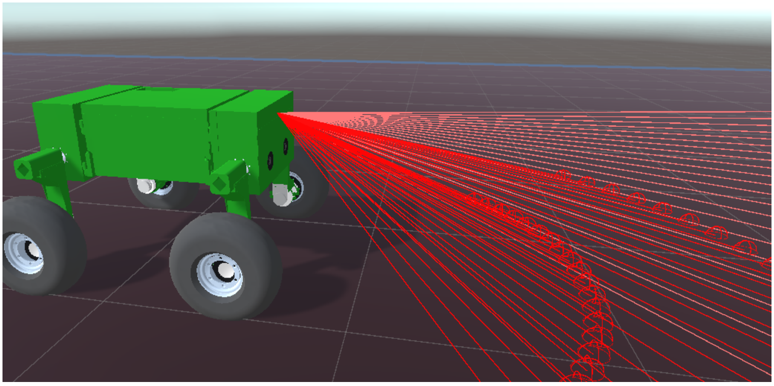


Figure 7.3: Visualization of laser range finders mounted on the robot, demonstrating the placement and orientation of the sensor.

Following the successful creation of the DT, reinforcement learning training is conducted using the ML-agents framework. The training process involves the following stages:

1. Environment Setup: The DT, equipped with programmable sensor and motor functionality, is integrated into the reinforcement learning environment provided by the ML-agents framework. This environment serves as the training ground for the twin to learn and adapt its behaviors based on rewards and penalties received during the training process.

2. Reward Design: An essential aspect of the reinforcement learning training is the design of appropriate reward functions. These functions define the desired behavior and tasks that the DT is expected to achieve. Positive rewards are assigned for successful completion of tasks, while negative rewards are applied for undesired behaviors or failures.

3. Training Algorithm: The ML-agents framework employs state-of-the-art reinforcement learning algorithms to optimize the DT's behaviors. Algorithms such as Proximal Policy Optimization(PPO) and Deterministic Policy Gradients (DDPG) are commonly used to fine-tune the twin's actions and maximize cumulative rewards over multiple training episodes.

In the domain of mobile robot navigation employing reinforcement learning, the robot is designated as an "agent", while its external surroundings are regarded as the "environment". This interaction between the agent and the environment can be formally represented as a Markov Decision Process (MDP), wherein the objective of the agent is to acquire knowledge on selecting the most optimal action, denoted as A, based on the current state of the environment, denoted as S. This choice of action is intended to maximize the reward, denoted as R, obtained from the environment. The selection of observations and actions plays a crucial role in the learning process. Observations are the information the robot receives from its sensors and the environment, providing it with insights into the current state S of the environment. These observations serve as inputs to the reinforcement learning algorithm, allowing the robot to make informed decisions on how to act based on the received data. For example, in a mobile robot, observations could include data from various sensors such as cameras, LIDAR, or other environmental sensors. The robot may receive information about its own position, orientation, nearby obstacles, and the presence of any targets or goals it needs to reach. All these observations contribute to creating a representation of the environment's state S. On the other hand, actions refer to the decisions made by the robot in response to the observations it receives. These actions are typically executed to perform some movement or manipulation in the environment. In a mobile robot navigation scenario, actions could involve moving forward, turning, stopping, or any more refined action such as applying torque to the motors. The set of available actions constitutes the "action space" of the reinforcement learning problem. The choice of observations and actions is critical for the success of the reinforcement learning algorithm. The observations must capture relevant information about the environment to allow the robot to learn an effective policy, while the action space should include a sufficient range of actions for the robot to navigate and achieve its objectives. Table 7.1 presents the specific observations and actions used in the training of the mobile robot for both locomotion modes.

Although the agent receives immediate rewards at each time step, the essence of reinforcement learning lies in the pursuit of maximizing the cumulative reward value over time, rather than solely focusing on short-term gains. Consequently, the goal is formulated to maximize the cumulative reward, R_t, as expressed in equation (7.1).

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}. \tag{7.1}$$

Numerous research endeavors have proposed diverse methods for solving such MDPs. For our specific case study, we have opted to employ PPO as proposed by [86]. PPO is a policy gradient-based deep reinforcement learning method designed to accommodate environments with either discrete or continuous action spaces. The core objective of PPO is to optimize the policy, denoted as π_θ, which refers to a neural network function approximation responsible for mapping the environmental state, S, to the corresponding agent action, A.

PPO stands out as a favorable choice for our use case due to its ability to strike a suitable balance between simplicity and efficiency. It should be noted, however, that alternative reinforcement learning methods could be employed in a similar manner to address this problem effectively.

Table 7.1: The reinforcement learning observation and action space for both locomotion modes of the mobile robot

Locomotion mode	**Observations**	**Actions**
Skid steering (Wheels only)	An arrays of sparse laser range finders; vehicle Pose and velocity; target relative location.	Wheels motors.
Hybrid steering (Wheels and legs)	An arrays of sparse laser range finders; vehicle Pose and velocity; target relative location; legs rotation.	Wheels motors; legs motors.

7.3 Designing the Testing Environments and Tasks

The robot can operate in two operational modes, the first operational mode involves the robot's wheel navigation while maintaining locked legs. The robot is required to execute a skid steering mechanism, applying varying torques independently to each wheel to effectively navigate the course. In the second operational mode, the robot is tasked with adjusting the leg angles to ensure contact between wheels and the ground. Additionally, the robot must employ the skid steering method to drive and rotate effectively.

This section presents a comprehensive analysis of the first and second operational modes of a hybrid robot, focusing on torque-controlled wheel navigation and leg rotation capabilities. The robot's center of gravity adjustment during hybrid operation is explored to facilitate obstacle clearance and traversal of steep slopes. Three distinct task environments were devised to evaluate the robot's performance, including target reaching on a flat surface, ascending slopes, and climbing steps. Reward shaping techniques were employed to quantify the robot's speed, slope traversal ability, and step-climbing capacity in each operational mode.

7.3.1 Target Reaching On Flat Surface

The primary objective in this task is for the robot to reach a static target with a known location as shown in Figure 7.4. To accomplish this seemingly trivial task, the robot needs to exhibit proficiency in both operational modes. The reward system is composed of two components: First, the robot receives positive rewards for progressing toward the target and negative rewards for moving away from it, scaled based on the initial distance from the target. The maximum reward of +10 points is attained upon successful target reaching. Second, additional rewards are provided based on the time (simulation steps) taken to achieve the target. The cumulative reward R_t collected during each episode directly reflects the robot's speed capabilities in each operational mode.

For the first operating mode, the robot must learn how to apply a skid steering mechanism to a navigator in order to navigate the course by employing a variety of torques on each wheel independently. While in the second operation mode, it must first learn to adjust the leg angles such that the wheels are in contact with the ground before it can use the skid steering method to drive and rotate the robot which in turn increase the difficulty for the second operation mode.

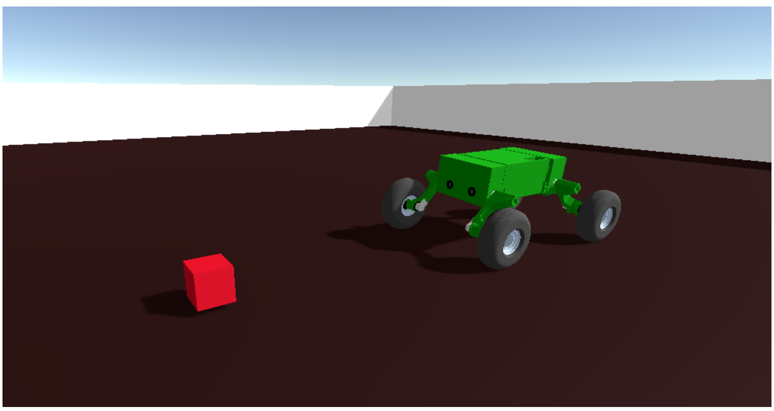


Figure 7.4: Target Reaching Task Environment [P3].

7.3.2 Ascending a Slope

In this task, the robot must reach a goal located at the end of a slope, as illustrated in Figure 7.5. The slope angle increases incrementally after the robot reaches the goal a predetermined number of times, making the task progressively more challenging. The robot must successfully reach the goal 100 times before the slop angle is increased by 0.5 degree. To evaluate the robot's performance, the reward system is structured similarly to the first task, employing cumulative rewards as a measure of the robot's slope traversal proficiency. Notably, when the robot attains the maximum slope inclination it can ascend for each operation mode, the earned rewards decline significantly throughout training, reflecting the robot's limitations in ascending steeper slopes.

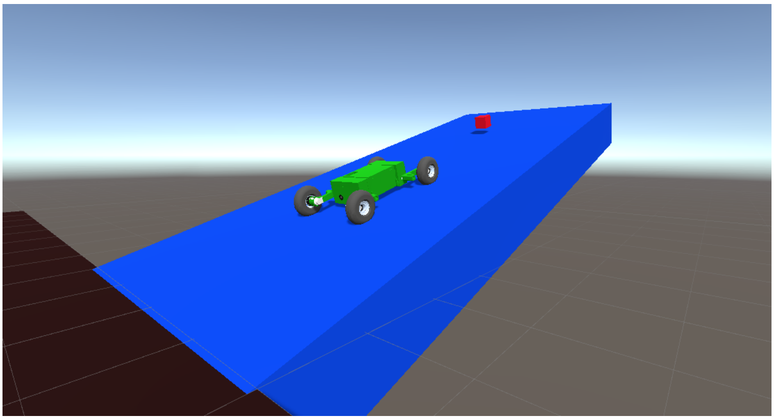


Figure 7.5: Ascending Slopes Task Environment [P3].

7.3.3 Climbing a Step

The hybrid robot capacity to climb steps is one of the reasons behind its design. The third test environment is specifically designed to assess the robot's capacity to climb steps of varying height. The robot must complete this task by reaching a goal positioned at the end of a step of varying height, as seen in Figure 7.6. Similar to the second task, the step height increases as the robot achieves the goal a certain number of times. The established threshold is 100, necessitating the robot to successfully accomplish the task at each step height before a subsequent increment of 0.05m is applied to the step's height. The reward system adopted in this task aligns with the first two tasks, allowing for the utilization of overall cumulative rewards to evaluate the robot's performance. As in the previous task, the robot's reward during training experiences a substantial drop when it reaches the maximum height of the step it can climb for each operation mode, and its inability to scale the step results in an inability to attain the maximum possible reward.

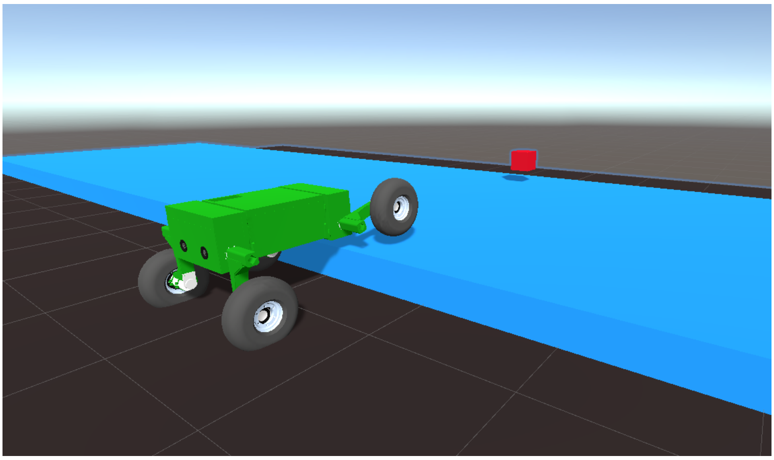


Figure 7.6: Climbing Step Task Environment [P3].

7.4 Comparison of Operational Modes for Different Tasks

Table 7.2 provides an overview of the different locomotion modes and evaluated capabilities of the hybrid mobile robot.

The results shown in Figure 7.7-a reveal a speed difference between the two robots. Initially, the first mode reached the goal with fewer simulation steps than the second mode. However, As shown in Figure 7.7-b, the robot in the second mode eventually learned a policy resulting in a higher speed than the first mode, reaching a maximum speed of approximately 1.6 m/s.

During the slope ascending task, both locomotion modes experienced a drop in the collected reward, as depicted in Figure 7.8, indicating the points at which the slope steepness increased and the robot's previously learned policy needed updating before ascending the new slope. In the first operation mode, the robot reached a terminal steepness of 18.5 degrees after 1.2M steps, while in the second mode, it reached 24 degrees after 5.45M steps.

Likewise, the drop in reward shown in Figure 7.9 illustrates the points at which the step height increased, requiring the robot's learned policy to be updated before climbing the new step height. In the first operation mode, the robot reached a terminal step height of 0.3 m after 400k steps, and in the second mode, it reached 0.8 m after 4.8M steps.

Throughout all three tasks simulations, the robot operating in the first mode consistently learned to reach the target faster than in the second mode. This was expected since the second mode increased control complexity, demanding the robot to manage both wheels and legs. As demonstrated in the results the robot in the first locomotion mode completed each task in approximately 110k, 90k, and 60k steps, respectively, while the robot in the second mode took 500k, 280k, and 190k steps to complete the same tasks.

These findings indicate that valuable insights into the capabilities and limitations of hybrid robot locomotion modes can be obtained. However, the knowledge is inevitably influenced by the task set used during training and the accuracy of the DT and simulation environment.

Table 7.2: Overview of the mobile robot different locomotion modes results

Task	First mode, skid steering (Wheels only)	Second mode, Hybrid steering (Wheels and legs)
Target Reaching On Flat Surface	Maximum speed= 1.64 m/s.	Maximum speed= 1.69 m/s.
Ascending Slope	Maximum ascended slope=18.5 degrees.	Maximum ascended slope=24 degrees.
Climbing Step	Maximum climbed step=0.3 m.	Maximum climbed step=0.8 m.

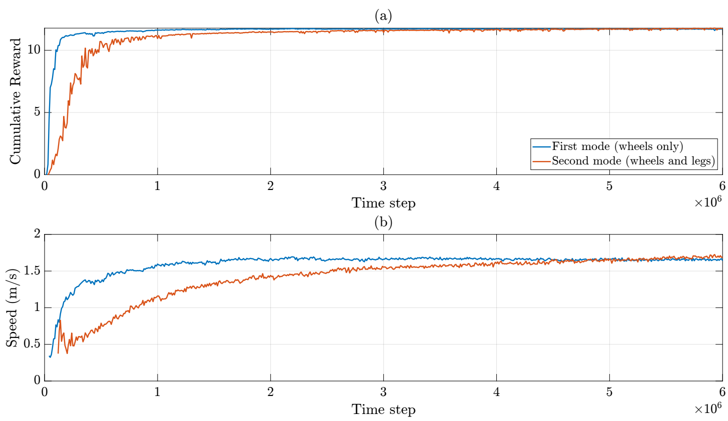


Figure 7.7: The cumulative reward and speed for the target reaching task environment.

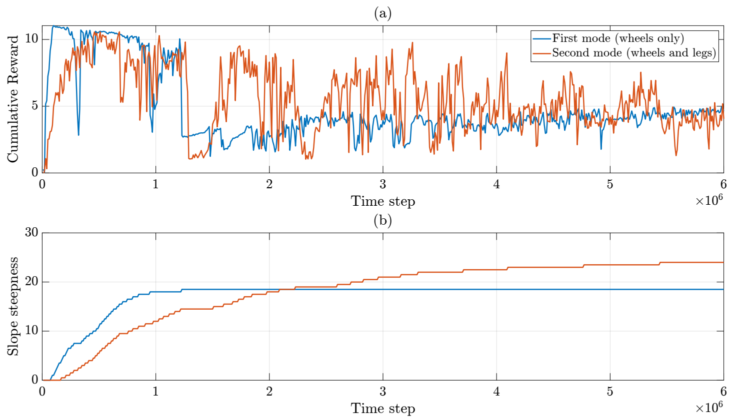


Figure 7.8: The cumulative reward and slope steepness for the ascending slopes task environment.

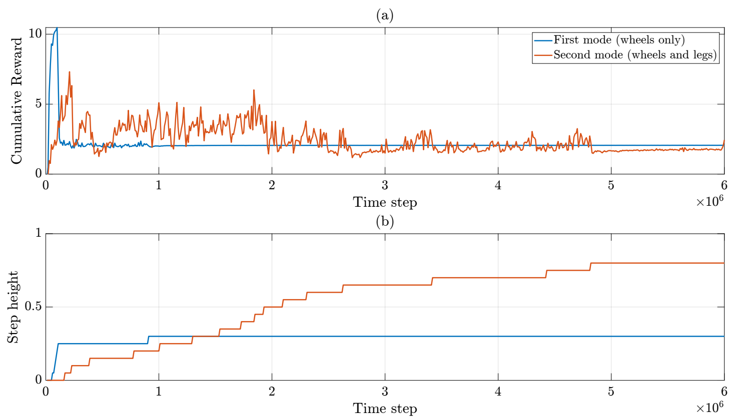


Figure 7.9: The cumulative reward and step height for the climbing step task environment
.

7.5 Conclusions

In this chapter, we delved deeper into the "ReImagine Lab" by presenting a data-driven approach that applies reinforcement learning to a DT simulation, specifically focusing on mobile robot locomotion. Through an extensive case study, we scrutinized the performance of a hybrid wheel-on-leg robot, evaluating its capabilities in speed, slope ascension, and step obstacle climbing. The findings revealed significant insights into the robot's strengths and weaknesses across various operational modes. By framing the challenge as a reinforcement learning task, we effectively enhanced the robot's adaptability and efficiency in a range of environments, thereby reinforcing the connection with the foundational concepts and goals of ReImagine Lab. In essence, the DT of the mobile robot discussed in this chapter can also be viewed as an "intelligent agent" the the context of the present work. The specific aspects of intelligence are twofold in this case:

1. The robot is learning to solve a task, in a similar way to how students interact with DT in control experiments, trying and failing and eventually succeeding, albeit automatically, though the use of reinforcement learning. This allows to develop interactions between the human user and the intelligent agent that would benefit the human user and provide additional insights as to how machine learning works.

2. The concept of automatic tuning. In control engineering, automatic tuning typically refers to the ability of a controller running in a process control loop, to self-adjust and find optimal settings to make sure the control loop is performing well. This concept is far more advanced with solving complex tasks like in the case of the mobile robot navigation, however, drawing these parallels is also important toward future research and development activities and further unification of aforementioned concepts.

Hence, this gives rise to further opportunities of endowing the immersive virtual environments with additional intelligence in the form of agents (autonomous DTs). Due to the extensible nature of the Reimagine framework, this development is seen as the natural step forward.

Conclusions

In this thesis, a novel solution for control system laboratories was proposed based on DT and XR technologies that significantly advances the state of the art. This framework combines the innovative use of DT and XR to transform the educational experience in engineering fields. Our exploration began with the proposal and analysis of a DT and XR-enabled framework for constructing a new generation of control system laboratories, demonstrating how these technologies can unify and enhance laboratory modalities. This not only elevates the educational experience by recreating remote and virtual laboratories as DT but also fosters interaction and collaboration between students and instructors, propelling the advancement of DT technology and XR applications in education and engineering.

Furthermore, the subsequent chapters demonstrated the practical implementation and efficacy of the "Reimagine" framework. Chapter 4 showcased the creation of cohesive DT for lab-scale objects using the framework. The examples illuminated the potential for developing mathematical and 3D visual representations of DT across different control objects, underscoring the versatility and reusability of the educational interfaces designed within the framework. This underscores how the proposed framework seamlessly integrates DT and XR, offering tangible applications that extend beyond theory to practical implementation, making a meaningful contribution to education and engineering fields.

Moreover, we conducted a study using the SUS study to evaluate the usability of the 3D crane DT experienced in an XR environment, highlighting the promising usability of DT and XR technologies for control systems education. This research not only complements the transformation of control system laboratories but also advances the understanding of how XR technologies can significantly enhance the educational experience in engineering and beyond.

Additionally, a data-driven replay and annotation system was introduced, leveraging datasets from VR laboratory experiments to enhance user interactions within VR settings. Aligning with the "Reimagine Lab" framework's principles, this showcased the utilization of data-driven techniques and machine learning to bolster engagement within VR spaces, serving as a pivotal contribution to the evolution of adaptive VEs aligned with the "Reimagine Lab" framework.

Lastly, we proposed an extended data-driven approach within the ReImagine Lab framework, employing reinforcement learning in a DT simulation of a mobile robot. This methodology offers crucial insights into the robot's functionalities and constraints across various operational scenarios. By showcasing how effectively Industry 4.0 technology can be utilized to refine the robot's performance in a multitude of settings, this approach not only aligns with but also significantly advances the objectives of "ReImagine Lab".

Collectively, these findings underscore the transformative potential of the "Reimagine" framework in shaping the future of control system laboratories, education, and engineering fields. The seamless integration of DT and XR technologies, coupled with the insights and methodologies outlined in this research, presents an innovative and impactful approach to redefining the educational and practical applications of control systems, positioning it at the forefront of advancements in engineering education and practice.

The "Reimagine" framework's suggests various future prospects in control systems education and engineering. Key areas include enhancing the DT and XR framework, potentially broadening its application to other control systems for more effective laboratory education. Improving real-time data integration could increase the virtual models' realism, enriching students' learning experiences. Additionally, exploring machine learning in XR environments is promising. Advancing machine learning techniques could improve user interaction in VR, leading to more responsive VEs. AI could also tailor the XR educational interface to individual learning styles, making education more personalized and human-centric. Future research should also focus on developing standardized metrics for evaluating these technologies' effectiveness in education, emphasizing human-centered design. This will provide valuable feedback for refining educational methods and curricula. Extending the "Reimagine" framework to other engineering fields could foster interdisciplinary innovation and enhance education across various disciplines, all while focusing on user-centric designs. Finally, integrating DT and XR technologies in industrial training as Industry 5.0 evolves could be beneficial. Adapting "Reimagine" for industry-specific training might enable professionals to acquire practical skills in a virtual setting before transitioning to real-world applications, aligning with human-centered design principles.

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Publications

Publication 1

Reference

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Abstract

Practical work is one of the most important instructional tools in control engineering. To address concerns linked to the cost and space requirements of traditional hands-on laboratories, technology-enabled laboratory modes, such as virtual, remote, and take-home laboratory modes are proposed. Each of these alliterative laboratory modes has its own set of benefits and emphasizes a distinct learning goal. Furthermore, due to lockdown and physical proximity restrictions imposed by policies in response to the COVID-19 pandemic, the employment of these laboratory modes has been quickly increasing. The laboratories' development, operation, and maintenance become more fragmented as a result of these many possibilities. In this study, we propose "ReImagine Lab" as a framework for leveraging digital twins and extended reality technologies to streamline the development and operation of hands-on, virtual, and remote laboratories. By increasing the level of interaction, immersion, and collaboration in technology-enabled laboratory forms, this framework intends to boost student engagement. The benefits of this framework are demonstrated by examining several use cases, and a 37-person "system usability study" is conducted to assess the usability of virtual laboratories employing desktop computers and immersive virtual reality.

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RESEARCH ARTICLE

ReImagine Lab: Bridging the Gap Between Hands-On, Virtual and Remote Control Engineering Laboratories Using Digital Twins and Extended Reality

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ABSTRACT Practical work is one of the most important instructional tools in control engineering. To address concerns linked to the cost and space requirements of traditional hands-on laboratories, technology-enabled laboratory modes, such as virtual, remote, and take-home laboratory modes are proposed. Each of these alliterative laboratory modes has its own set of benefits and emphasizes a distinct learning goal. Furthermore, due to lockdown and physical proximity restrictions imposed by policies in response to the COVID-19 pandemic, the employment of these laboratory modes has been quickly increasing. The laboratories' development, operation, and maintenance become more fragmented as a result of these many possibilities. In this study, we propose ''ReImagine Lab'' as a framework for leveraging digital twins and extended reality technologies to streamline the development and operation of hands-on, virtual, and remote laboratories. By increasing the level of interaction, immersion, and collaboration in technology-enabled laboratory forms, this framework intends to boost student engagement. The benefits of this framework are demonstrated by examining several use cases, and a 37-person ''system usability study'' is conducted to assess the usability of virtual laboratories employing desktop computers and immersive virtual reality.

INDEX TERMS Control system, digital twins, extended reality, virtual reality, industry 4.0, remote laboratories, virtual laboratories, metaverse.

I. INTRODUCTION

Control engineering is a major interdisciplinary topic that exists in almost every engineering discipline [1]. Automatic control is fundamental to advancements in a wide sector of industries, including the energy sector, transportation, manufacturing, aerospace, smart homes and consumer appliances. Control engineering is devoted to the use of mathematical modeling and analysis to understand systems and their interactions in nature, as well as applying control theory to the controllers' designs that drive these systems to reach desired states. Control engineering is applied to systems that can vary in nature and include mechanical, electrical, fluid, chemical, financial or biological systems [2]. While they are conventionally taught in educational institutions, control courses have roots in mathematical theory, and at the same time, they require an intuitive understanding of different concepts from students, which allows students to relate the acquired knowledge to actual practical applications of control theory. As a result, control engineering instructors

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persistently highlight the importance of practical hands-on experience in successful control engineering education from the early stages of learning [3].

There are many pedagogical tools that can be applied to build the practical hands-on expertise required by control courses, including course project assignments, internships and laboratory experiments. Practical work in the laboratory (“control laboratory”) has become a standard component of automatic control courses, as they aim to [4]:

- connect theory to implementations and observations in the laboratory,
- identify differences between models and physical systems,
- design and verify controllers that meet specifications,
- collect and visualize data.

Traditionally, these laboratories were based on working with laboratory-scale *control objects* that were used to demonstrate dynamic phenomena that was observed in full-scale, industrial counterparts of these objects.

These experimental setups incorporated computer interfaces to enable students to design and tune controllers and observe how the system behaves under these new conditions. For example, in [5], the laboratories included experiments with a coupled tank system, an inverted pendulum and a rotary table. These systems were used to demonstrate the use of modeling, simulation and control design to students.

However, actual physical laboratories are costly to build and maintain. They require a considerable amount of space and are composed of specialized hardware, which increases the complexity of the necessary infrastructure. Moreover, as the number of students increases, managing the infrastructure and organizing physical laboratories becomes extremely challenging. In other words, this infrastructure does not scale well.

Thus, leveraging the recent advances in information and communication technologies, educators have created different alternative modes of technology-enabled laboratories to tackle the issues related to traditional physical hands-on laboratories. Works [2] categorized these different laboratory modes based on the nature of the experimental resources (real or simulated) and the location of these resources (local or remote), as shown in Table 1. Further discussion is largely based on this taxonomy.

A. SEEKING THE ULTIMATE LABORATORY MODE

There is an ongoing debate on the effectiveness of the different laboratory modes. A comparative analysis of the different laboratory modes has shown that when these laboratory modes are developed, their efficiency is measured by their ability to achieve different learning objectives [29]. For example, remote laboratories are more suited for understanding concepts, while virtual laboratories are better suited for learning design skills. This makes it difficult to prioritize any single laboratory mode.

Another important factor to consider is the way that students’ interaction with laboratory objects, instructors and other students is affected by the specific laboratory mode. Analysis of results from studies of students’ interaction in face-to-face and remote hands-on laboratories have shown that there is a lack of systemic analysis of students’ interactions in the alternative technology laboratory modes. Before we are able to understand the full implications of the use of such laboratory modes, we need to have better tools to investigate the students’ interactions [30].

While hands-on physical laboratories have evident disadvantages related to cost and space requirements, remote and virtual laboratories also have drawbacks:

- In remote laboratories, students report a lack of personal engagement because of the separation between them and the experimental objects [31], [32].
- Virtual laboratories have even more of a separation, as the virtual system does not physically exist and the relationship is not clear between the physical and the virtual environment.
- The usability of virtual laboratories is questioned, as it is not the focus point when designing virtual laboratories [33].

In addition to the learning objectives of control engineering courses, to meet the needs of the industry as well as the accreditation criteria imposed on the university study programs, engineering students should develop not only professional skills but also soft skills. In this case, the working patterns that happen in hands-on laboratories are more suited to foster these skills compared to remote and virtual laboratories [34]. An overview of laboratories in control engineering and their alternatives is presented in Table 2.

Regardless of the ongoing debate, the recent coronavirus pandemic has forced the use of these alternative laboratory modes as physical distancing and lockdowns prevented the use of traditional physical laboratories [35], [36]. The lockdowns and related movement restrictions resulted in the need for organizing classes in hybrid form, and thus, the option of distance learning was made available to students. In a similar way, a hybrid approach combining several laboratory modes has emerged that allowed for the modes to complement each other. For example, virtual and remote laboratories concerned with the same control object can be used as follows [26]:

- the virtual mode is applied during the control design stage when no interaction with the real system is strictly necessary;
- the remote mode is applied for observing the behaviors introduced by the real system and deepening the understanding of related concepts.

As a result, rather than searching for the ultimate laboratory mode, one might devise a method for combining all of the modes within the same laboratory activity.

B. EMERGING INDUSTRY 4.0 TECHNOLOGIES: DIGITAL TWINS AND EXTENDED REALITY

Hands-on laboratories in control engineering are often extended with mathematical models and simulations that, on the one hand, provide the theoretical foundations for

TABLE 1. Laboratory mode classifications.

Laboratory mode	Resource nature	Resource location	Description
Traditional practical laboratory	real resource	local access	It represents the traditional practical laboratory and the take-home laboratory kits where a student is in front of a computer connected to the real plant to carry out the experiment
Remote laboratory	real resource	remote access	It represents remote real experiments where students access the real plant equipment laboratory through the internet. The user operates and controls a real plant through an experimentation interface in a remote way.
Locally hosted virtual laboratory	simulated resource	local access	It represents the virtual experiment where the whole environment is software and the experimentation interface works on a simulated, virtual and physically nonexistent resource.
Cloud hosted virtual laboratory	simulated resource	remote access	It represents remote virtual experiments where the students access the remote virtual environment through the internet and the software and the experimentation interface works on simulated, virtual and physically nonexistent resources.

modeling the specific control object and, on the other hand, allow the students to design control systems based on these models. The models themselves are often based on approximations leading to unmodeled dynamics. For example, the parameters of the studied systems are assumed to be time-invariant, yet in real life, the parameters of the systems are subject to change. Thus, updating these models and simulations requires manual effort and specialized expertise, which makes creating, operating, and maintaining the laboratories even more costly.

The *industry 4.0* revolution, however, emphasized the usage of data as the cornerstone for improving processes and operations across all industries. For example, industry 4.0 builds on a data-driven architecture by utilizing models that are capable of using data from real systems, which are used to synchronize the virtual representation of these systems with their real life counterparts, leading to the concept of *Digital Twins* (DT). The most cited definition for a digital twin reads as follows [37]. Note that the quote is taken from the document published by NASA, hence the occurrence of the "flying twin" concept, but the applications of the digital twins are obviously not limited to the aerospace industry.

> A digital twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, and fleet history to mirror the life of its corresponding flying twin.

The digital twin concept has many other definitions in the literature, as it is an emerging technology, and researchers are experimenting with its applications across different types of industries.

In our work, we follow the definition presented by the Digital Twin Consortium: "A digital twin is a virtual representation of real world entities and processes, synchronized at a specified frequency and fidelity" [38]. Toward the dynamical modeling aspect of a digital twin, we turn to [39], which describes the digital twin as having three main parts:

- a model of the object,
- an evolving set of data relating to the object,
- a tool for dynamically updating or adjusting the model in accordance with the data.

Concerning the last item, we note that the need for transferring data from virtual simulation to DT-based virtual laboratories specifically has been stressed in [9].

C. CONTRIBUTION

In this paper, we build upon this idea by showing that DT-based laboratories replace traditional simulated virtual laboratories and remote laboratories. Furthermore, with this approach, the traditional hands-on experiments are enhanced by enabling shared and mixed experiences coupled with the use of the extended reality technology.

The proposed framework is composed of multiple levels of fidelity based on digital twin implementation and extended reality (XR), with the ability to create unified and compliant modes for hands-on, virtual and remote laboratory experiments:

- First, remote laboratories are replicated as digital twins of the original laboratories synchronized at high frequency.
- Second, locally hosted virtual laboratories are digital twins of the original laboratories synchronized periodically to ensure the validity of the virtual representation.
- Finally, XR is used to enable a higher level of interaction and visualization offered by digital twin representation.

A comparison of the characteristics of different laboratory modes and hybrid ReImagine laboratories is presented in Table 3.

The main contribution of this study is presented in the following paragraphs. We first introduce the "Reimagine Lab" framework and show how the use of digital twins and extended realities streamlines the creation of virtual and remote laboratory modes. We then review the benefits of using the framework for both remote and virtual laboratories,

TABLE 2. Overview of laboratories in control engineering and their alternatives.

Ref.	Using Extended Reality	Using Digital Twins	Laboratory mode(s)	Description
[6]	-		Virtual Laboratories	Cloud-hosted virtual laboratories have high scaling capacity and low computational requirements for the devices used to access them.
[7]	-	-	Virtual Laboratories	The flexible nature of virtual laboratories allows changing models and running experiments in non-real-time manner, which makes them ideal for fulfilling the learning objective of control design in control engineering education.
[8]	-		Virtual laboratories	Virtual laboratories are a critical part in massive open online courses as an easy-access and cost-efficient way of online learning.
[9]	-	Yes	Virtual laboratories	The need for transferring from virtual simulation to digital twin-based virtual laboratories has been stressed.
[10]	-	Yes	Virtual laboratories	A web-based digital twin of a thermal power plant was introduced. The authors highlight the advantages of this type of system in education and training.
[11]	VR	-	Virtual laboratories	An investigation into how the connection of digital twins and virtual reality can be used to create a safe working environment for students in the field of robotics.
[12]	VR	-	Virtual laboratories	A virtual reality experience that enables a higher level of interaction is introduced for investigating electrical connections.
[13]	-	-	Remote laboratories	Remote access enables the students to have a safe experience in safety critical plants.
[14]	-	-	Remote laboratories	A lower cost alternative where multiple low-cost experimental platforms can be stored in a smaller space.
[15]	-	-	Remote laboratories	The development, structure, implementation, and applications of a remote laboratory for teaching control engineering have been presented.
[16]	-	-	Remote laboratories	Laboratory federations are introduced, which make it possible to distribute the cost of hosting remote laboratories between those institutions and provide students with access to a wider variety of laboratory experiments based on different equipment.
[17]	-	Yes	Remote laboratories	The authors identify two key issues that need to be addressed before the transformation from simulated laboratories to digital twins can occur: (1) devising the control architecture; (2) solving the problem of synchronization.
[18]	AR	-	Remote laboratories	The use of augmented reality to enhance remote laboratories has shown to increase students' performances, as it allows students to experience the laboratory in a way that is not possible with a traditional hands-on laboratory.
[19]	-	-	At-home laboratory kits	A DC motor control experiment kit was created to allow students to learn from home during the COVID-19 health crisis.
[20]	-	-	At-home laboratory kits	home laboratory kits composed of a mass-spring-damper system and an analog filter were used to assist in teaching the undergraduate level of the control course.
[21]	-	-	At-home laboratory kits	build-it-yourself home laboratory kits were proposed to make it possible for the students to do the experiments at home.
[22]	-	-	At-home laboratory kits	take-home laboratories have been used to overcome the lack of hands-on experiments in massive open online courses.
[23], [24]	-	Yes	Remote laboratories / Virtual laboratories	The digital twin concept was introduced to students as part of the mechatronics course, as it involves the application of identification, modeling, analysis, controller design and validation.
[25]	VR/AR	-	Remote laboratories / Virtual Laboratories	showed how the use of virtual and augmented reality in remote and simulated laboratories, which can be used to enable collaboration using avatars.
[26]	-	-	Remote laboratories / Virtual Laboratories	A web-based hybrid laboratory framework for research and education was proposed. The framework has a highly modular design providing flexible online experiments.
[27]	-	-	Virtual laboratories	A 3D control laboratory, which can be used for classroom demonstration and online experimentation was introduced. The solution is composed of various learning-oriented technologies and provides great flexibility for the users.
[28]	MR	Yes	Remote laboratories	A mixed reality human-machine interface for controlling and monitoring a digital twin of an industrial crane platform. The device uses interactive holograms to both monitor and control the crane's status.

TABLE 3. Characteristics comparison of different laboratory modes and hybrid ReImagine laboratories.

Laboratory mode	Usability	Scalability	Flexibility	Immersion	Collaboration
Hands-on laboratories	High	Low	Low	High	High
Simulated laboratories	Medium	High	High	Low	Medium
Remote laboratories	Medium	Medium	Medium	Medium	Low
ReImagine laboratories	High	Medium	High	High	High

as well as how it enables the creation of shared experiments with hands-on laboratories. A specific use case is studied to test the validity of the framework, where a digital twin of an actual control object, a laboratory-scale model of a 3D crane located in the CS laboratory at Tallinn University of Technology, Tallinn, Estonia [40] is created.

The structure of the manuscript is as follows. The proposed DT and XR laboratory framework is detailed in Section II. A use case of a digital twin-based implementation of a 3D crane is described in Section III. Next, the system usability study comparing the use of immersive virtual reality and desktop virtual experiments is put into context and presented in Section IV. The results of the experiments are presented and discussed in Section V. Finally, conclusions are drawn in Section VI.

II. REIMAGINE LAB: A DIGITAL TWINS AND EXTENDED REALITY FRAMEWORK

The proposed framework is underpinned by two major components: digital twins and extended reality. Fig. 1 presents an overview of the proposed framework. The components highlighted by dashed outlines represent the different lab modes (with the exception of hands-on labs):

- Remote laboratory mode;
- Virtual laboratory mode;
- Cloud hosted virtual laboratory mode.

In all cases, while multiple fidelity levels of digital twin implementations are used to represent the controlled physical object, XR is used to enable a higher level of visualization and interaction required by the digital twin representation. The components on the bottom left represent:

- the physical lab asset, which allows for the hands-on lab mode to be employed;
- the big data server that handles data storage for digital twin synchronization and other tasks;
- a cloud-hosted version of the digital twin of the physical lab asset.

The suggested framework addresses all of the issues raised previously. Table 4 presents an overview of the characteristics of the framework, and each lab mode is discussed separately in the next section.

A. REIMAGINE-LAB MODES

1) REMOTE MODE

As illustrated in Fig. 2, the framework performs remote teleportation of the laboratory asset by substituting video streaming with synchronization of the local digital twin of the real asset. Extended reality is being utilized to offer a more intuitive and natural form of engagement using hand gestures and other tools, allowing for an experience comparable to that found in the hands-on laboratories. Because this type of engagement does not need any user to have control privileges, the usage of XR facilitates collaboration by establishing virtual environments where users may interact with one another and the laboratory object.

2) VIRTUAL MODE

Fig. 3 shows how the proposed solution enables locally hosted virtual laboratories by replacing the simulated model with a digital twin:

- first, the bidirectional evolving set of data guarantees that updates from the actual laboratory object are applied automatically to the digital twin;
- second, adhering to the digital twin principle, ReImaginedata that describes the uncertainty and divergence between the digital twin and the physical twin is also available;
- finally, usingf XR technology as a medium of interaction to take advantage of the rich amount of information is available through the digital twin architecture.

The first two features are intended to foster greater trust in the virtual simulation, while the use of XR enables the creation of environments that promote student collaboration.

Cloud-hosted virtual environments provide additional benefits from the framework because they enable the use of higher-fidelity twin models. As illustrated in Fig. 3, the simulation is distributed across the network, with the local device rendering the visual representation of the digital twin asset while computation is offloaded to the cloud.

3) HANDS-ON MODE

The benefits of utilizing the framework are not limited to technology-enabled laboratories; they also benefit hands-on laboratories by allowing for mixed experiences in various laboratory modes. The use of XR and digital twins in Fig. 4 enables a mixed experience where a group of students can interact directly with the laboratory asset while others can interact remotely. This interaction can be bidirectional if local students are also utilizing augmented reality to interact with laboratory assets.

B. CREATION OF THE REIMAGINE LAB ASSETS

The following section defines the core process of creating digital twins in the context of automatic control systems. This involves mathematical modeling, the creation of 3D assets, interaction and visualization design.

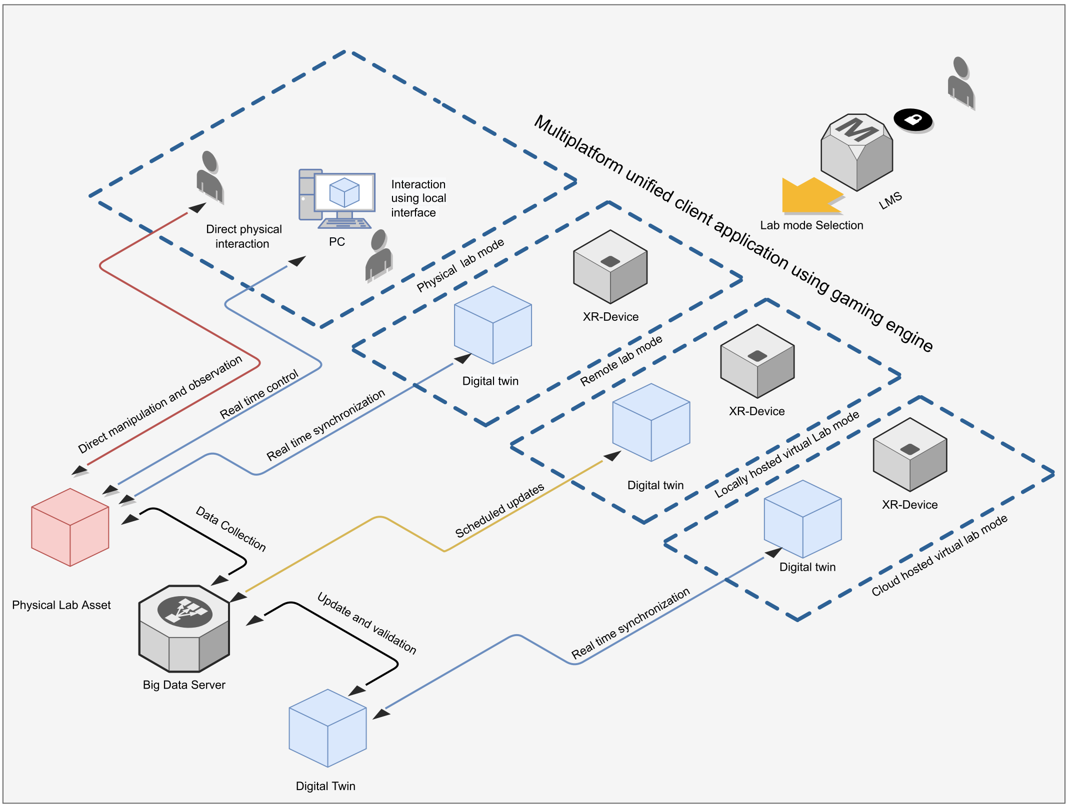

FIGURE 1. The overall schematic diagram for the ReImagine-laboratory framework.

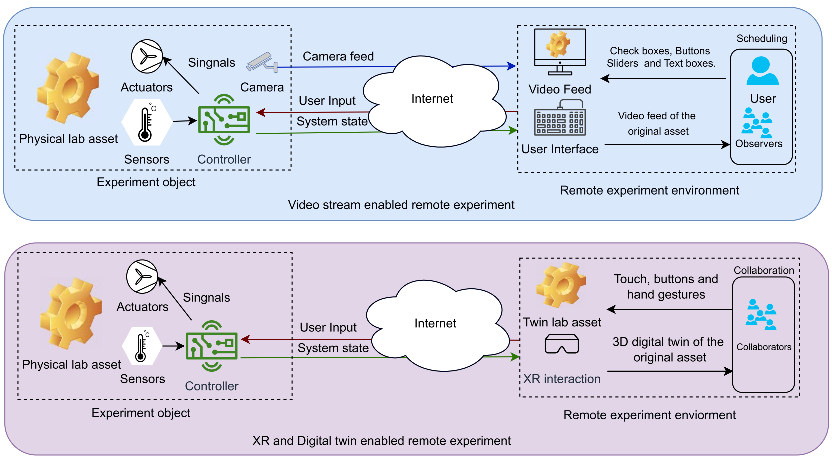

FIGURE 2. The schematic diagram for a remote laboratory and ReImagine enabled remote laboratory.

1) MATHEMATICAL MODELING

We first address the modeling and simulation aspect of digital twins. Here, modeling broadly refers to the problem of the coherent representation of the dynamics of the system studied by computing the evolution of its internal variables (states) under external stimuli (inputs). States and inputs represent

TABLE 4. Characteristic of the ReImagine Lab.

Characteristic	Details	Enabling technology (XR /DT)	Benefited lab modes
Uniformity	Hands-on, remote, and virtual laboratories each have their own strengths, and educators have experimented with many laboratory modalities to accomplish high educational goals. Creation of each lab mode requires specialized skills and an approach leading to fragmentation and increasing the cost of development and maintenance. The use of the digital twins framework attempts address the issue of fragmentation by adopting a simplified and consistent approach that can be applied to diverse control laboratory objects.	DT and XR	Virtual Laboratories Remote Laboratories Hands-on Laboratories
Usability	There is a psychological separation between the student and the object in virtual and remote laboratory modes. We believe that providing students with a thorough introduction to the use of digital twins in the creation of various laboratory modalities can assist to bridge this gap. Students may take these alliterative laboratory modes more seriously because they are twins of the original laboratory object, thus boosting the student-object engagement level.	XR	Virtual Laboratories Remote Laboratories
Flexibility	Because laboratory modes are digital twins based on the original object, they allow for greater flexibility in laboratory mode selections. For example, students can begin conducting design experiments in a virtual mode and then employ remote or hands-on modes to understand topics. This transformation makes it easier to choose a laboratory mode based on the available resources (physical access, connection, application) without jeopardizing the educational experience.	DT and XR	Virtual Laboratories Remote Laboratories Hands-on Laboratories
Immersion	One of the main advantages of using immersive virtual reality is the ability to induce what is known as immersion, which is the sensation that the user has been transported to another location. While this effect can be achieved with a traditional desktop computer, it is much easier to achieve with immersive virtual reality. Students' involvement and interaction with the laboratory object can improve when the level of immersion is increased.	DT and XR	Virtual Laboratories Remote Laboratories
Collaboration	In virtual and remote laboratories, there are little opportunities for students to develop social skills and collaborate. It is feasible to create a shared virtual reality experience using XR where students are portrayed as avatars inside the environment and may communicate and collaborate as a group.	XR	Virtual Laboratories Remote Laboratories
Transparency	The employment of several laboratory modes introduces variations in factors that affect the system response and may result in unanticipated behavior. Virtual laboratories, for example, are usually driven by an approximate model of the real object, which introduces uncertainty. Moreover, communication latency has a substantial impact on system response in remote laboratories. It's critical that users are aware of these factors and their implications for the system. Following appropriate DT methodology involves being open about the differences between the digital twin model and the real system, resulting in a transparent experience.	DT	Virtual Laboratories Remote Laboratories

some physical properties of the system. In general, a dynamic model can be represented in *state space* form using a system of differential equations as follows:

$$\begin{aligned} \dot{\mathbf{x}} &= f(\mathbf{x}, \mathbf{u}, t) \\ \mathbf{y} &= h(\mathbf{x}, \mathbf{u}, t), \end{aligned} \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the state vector, $\mathbf{u} \in \mathbb{R}^m$ is the input vector, $\mathbf{y} \in \mathbb{R}^p$ is the output vector, and t is the time argument, and $f(\cdot)$ and $h(\cdot)$ are nonlinear functions. For convenience, linear, time-invariant approximations of (1) are often used and are of the form as follows:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \\ \mathbf{y} &= \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}, \end{aligned} \tag{2}$$

where $\mathbf{A} \in \mathbb{R}^{n\times n}$, $\mathbf{B} \in \mathbb{R}^{n\times m}$, $\mathbf{C} \in \mathbb{R}^{p\times n}$, and $\mathbf{D} \in \mathbb{R}^{p\times m}$ are state, input, output, and direct transmission matrices with numerical entries, respectively [41]. For single-input, single-output linear, time-invariance systems, the concept of the *transfer function* can be employed. The corresponding dynamics equation in the Laplace domain is given as follows:

$$G(s) = \frac{b_m s^m + b_{m-1} s^{m-1} + \cdots + b_0}{a_n s^n + a_{n-1} s^{n-1} + \cdots + a_0}, \tag{3}$$

where s is the Laplace operator, and a_i and b_j are real numbers, and n is the order of the model. For the system in (3) to be practically realizable, it must be proper, i.e., the condition $n \geqslant m$ must be satisfied.

In terms of modeling approaches, the usual "box" models are considered:

- *White box* modeling (also known as *First Principles* modeling). The structure of the model is known, and the model is derived from physical laws.
- *Gray box* modeling. The model is partially derived from physical laws. Certain parts of the model are approximated such that these approximations have no direct physical interpretation but are nevertheless suitable for modeling purposes.

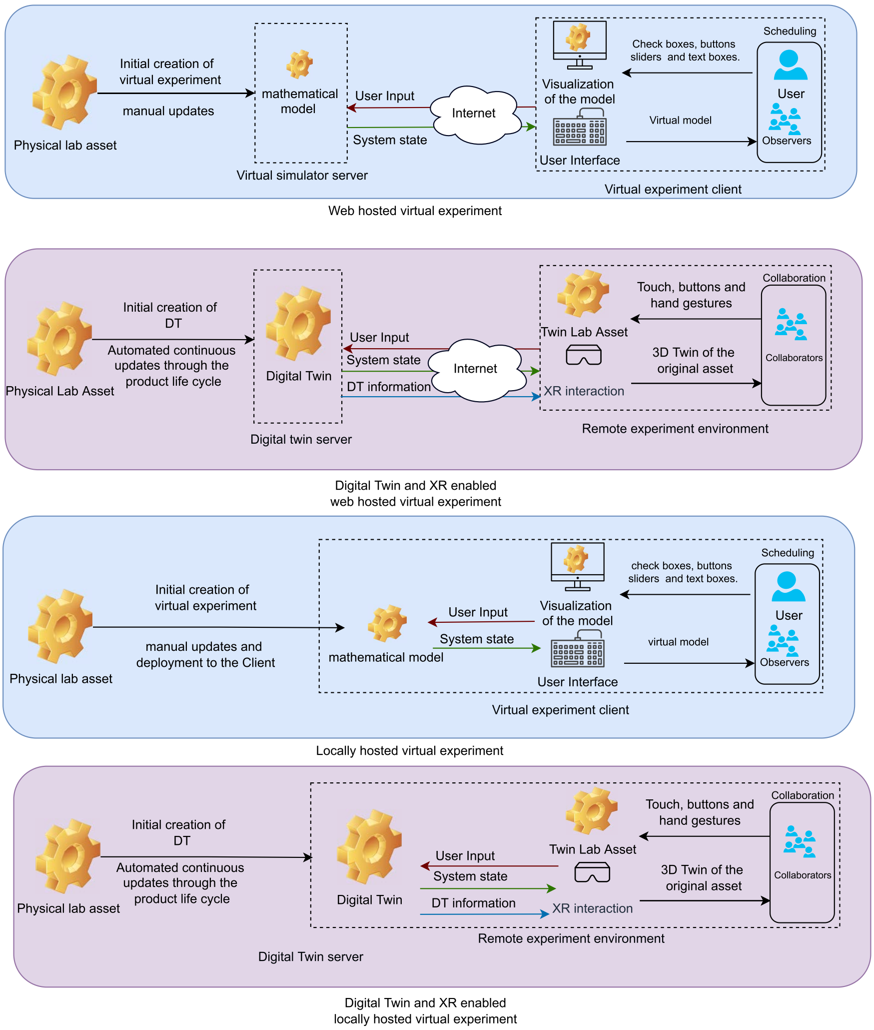

FIGURE 3. The schematic diagram for a virtual laboratory and ReImagine enabled virtual laboratory.

- *Black box* modeling. No information about the physical structure of the system is given *a priori*. As a result, the model is created by fitting experimental data to a mathematical type of model and structure that has been arbitrarily chosen. This is a data-driven technique that is ubiquitous, although it may be less beneficial if the structure of the systems under investigation is known.

In the case of gray and black box modeling, data must be collected from real life plants. In the present work, data are collected by sampling the sensors of the real life plant. The system under investigation is connected to a desktop computer through a data acquisition device that allows the collection of all relevant data for creating a mathematical model of the digital twin. The complete process is presented in Fig. 5.

After the collection and preprocessing of data, the model identification procedure is carried out. In this work, we consider linear approximations of the system in question and for the linear models in (2) and (3), the estimated parameter sets are as follows:

$$\theta_{ss} = \begin{bmatrix} \theta_{\mathbf{A}} & \theta_{\mathbf{B}} & \theta_{\mathbf{C}} & \theta_{\mathbf{D}} \end{bmatrix} \tag{4}$$

and

$$\theta_{tf} = \begin{bmatrix} \theta_b & \theta_a \end{bmatrix}, \tag{5}$$

respectively, with the individual entries of θ_{ss} and θ_{tf} representing row vectors of parameters stemming from either the

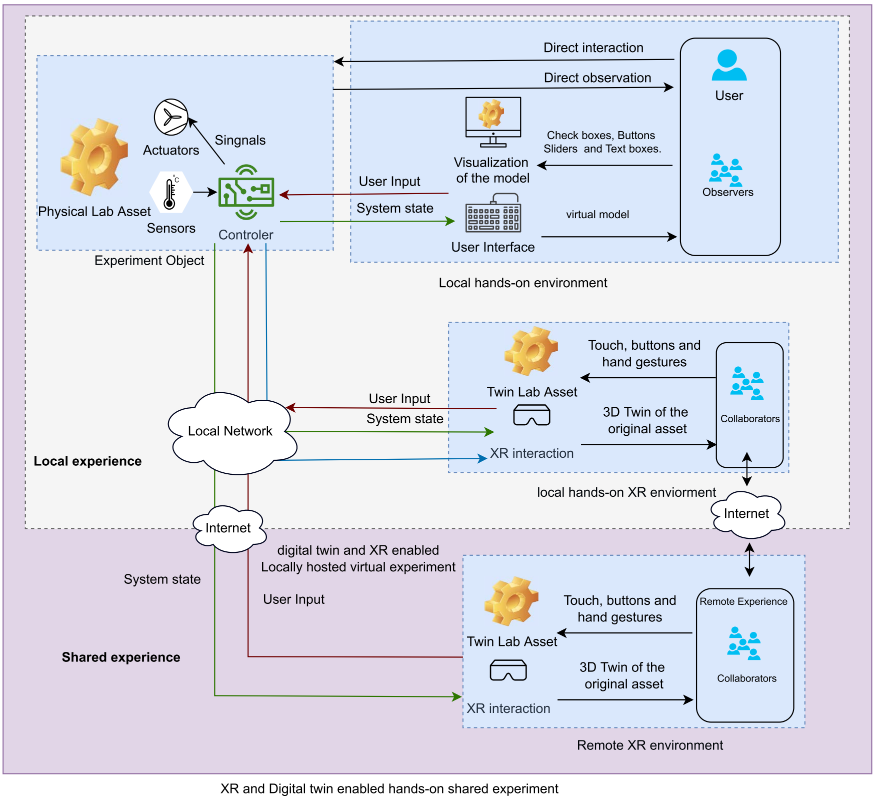

FIGURE 4. **The schematic diagram for a hands-on laboratory and ReImagine enabled hands-on laboratory.**

corresponding system matrices or the zero and pole polynomials. Time identification is employed such that the output error criterion (residual norm) is as follows:

$$F = \sum_{i=1}^{N} \varepsilon_i^2 = \|\varepsilon\|_2^2 \tag{6}$$

is minimized, where $\varepsilon_i = y_i - \hat{y}_i$ is the residual (simulation error), y_i is the true system output and $\hat{y}_i$ is the predicted output for collected samples $i = 1, 2, \ldots, N$. In the case of a multi-input, multioutput system, the residuals resulting from modeling individual outputs are scaled according to the magnitude of the modeled physical variable, and a weighted sum is used as the cost function. Several optimization algorithms are used to estimate the parameters of the model, including the Trust Region Reflective algorithm [42], [43], the Levenberg–Marquardt algorithm [44], [45], and the Nelder–Mead direct search method [46]. The latter is well-suited to optimize a function with derivatives that are unknown or nonexistent. Addressing the problem of the initial parameter estimation, the subspace estimation method is used [47].

Concerning control, in the present work, we consider the classical negative unity feedback control loop as follows:

$$H(s) = \frac{C(s)G(s)}{1 + C(s)G(s)} \tag{7}$$

consisting of a controller denoted by $C(s)$ and the plant denoted by $G(s)$. Here, the objective of the control system is to manipulate the plant input u via the controller to minimize the error e, i.e., difference between the desired output r (reference value) and the true output of the plant y, and we consider the *output tracking* problem. In real life industrial applications, a proportional-integral derivative (PID) controller is typically used [48], [49], [50]. In this work, we employ the parallel form of the PID controller that has the form as follows:

$$C(s) = K_p + K_i s^{-1} + K_d s, \tag{8}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively. These parameters must be properly tuned for each control loop that composes the full system.

An important point to make is that in the case of digital twin synchronization with real systems, the parameters of the models obtained using the methods described above are not static and coevolve with the changes in real systems. Therefore, the process depicted in Fig. 5 can be thought of as the creation of a mathematical model snapshot. At preset time intervals, new model snapshots are created. Hence, the process of parameter estimation and controller parameter transfer is continuous. As the specific physical lab asset is utilized, it generates valuable data that are stored on the server and used to obtain the updated mathematical models.

2) 3D MODELING

All digital twins of control objects are recreated by either measuring the dimensions of the parts of physical devices or by using available blueprints and then implementing the 3D models using CAD software, such as the Blender 3D modeling software [51]. For XR applications, efficient real-time rendering of the objects must be ensured. Therefore, the following important considerations are in effect when modeling all objects:

- All 3D models must be optimized, i.e., the number of polygons forming the part reduced and visualization tradeoffs sought in terms of applying textures, displacement maps and lightmaps.
- A sufficient level of detail must be ensured such that the effect of immersion is achieved [52].

The complete procedure for 3D modeling thus is composed of the following: steps:

1) Measuring the physical devices or using a previously known blueprint data;
2) 3D modeling in Blender ensuring a sufficient level of detail is achieved;
3) Optimization, meaning the application of necessary textures, baking displacement- and lightmaps;
4) Exporting the 3D model from Blender into a common 3D asset exchange format (usually FBX);
5) Importing the 3D asset into the real-time rendering engine, creation of materials that are used on the 3D model, validation in the target extended reality application.

If necessary, we may return to step 2 to correct any issues discovered in the real-time application.

The process of 3D modeling can also be semiautomated by introducing photogrammetry [53]. This approach, however, falls outside the scope of the present paper.

3) PROTOTYPING PLATFORM

To efficiently codevelop the 3D visualization and XR and the mathematical modeling parts, a coherent prototyping platform is needed. In the present work, the following software packages are chosen to implement the platform:

- Unreal Engine 4 [54] as the visualization platform due to highly sophisticated support for virtual reality and rapid game logic prototyping via Unreal Engine Blueprints.
- MATLAB/Simulink environment [55] as the mathematical prototyping platform with real-time simulation support via the Simulink Desktop Real-Time toolbox.
- UDP communication plugin for Unreal Engine 4 that makes real-time simulation possible and was developed for Re:creation Virtual and Augmented Reality Laboratory-related applications [56].

The diagram showing the prototyping configuration is depicted in Fig. 6. This configuration allows for true real-time simulations to be carried out. Prototyping involves the following stages:

1) Development of mathematical models based on the methods discussed in Subsection III-B. Design of mathematical models of interaction mechanics. Validation of the models using data from real control objects. This part is done in either the MATLAB or Simulink environment. As a final stage, functions or blocks enabling real-time data communication through the UDP protocol are added to the project.
2) Development of the 3D models per the methods discussed in Subsection II-B2. After importing the models into Unreal Engine 4, correct assembly of all parts in the hierarchical structures follows. This has to do with ensuring correct coordinate transformations to be applied to connected parts of the given object.
3) Evaluation of the developed application in virtual reality. Assessment of the immersion effect, correctness of dynamics and interaction mechanics.

Once refined, the mathematical models can be directly exported from Simulink as C++ code and integrated into Unreal Engine 4 as blueprint-accessible code plugins. This approach provides the greatest amount of flexibility because the developed mathematical models of dynamics are computed in separate modules that are accessible as blueprint blocks with the required number of inputs and outputs. The plugins are also reusable in other projects.

The prototyping platform can also be used to teach control system design effectively. In this case, the student receives the Simulink block, which represents the system and internally implements communication between the mathematical model and visualization. The visualization application can then be kept running at all times while the mathematical model with the designed controllers is launched several times to enable experimentation with different controllers or controller settings. This can also be done as part of group work, with one student controlling the experiment from the VR environment and the other designing the control experiment in MATLAB/Simulink.

4) INTERACTION DESIGN

Interaction is the most important aspect of an immersive XR environment. While developing digital twins of control systems, the design of meaningful interactions is the main goal of the training aspect of the application [57]. As a result, the development of coherent interactions is regarded as a top priority for ensuring effective laboratory instruction.

In this work, we explore two types of interactions that arise in the area of control systems:

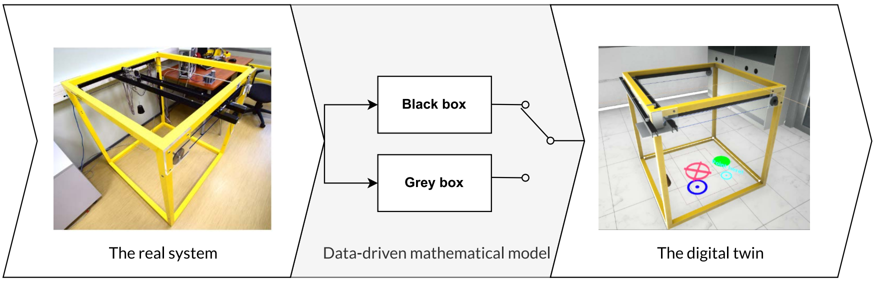

FIGURE 5. The process of creating a data-driven mathematical model for the digital twin. Relevant data are first collected from the real plant. Then one of the box models is used with system identification (the choice is determined by the position of the switch in the figure). Finally, the digital twin can use the model of the dynamics. The model is periodically updated in a process referred to as synchronization of the real system and the digital twin.

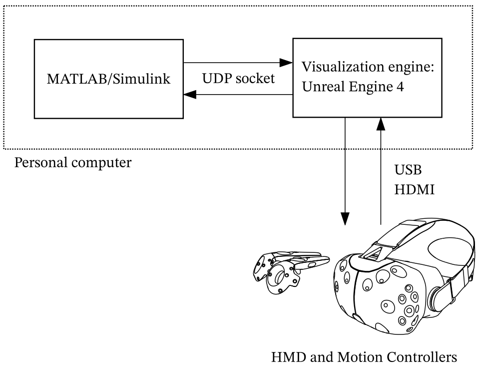

FIGURE 6. Real-time prototyping platform for developing digital twins of control objects.

1) Interactive selection of the control system tracking reference (set point);
2) Interactions with floating information panels that display valuable data concerning the setup and the state of the laboratory experiment.

Next, we focus on key aspects of the implementation of these interactions. There are several options available when designing interactions. First, we can implement those using the physics engine available in the target platform. In this case, the mathematical description of the process is largely unclear. The task is, however, to obtain a valid mathematical model of the whole system, including interactions, which must be reproduced in the digital twin. Thus, interaction design is also seen as a mathematical problem and all modeling methods discussed in Subsection III-B are valid for this purpose. Several methods are used for developing interaction mechanics:

- Interactions are coupled with the object dynamics, that is, the corresponding (non)linear mathematical model is augmented with corresponding inputs and states;
- Interactions are decoupled from the object dynamics, that is, a separate mathematical model is designed for the interaction. This approach is feasible only if the interaction does not affect the control system performance, and thus, its use is usually limited.
- An interaction is designed for the supporting components of the XR experience (such as using the information panels). Mathematical models of these interactions are, at first glance, not needed; however, if one considers the concept of intelligent immersive virtual environments (IIVEs), useful intelligent mechanics can be employed as well [58].

Interaction mechanics are first evaluated by comparing the performance of the model with that of the original control object. Then, the subject-based evaluation is performed in XR internally by developers and through subject-based experiments. If the results are not satisfactory based on the feedback, the mechanism is revised.

Another important interaction mechanic is not considered in the case study presented in this work, but it should be mentioned. This is the direct physical interaction with the moving parts of the recreated control objects. From the control systems perspective, this is generally used to introduce disturbances into the studied systems. From the user perspective, such interactions are of curiosity driven experimental nature, and hence, are very valuable features.

5) GRAPHICAL DATA ANALYSIS

Graphical representation of data is a very convenient tool for analyzing the underlying phenomena [59]. Consequently, one of the key aspects of learning control system dynamics is related to the study of time series charts depicting system dynamics [41]. For this reason, the corresponding feature must be implemented in the XR visualization, that is, a real-time time series chart must be available. Therefore, the following items are considered:

- Due to the flexibility of presenting data in XR, the graphs can be presented to the user upon request and attached to the view port in an unobtrusive way. For example, the dynamic chart may be attached to one or both of the motion controllers and shown upon the user pressing a preset button;

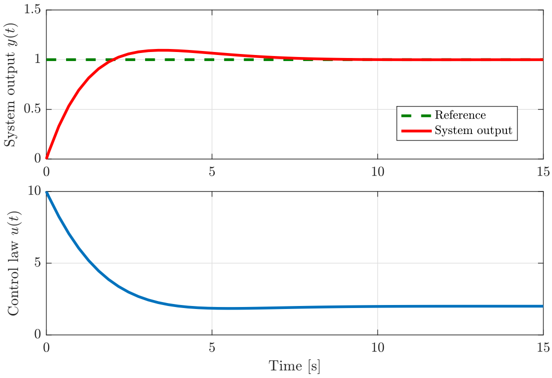

FIGURE 7. Typical time series chart for studying control system dynamics, here for a single input single output system. Top: tracking performance analysis through step response evaluation. Bottom: control law dynamics analysis (system input generated by a controller).

- The structure and types of charts shall depend on the particular study. In studying control systems, one is generally interested in control system tracking performance and control law behavior. Thus, the most general chart is presented in Fig. 7.

In this work, for implementing charts in the XR application, an Unreal Engine 4 plugin called *Kantan Charts* is used [60].

III. CASE STUDY: DIGITAL TWIN BASED IMPLEMENTATION OF A 3D CRANE IN EXTENDED REALITY

Hereinafter, a case study of developing a coherent digital twin of a lab-scale model of an overhead crane is provided in the context of the proposed framework. The original real life control object was produced by the Inteco company [61] and is commonly referred to as the "3D crane" as a reference to the number of degrees of freedom involved in moving the payload.

The 3D crane is a nonlinear electromechanical system that possesses a complex dynamic behavior and creates challenging control problems [61], [62]. The industrial counterpart of this laboratory model is used in various industries and seaports to transport large and heavy containers and other payloads. To ensure efficiency and productivity, the crane must transport the payload as fast as possible to its destination. However, a certain motion profile must be employed such that the control actions leading to the acceleration and deceleration of the payload ensure secure and sway-free transportation [63]. The characteristics of the system allow the application of various control strategies [62], [64], [65]. This makes it very appealing as an educational tool in the control systems laboratory.

The present control object is depicted in Fig. 8. It consists of a frame, a moving rail attached to a moving cart. The payload is attached to the cart via a rotating spool. Thus, three degrees of freedom are achieved. The rail, cart and payload spool are actuated by DC motors, and their positions are determined with incremental encoder sensors. In addition, the two encoders are attached to the cart that measure the swing angle of the attached payload.

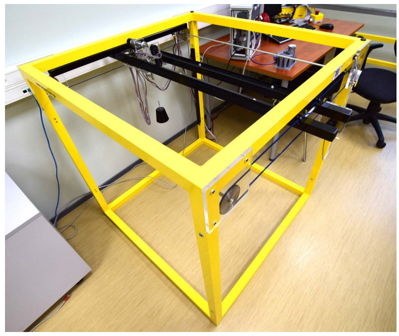

FIGURE 8. Real-life 3D crane control object.

A. 3D MODEL OF THE OVERHEAD CRANE

Following the discussion above, the 3D model of the crane is developed. The following major components are recreated:

- Yellow frame;
- The moving rail;
- The moving cart with the moving spool;
- The payload itself attached to its cable.

Thus, all critical mechanical components and the frame have been faithfully recreated, while the wires, DC motors, encoders, pulleys and belts were ignored. It was confirmed through initial experiments that as long as the recreated components had the correct scale and behaved exactly as expected, the 3D model would be convincing enough for immersion to occur [58]. In the future, the other components can be recreated as well, but the additional complexity may not necessarily benefit the present digital twin. The resulting model is shown in Fig. 12.

B. MATHEMATICAL MODEL OF THE 3D CRANE

The discussion below pertains to obtaining a single snapshot of the physical twin dynamics using the methods described in Sec. II-B1. The model shall be updated periodically based on the data generated during the operation of the physical overhead crane.

In this work, we use the physical model of the object shown in Fig. 9. Instead of using a complicated nonlinear model as in previous cases, linear models are used for two purposes:

- Describing the motion of the rail and the caret in the (x, y)-plane (transfer functions);
- Determining the dynamics of the payload swing angles α and β (state space model).

The third degree of freedom (payload height) is not used. The payload is fixed at a height of approximately 30 cm from the floor. Time domain identification is used to obtain a snapshot of a decoupled set of models. For the transfer from

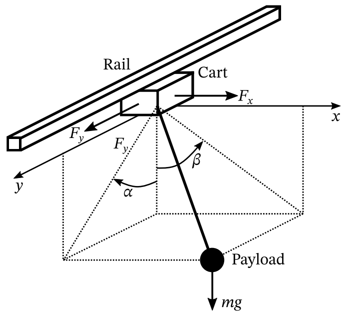

FIGURE 9. Physical model of the 3D crane system.

the normalized actuator control signal $u_x, u_y \in [0, 1]$ to the rail and caret positions, we obtain the following:

$$G_x(s) = \frac{1}{s}\frac{0.30651}{0.035073s + 1} \tag{9}$$

and

$$G_y(s) = \frac{1}{s}\frac{0.33821}{0.041963s + 1}, \tag{10}$$

and for the transfer from the inputs to the swing angles the state space model of the form (2) is obtained, where the state matrix is as follows:

$$\mathbf{A} = \begin{bmatrix} -0.4377 & 3.513 & 0.5393 & -1.9075 \\ -3.804 & 0.2155 & -1.5478 & -0.8172 \\ -0.0913 & 1.3392 & -0.0178 & 4.3422 \\ 1.1336 & 0.0534 & -3.0303 & 0.1400 \end{bmatrix}, \tag{11}$$

The input matrix is as follows:

$$\mathbf{B} = \begin{bmatrix} 0.56505 & 0.21808 \\ -1.1166 & -6.7447 \\ -0.13395 & -2.3007 \\ 4.8125 & -3.1489 \end{bmatrix}, \tag{12}$$

The output matrix is as follows:

$$\mathbf{C} = \begin{bmatrix} -0.0123 & 0.02454 & -0.00524 & -0.03695 \\ -0.04552 & 0.09786 & 0.03010 & -0.02335 \end{bmatrix}, \tag{13}$$

and the direct transmission matrix is as follows:

$$\mathbf{D} = \begin{bmatrix} -0.0011281 & 0.0013873 \\ 0.0011836 & 0.0012102 \end{bmatrix}. \tag{14}$$

Furthermore, the model in (11)–(14) was modified so that the second swing angle motion needed to be corrected. This was done by multiplying the real part of the corresponding eigenvalues by a factor of 2.5. Then, a balanced reduction technique was applied to the modified model, which also resulted in a nonzero matrix **D**. The corresponding validation plot is shown in Fig. 10.

Some modeling discrepancies can be observed. However, when the digital twin of the 3D crane is observed in the XR environment, the modeling errors do not, generally, result in breaking the effect of immersion; the dynamics of the crane are perceived by the subjects as believable. For the present work, the accuracy of the model is not critical as long as immersion is achieved because the goal of the experimental study is not related to demonstrating the precision of the mathematical model but rather demonstrating some high-level control concepts. However, when further experiments are designed, a different modeling approach should be used. Therefore, instead of using the black box route in Fig. 5, which yields a linear approximation for a fixed line length of the 3D crane, the gray box route should be used instead of involving a nonlinear model of the system. That way, a more precise model can be achieved, the state variable corresponding to the line length can be integrated into the model, and relevant experiments that are, e.g., related to controller tuning, can be designed and carried out in the real environment and with the digital twin.

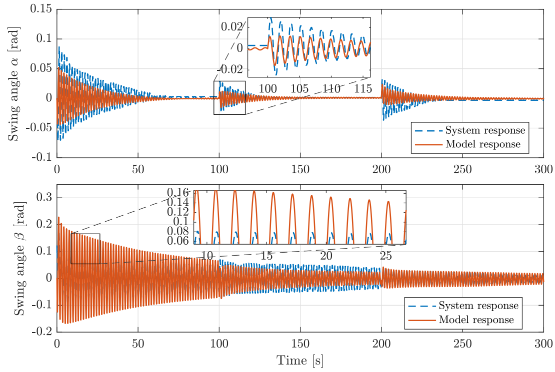

FIGURE 10. Results of model validation for the swing angle dynamics of the 3D crane.

Finally, although the identification procedure for the models in (9)–(10) and (11)–(14) is carried out separately, since the inputs are the same in both cases, the mathematical model can be combined into a single 8th order state-space formulation for convenience.

C. 3D CRANE INTERACTION DESIGN

The following two interaction mechanics have been implemented for the experiment with the 3D crane:

- Interaction with the control object variables: changing the set-point, which refers to the desired location of the crane's payload—and changing the control mode of the crane;
- Interaction with the plot widgets: moving them to the predefined locations, grabbing and moving them to a new location, or grabbing and throwing them anywhere in the virtual environment.

IV. EXPERIMENTAL VERIFICATION OF A DIGITAL TWIN OF AN OVERHEAD CRANE MODEL IN EXTENDED REALITY

The goal of this section is to show evidence of a successful implementation of an overhead crane digital twin that can be

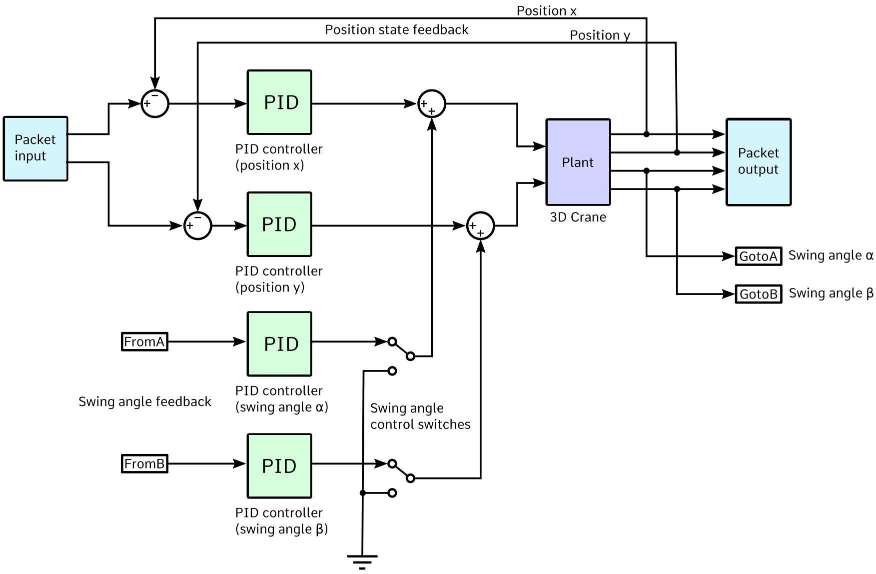

FIGURE 11. **The schematic diagram for the 3D crane control experiment.**

experienced in an extended reality environment. We cover a single lab mode in the experiment, namely, the virtual lab mode; however, because the digital twin and extended reality technologies underpin all of the other lab modes as well, the data obtained through subject-based testing should contain information about the usability of these technologies in general for the intended application. As a result, if the data show that the digital twins and extended reality are effective in the intended application, then this result can be valid for all other lab modes.

A. THE DESCRIPTION OF THE LAB EXPERIMENT

The experimental configuration is shown in Fig. 11. The main control loop addresses the position of the payload in the (x, y)-plane. The task is to transport the payload from one point to another as fast as possible. The secondary loop compensates for the payload swing and can be turned on and off; the goal of the experiment is to assess the performance of the control loop in both these cases. A screenshot from the application is depicted in Fig. 12. Here, the user points the motion controller away from the reference cube, so the set point is unchanged but is shown on the floor in the form of a crosshair.

The charting facility in this case serves as a reference for the performance of the control loop with and without swing compensation enabled. An exemple depicting the situation when the swing compensation is enabled is shown in Fig. 13. By introducing control actions that lead to some oscillations in the caret position, the swing is effectively damped. The specific parameters of the PID controllers are not shown to the subjects in the experiments. Tuning the PID controllers is

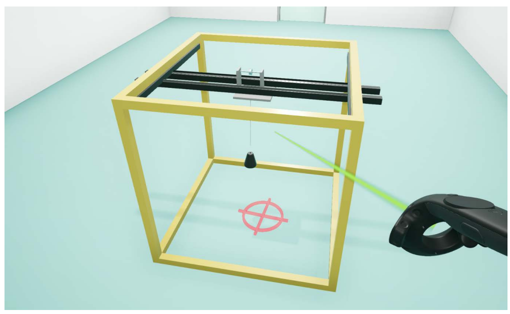

FIGURE 12. **Screenshot from the VR-based 3D Crane application. The user is pointing the motion controller to an area outside of the reference box, so the crosshair appears only to show the current set point.**

a topic for a different kind of experiment along the lines of what was presented previously in [66].

B. VALIDATION OF THE SOLUTION WITH A SYSTEM USABILITY STUDY WITH SUBJECTS

In the educational setting, cognitive ergonomics is the study of the design of learning activities that conform to students' cognitive capabilities by applying principles based on human perception, mental processing, and memory to improve the usability of the learning activities. Since we are interested in understanding the usability of using VR in control systems courses, we conduct a system usability study (SUS) to compare a classical experiment that introduced the concept of automatic control application for the 3D crane object and a similar experiment in VR. The original experiment uses an

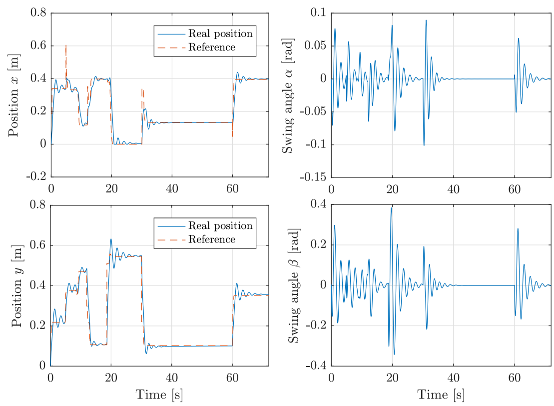

FIGURE 13. Experimental chart showing the performance of the control system with payload swing compensation enabled.

TABLE 5. Hardware components of the desktop and VR experiment computers.

Component	VR experiment	Desktop experiment
CPU	Intel i7-6700K @4.00GHZ	Intel i7-7700HQ @2.80GHZ
Graphics card	NVIDIA Geforce GTX 1080 - 8.0 GB GPU memory	NVIDIA Geforce GTX 1070 with Max-Q Design - 8.0 GB GPU
RAM	32GB	16GB

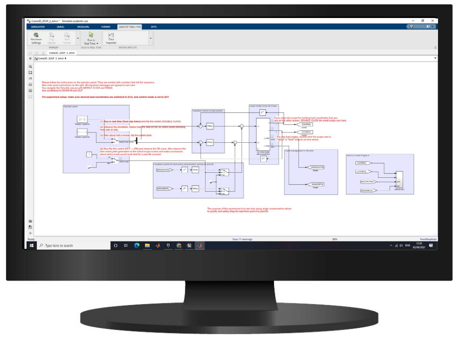

FIGURE 14. Simulink model of the 3D crane and the swing compensation PID controller.

interactive Simulink environment enhanced with a 3D model of the crane. The VR experiment uses a digital visual twin of the 3D crane in Unreal Engine driven with a mathematical model implemented in the MATLAB environment.

The experiment is divided into three parts. First, a presentation created by the course instructor introduces the participant to the experiment and the 3D crane control object.

The second part is a classical control course experiment conducted on a desktop computer where a Simulink model of the 3D crane and swing compensation PID controller is presented. The Simulink interface shown in Fig. 14 is displayed on one screen, while the second screen shows graphs that display the model's real-time response and a 3D model of the crane that is moving in real-time based on data received from the Simulink model shown in Fig. 15.

The third part is a similar control course experiment conducted in a VR laboratory environment that includes the "3D Crane" control object, a laboratory-scale simplified model of a gantry crane produced by Inteco and recreated as a digital twin in VR, as well as two interactive plot widgets; the first widget shows real-time data representing the 3D crane dynamics and the other graph shows an explanation of the control object parameters. Fig. 16 shows the different elements of the VR laboratory.

For the desktop experiment, we used a laptop computer connected to two monitors. The Simulink model was shown on the first screen, and a 3D presentation of the 3D crane that was created using Unreal Engine was shown on the second screen. Table 5 demonstrates the component configuration of the desktop PC.

To create a VR environment, we used an HTC VIVE Pro Eye virtual reality headset. The HTC VIVE Pro Eye HMD features dual-OLED displays with a combined resolution of 2880 $\times$ 1600 pixels and precision eye tracking sensors. In addition to the headset, we used two HTC Vive Controllers that track the location of the user's hands and receive input commands. The tracking area was set up with two sensors, and the size of the tracking area was approximately 3 meters by 2 meters. The headset was connected to a PC that hosted the virtual environment. Table 5 shows the component configuration of the VR PC.

Our study included 37 participants (20 male, 17 female; an average age of 25.0 years old). Table 6 summarizes the distribution of participants according to several key variables.

All test participants were given the same instructions that are described below.

All three phases of the study took place in the same room. The participant was given a summary of the three main activities they would perform, as well as the sort of data that would be collected. They were requested to sign an informed consent form after agreeing to participate, which specifies the three parts of the experiments, as well as the nature and the extent of data usage and their right to quit the tests at any time.

Participants were directed to a desktop computer where the presentation was shown once they were ready. Participants were encouraged to go over the slides and ask questions if they had any questions.

Once the participant indicated that they had finished going through the slides, they were presented with the second part of the experiment and given the following instructions:

1) Select run in real-time (from the top menu) and flip the first switch (DOUBLE CLICK);
2) Observe the animation. Notice how the load on the 3D crane keeps swinging from side-to-side;
3) After approximately half a minute, flip the first switch back;

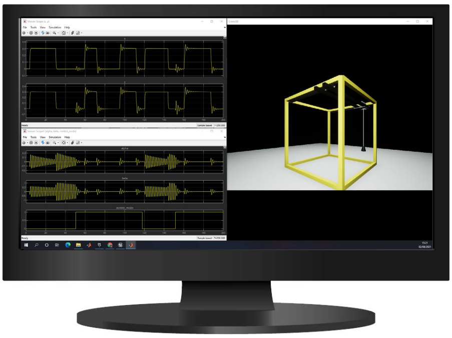

FIGURE 15. Charts display the model's real-time response and a 3D model of the crane that is moving in real-time based on data received from the Simulink model graphs that display the model's real-time response and a 3D model of the crane that is moving in real-time based on data received from the Simulink model.

TABLE 6. Distribution table of participants.

Variables	Description	Frequency
Gender	Male Female	20 ($\approx$ 54.1%) 17 ($\approx$ 45.9%)
Dominant hand	Right Hand Left Hand	35 ($\approx$ 94.6%) 2 ($\approx$ 5.4%)
Study status	Current student Not a current Student	23 ($\approx$ 62.2%) 14 ($\approx$ 37.8%)
Confidence level using VR	Not confident Neutral Confident	20 ($\approx$ 54.1%) 5 ($\approx$ 13.5%) 12 ($\approx$ 32.4%)
General IT skills and knowledge confidence level	Not confident Neutral Confident	5 ($\approx$ 13.5%) 10 ($\approx$ 27.0%) 22 ($\approx$ 59.5%)
Confidence level with the topic of Control systems	Not confident Neutral Confident	19 ($\approx$ 51.4%) 7 ($\approx$ 18.9%) 11 ($\approx$ 29.7%)

4) Now flip the second switch (OFF / ON) and observe the 3D crane. Additionally, observe the time series plots generated on the virtual scope screen and make conclusions about which mode would work best for in a real life scenario.

When the second part of the experiment was finished, the participant was guided to an area in the same room where the VR HMD was located.

In the third part of the experiment, a set of steps that served as an introduction to the VR controllers and HMD, as well as performing eye calibration, which allows the capturing of the participant's gaze direction, are performed.

1) An introduction to the VR headset and controllers is given;
2) The headset is put on and adjusted so the display is centered in the view;
3) The controllers are located and picked up;
4) The eye-tracker is calibrated:
   a) The headset is adjusted vertically so that the display is centered on the eyes;

FIGURE 16. Virtual environment used in the experiment.

   b) The lens distance is adjusted based on the participants' eyes;
   c) The participants are asked to follow a set of dots using only their eyes.
5) The operator starts the experiment.

At the beginning of the experiment, the participants are transferred to a virtual laboratory environment where they can see the "3D Crane" control object, a laboratory-scale simplified model of a gantry crane produced by Inteco and recreated as a digital twin in VR, as well as two interactive plot widgets; the first widget shows real-time data representing the 3D crane dynamics and the other graph shows an explanation of the control object parameters. Fig. 16 shows the different elements of the VR laboratory.

During the experiment, the participant's first task was to walk to a predefined location adjacent to the control object. This location was clearly marked in the VE. Once the participants reached the marked location, they were free to do any of the following actions:

- Interact with the control object (change the set-point, i.e., the desired location of the crane's payload—and change the control mode of the crane);
- Interact with the plot widgets (move them to the predefined locations, grab and move them to a new location, or grab and throw them anywhere in the VE).

C. QUESTIONNAIRE AND SYSTEM USABILITY SCALE (SUS)

After participants finished the third part of the experiment, they were asked to complete a questionnaire of 10 SUS question items for the desktop experiment and 10 SUS question items for the VE experiment with three additional questions about their confidence level in the VR, IT and control systems. The system usability scale includes 10 items with five responses that range from strongly agree to strongly disagree. The example questionnaire includes the following: I found the system was easy to use, and I would imagine that most people would learn to use this system very quickly. To examine perceived task loads:

1) I think that I would like to use this system frequently.
2) I found the system unnecessarily complex.
3) I thought the system was easy to use.

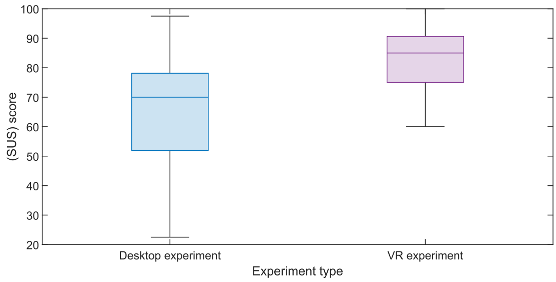

FIGURE 17. **System usability scale results for all participants in the desktop and VR experiments.**

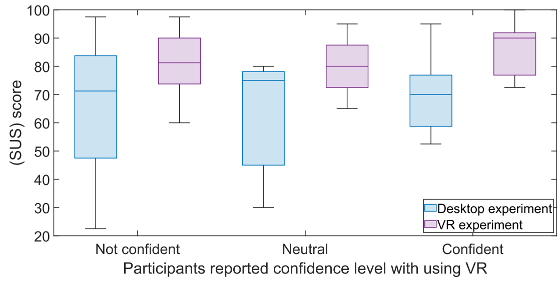

FIGURE 18. **System usability scale results based on participants' self-evaluated confidence using VR.**

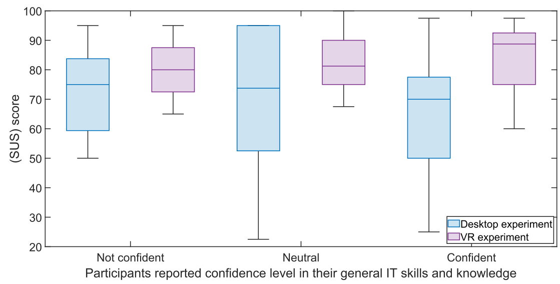

FIGURE 19. **System usability scale results based on participants' self-evaluated confidence in general IT skills and knowledge.**

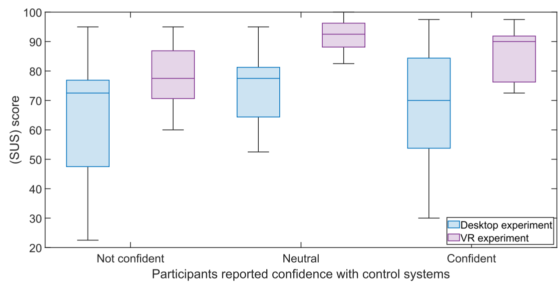

FIGURE 20. **System usability scale results based on participants' self-evaluated confidence with control systems.**

4) I think that I would need the support of a technical person to be able to use this system.
5) I found that the various functions in this system were well-integrated.
6) I thought there was too much inconsistency in this system.
7) I would imagine that most people would learn to use this system very quickly.
8) I found the system very cumbersome to use.
9) I felt very confident using the system.
10) I needed to learn a lot of things before I could get going with this system.

V. RESULTS

The SUS elements are divided into two categories: positive and negative. Even items are negative, while odd items are positive. To acquire the actual score of the SUS results, we deduct 1 for each of the users answers for the five odd components, then subtract the user answer from 5 for the even components. Finally, we multiply all the components by 2.5 to obtain a score in the range of 0 to 100.

The quartile distribution of the SUS score for all participants in both experiments is shown in Fig. 17. The average SUS score for all participants in the desktop experiment was 70 with a *standard deviation* (SD) = 20.8279, while the average SUS score for all participants in the VR experiment was 85 (SD = 10.2977). This shows that the suggested solution's usability is superior to that of the desktop experiment. Furthermore, the lower SD suggests that in the VR experiment, there was more of an agreement on the system's usefulness.

Further analysis was conducted to determine how the self-reported participant distribution affected the usefulness of both experiments. First, as shown in Fig. 18, the system usability scale results, which were categorized based on participants' self-evaluated confidence in using VR, revealed that users who reported being confident in using VR had the highest average usability score. This finding reveals that as users become more comfortable with virtual reality and their confidence grows, the system's usability will improve. These findings support the use of VR experiments in a broader context throughout the control systems course.

Second, we examine whether individuals who are confident in their overall IT skills are more likely to favor the VR option. The average SUS results for participants with greater levels of confidence in general IT skills and knowledge were higher in the case of the VR solution, as shown in Fig. 19, whereas the average score for the desktop experiment did not change significantly.

Finally, we looked to see if the participants' level of confidence in the targeted study material had an effect on the SUS results in this instance control system. The findings of the system's usability scale were categorized based on the participants' self-evaluated confidence in control systems (Fig. 20). The results show that in both the desktop and

VR experiments, participants who reported neutral confidence with control systems provided the greatest usability score. In general, the VR experiment was rated as being easier to use than the desktop trial by the participants. While the limited sample size restricted any conclusions taken from this research, the findings highlighted the need to leverage virtual reality in the creation of more realistic rich experiments for control object digital twins.

VI. CONCLUSION

In this paper, a digital twin and an extended reality-enabled framework for constructing control system laboratory modes is developed and examined as a full framework integrating all lab modes. The developed solution fits naturally into the scope of Industry 4.0 in the context of these emerging digital technologies, each having an important role in transforming the manufacturing landscape. We thoroughly explain how virtual and remote laboratories can be recreated as digital twins of physical control objects. Incorporating extended reality into the proposed digital representation allows for greater interaction with the object while also allowing students and instructors to collaborate with one another.

To verify the main innovation in the proposed contribution, a case study was conducted with a laboratory model of an overhead crane. An immersive virtual reality simulation was created for the crane using the proposed framework. A subject-based experiment was then designed focusing on the usability of the proposed solution versus a traditional desktop-based environment. For this, a typical lab assignment was considered part of the subject-based testing. There were 37 participants involved in the study.

The main conclusion based on the conducted study is as follows. It was successfully confirmed that the proposed framework, from the perspective of combining the digital twins and extended reality technologies, substantially improved the usability of the simulated laboratory environment. While only the virtual lab mode was considered and advanced features, such as remote collaboration, were not addressed, it is possible to say that the technologies supporting the proposed framework have a high potential to improve lab work outcomes for students.

The ability to manipulate the control object and study the outcomes from several perspectives was identified as a critical factor during the design and development of the simulation. This is not particularly surprising because hands-on labs have known similar favorable qualities. However, when implemented in extended reality, new possibilities emerge to provide a more complete experience. For example, the user can manifest and position a time series chart in the surrounding space near the control object. The chart allows us to interpret the results of the experiment from a time domain analysis perspective, which is common in industry. The solidification of this important connection between the time series and actual events can be achieved naturally with the proposed solution.

Future work must be concentrated on implementing the framework in its entirety. Additional subject-based tests with larger sample sizes will also be conducted as the restrictions related to the COVID-19 pandemic are fully lifted.

Furthermore, the design of advanced control system experiments must be done in accordance with the desired learning outcomes of the related study courses. One pressing issue in the industry is the ability to coherently tune PID controllers subject to certain performance specifications. It is expected that the proposed framework will positively influence the ability of the students to manipulate the parameters of the PID controllers in hands-on XR experiments toward achieving better performing control loops with both digital twins of control objects and real objects, as demonstrated in [66].

To conclude the paper, we would like to acknowledge the contribution from Ms. Dolores Freiberg for her work on the 3D crane model described in this article. Additionally, we would like to express our gratitude to Ms. Oleksandra Zamana for assisting us in safely conducting the experiments with the subjects during a particularly trying period of the pandemic.

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Abstract

Natural interaction plays a significant role in the credibility of the virtual reality (VR) environments; unwanted or unexpected user interaction with the objects in the environment will negatively affect the immersion level for the user. Users have different level of skills when it comes to using VR. Therefore, handcrafting rule-based robust behaviour interaction that adapts to varying abilities of users is an ongoing challenge. In this study, the potential of using a data-driven method allowing researchers to gain insight into user behavioural data is investigated. A VR data replay and annotation method that allows for the analysis and classification of VR collected data through a graphical user interface is introduced. This method is applied to data collected from a VR lab study, including users with different skills in VR. Finally, the system is used to identify unwanted user interaction and Machine learning methods are investigated as an alternative for user interaction classification.

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Towards Artificial Intelligence Driven Immersive Environments in Virtual Reality for Industrial Applications

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***Abstract*—Natural interaction plays a significant role in the credibility of the virtual reality (VR) environments; unwanted or unexpected user interaction with the objects in the environment will negatively affect the immersion level for the user. Users have different level of skills when it comes to using VR. Therefore, handcrafting rule-based robust behaviour interaction that adapts to varying abilities of users is an ongoing challenge. In this study, the potential of using a data-driven method allowing researchers to gain insight into user behavioural data is investigated. A VR data replay and annotation method that allows for the analysis and classification of VR collected data through a graphical user interface is introduced. This method is applied to data collected from a VR lab study, including users with different skills in VR. Finally, the system is used to identify unwanted user interaction and Machine learning methods are investigated as an alternative for user interaction classification.**

***Index Terms*—Virtual reality; Immersive environments; Control system; Data-driven; Data annotation; Supervised learning; Machine learning**

I. Introduction

The Virtual Reality technology (VR) has a significant role to play in the technology stack of Industry 4.0. As the cost of integration of VR into existing and novel solutions is steadily decreasing, it is without a doubt that VR, along with augmented reality (AR) will take firm roots in the fourth industrial revolution complementing such technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) [1].

One of the exceptional qualities of VR is the ability to induce the so called effect of *immersion* when the user experiencing the virtual environment (VE) actually believes he or she has been transported into an entirely different reality. This has positive sides as well as negative ones. On the one hand, the user will benefit from the learning opportunities afforded by introducing such an environment to him or her exactly due to the believability of the experience which may not be any different from the real world experience except any artificial components of the such an environment may be synthesized easily unlike in the real world. On the other hand, immersion can also cause the user to feel really vulnerable in the artificial environment which is why some users prefer to use AR instead [2].

To circumvent this issue, trust must be established between the user and the virtual environment. One of the ways to do it, irrespective whether the VE is intended for consumer or industrial application, is to make the environment adapt to the user based on the user's behavior.

In this paper, we investigate a possible solution for this specific problem. Namely, we consider a situation, when the VE is endowed with basic intelligence that allows to predict the user's action by applying signal processing and classification to collected biometric and human motion data to seamlessly assist the user with performing that action.

A. Contribution

In this paper, a data-driven replay and annotation system is proposed and applied to data collected from VR lab experiments. Furthermore, data-driven and machine learning methods are investigated as alternative methods for user interaction using data classification based on data collected from the experiment using the system.

B. Outline

The paper organized as follows. In Section II, a literature review is provided, forming the basis of our study. In Section, III the proposed methodology is detailed and the replay system is introduced. The experimental setup is described in Section IV. The results are presented in Section V. In Section VI, some items for discussion are given. Finally, in Section VII, conclusions are drawn.

II. Related Works

Over the last years, industries have seen a wide application of Virtual Reality (VR). Researchers have developed VR-based applications that aim to create more efficient manufacturing, logistics, and training processes [3]. Another recent trend is the use of VR in the medical field. Hospitals and clinics are experimenting with the use of VR for the rehabilitation of patients and training of surgeons [4]. Education is another field that holds promise for the use of VR. researchers and educators are attempting to introduce VR technology as part of their curriculum with varying scales and success [5], [6].

As the range of the target audience of VR applications grows, researchers face the challenge of creating environments that can adapt to the varying degree of skills and knowledge of the users.

The quality of immersion of the VR environment or presence divided into two parts [7]:

1) *The place illusion*: The user is feeling that he or she is moved into another place;
2) *The plausibility illusion*: the user's satisfaction with the environment in response to his or her interaction with it.

This work focuses on the latter, i.e., on the plausibility illusion. This task is of interest because it involves the interface devices (controllers), and the algorithms that drive the level of interaction the user can have in the environment.

Using natural gestures for interacting with the VE is likely the preferred method for the user as it does not involve learning the operation of a physical device such as an HTC Vive controller—so, the users can learn to interact with the VE quickly, just like they learn quickly to operate, e.g., a smartphone [8]. However, this brings about other issues, namely there is no physical feedback when interacting with artificial objects in VE which is partially provided by physical controllers. Novel technology like the Myo Armband [9] has been introduced to tackle this issue, but the technology still presents some drawbacks, especially in the face of maintaining user immersion in the VE [10].

Another approach was to use multi-modal input techniques, for example "gaze and pinch" is an input technique that combines gaze tracking information with hand gestures to create a more flexible method of interaction with objects [11].

Another factor in determining the plausibility of the interaction is the type of algorithms that controls the VEs reaction to the users interaction; for example hand crafted rule-based VEs algorithms are difficult to make adaptable for a wide range of people.

We have seen many examples in recent years of using data-driven approaches to classify patterns and recognize human behaviour. For example, eye gaze data patterns were used to classify a person's movement direction in collaborative robots VE [12].

Moreover, the authors of [13] report on a semantic extraction and reasoning system that is able to collect data in real time and perform ontology-based reasoning to learn and classify activities performed by the user in the VE. Furthermore, in [14], the authors propose a deep learning framework for continuous monitoring of human behaviors suitable for application in many areas such as sports, rehabilitation, elderly care and smart home environments. Obviously, similar techniques can be applied to VEs as well.

In this paper, we explore machine learning methods for implementing user behavior prediction such that endows the VE with the ability to assist the user in performing the actions intended by the user in a seamless way.

III. Methodology

Figure 1 shows the proposed procedure for creating Data-driven VE. It starts with the VE design; while the VEs are different across different applications and industries, they usually are a combination of three main components, visual elements, which are graphical representations of the objects and the environment; Sensory feedback that is used increases the effect of immersion for the user and final part is the algorithms that determine the environment's responses to the user interaction (input). An example of such a VE was presented in [15] where the authors introduced a VE for digital twins applications in the industry.

The second step in the procedure is data collection.To fully capture the user's behaviour, all of the input data delivered to the environment by the user must be recorded. This includes the tracking information of the HMD and controllers and the input events created by pressing buttons on the controllers.

The third step is labelling and data processing which is accomplished using the proposed replay and annotation system described in Section III-A.

Using this system, unwanted interactions or behaviours of the VE can be identified and labelled. This system can also be used to give developers insights about the users' action in the VE.

Finally, we apply machine learning algorithms to train classifiers that can better predict the intended human behaviour using the annotated data from the replay and annotation system. Here, a wide range of algorithms can be used: for example, a naive Bayes classifier—a simple probabilistic model that assumes that the different features are independent; support vector machine and decision trees can also be applied as well as other methods.

Once we obtain a model with satisfactory accuracy, we can use that model in our original VE as an alternative to the initial rule-based algorithm that caused the unwanted interaction behaviour.

A. *Replay and annotation system*

Figure 2 shows the VR data replay and annotation method that is proposed for the analysis and classification of VR collected data through an interactive visual interface. This data-driven replay system enables developers to:

- Replay the participant's behaviour in the experiment;
- Annotate the user behaviour and actions in the experiment;
- Test alternative algorithms for the user interaction with the environment without the need to record new data;
- Automate post-processing and annotation of the data.

IV. Experimental setup

In this section, an experiment where the participants have varying skill levels (self-evaluated) using VR is presented. The experiment is based on an experiment created for educational purposes in the field of automatic control system design.

Before the the experiment begins, a set of steps that serve as an introduction the VR controllers and HMD, as well as

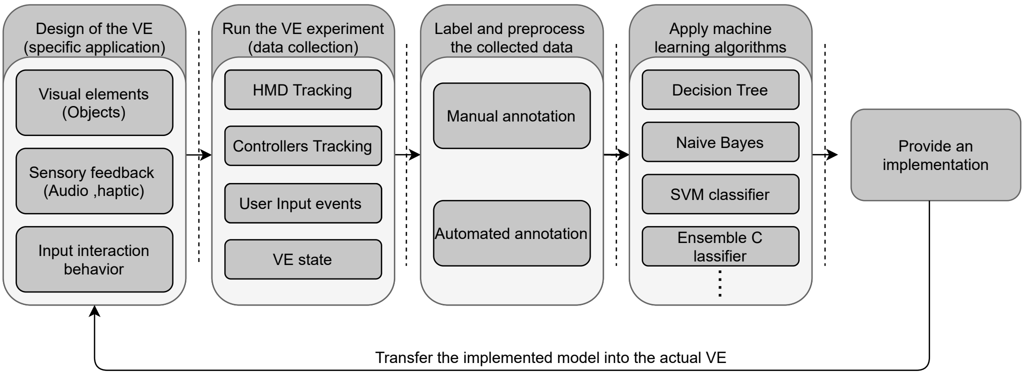


Fig. 1. Diagram of the data driven procedure for the implementation of assistive features in a VE

Fig. 2. VR data replay and annotation system

Fig. 3. VE used in the experiment

preforming eye calibration which allows the capturing of the participant's gaze direction are preformed:

1) An introduction to the VR headset and controllers is given;
2) The headset is put on and adjusted such that the display is centred in the view;
3) The controllers are located and picked up;
4) The eye-tracker is calibrated:
   a) The headset is adjusted vertically so that the display Is centred on the eyes;
   b) The lens distance is adjusted based on participants eyes;
   c) The participants are asked to follow a set of dots using only their eyes.
5) The operator starts the experiment.

At the beginning of the experiment the participants are transferred to a virtual laboratory environment where they can see the "3D Crane" control object—a lab scale simplified model of a gantry crane produced by Inteco and recreated as a digital twin in VR,—as well as two interactive plot widgets, the first one showing real-time data representing the 3D crane dynamics, and the other graph showing an explanation of the control object parameters. Figure 3 shows the different elements of the VR lab.

During the experiment, the participant's first task is to walk to a predefined location adjacent to the control object. This location is clearly marked in the VE. Once the participants reach the marked location, they are free to do any of the following actions:

- Interact of the control object (change the set-point—i.e., the desired location of the crane's payload,—and change the control mode of the crane);
- Interact with the plot widgets (move them to the predefined locations, grab and move them to a new location, or grab and throw them anywhere in the VE).

In this work, we will be focusing on the participants' interactions (grabbing, moving, throwing) with the interactive plot widgets.

V. Results

In this section, two examples of the workflow of the system are showcased. We identify cases of undesired results stemming from users' interaction in the experiment and show the potential of using the data-driven approach to derive alternative more accurate interaction algorithms.

A. Grabbing objects

In this section, we will showcase the first example of using the replay system for creating a better performing interaction

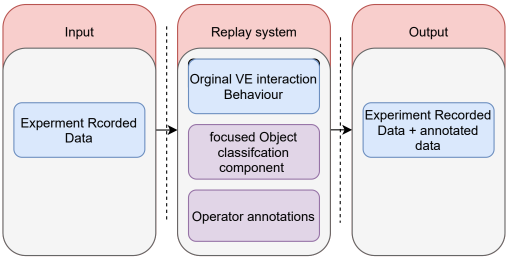


Fig. 4. Replay system workflow for data annotation

in the VE using insight gained from the collected data and using the replay system to annotate and classify the user's objects.

During the experiment, it was observed that users had struggled with the task of grabbing the objects. Further analysis of the data confirmed that across the 26 participants, there were 421 grab attempts, out of which 180 were failed attempts ($\approx$ 42.8%). Some of these attempts can be random incidents where the user was not attempting to grab the objects. The replay and annotation system was used to confirm the observation that the user was in fact struggling with the grabbing action.

At first, we must consider the rule-based algorithm defining the interactive plot widgets interaction which is shown in Figure 5a.

There are many factors that might have caused this unwanted interaction behavior of the experiment. For example, the different depth perception or the level of VR experience across participants could have played a role in this. Using the replay system, we start to look at the data and build a more robust gripping implementation by investigating trends in user collected data from the perspective of the grabbing action.

It was concluded that the combination of the gaze data with the grabbing input event could decrease the number of failed grabbing attempts.

To test the idea of using the object that is focused by the user gaze at the point of grabbing, we collect new data of the human focused gaze object in the environment by adding a new component to the replay system that uses the collision detection boxes for the object of interest in the environment. The Replay system was used to annotate and obtain the gaze focused object at each frame for the participants. The overall workflow of this annotation method using the replay system is shown in Figure 4.

The final step was to include the user gaze focused object in the interaction behaviour of the grab action as shown in Figure 5b.

The new approach reduced the number of failed attempts to 84, reducing the percentage of failed attempts to ($\approx$ 20.0%). Table I shows a comparison of the failed grab attempts between the original and improved rule-based algorithms.

While this example is quite simple in its application, it highlights the advantage of using data in the iterative process of building immersive environments.

Table I. Grabbing objects interaction algorithms comparison

Algorithm	**Total grab attempts**	**Failed grab attempts**
Original rule-based algorithm which is shown in Figure 5a	421	180 ($\approx$ 42.8%)
Improved rule-based algorithm which is shown in Figure 5b	421	84 ($\approx$ 20.0%)

B. *Moving-Throwing objects*

After the plot widgets have been grabbed, the user can either move them to a new location or throw them away—the latter results in the plot widgets reappearing on the virtual window frame.

Similar to the first case, it was observed that some of the participants were attempting to proceed with throwing the plot widgets. However, they either did not release the grip button on the VR controller at the right time, or their speed did not reach the desired threshold, and therefore their throw attempt failed. Here we can see that the difference in reaction time and dexterity of the users leads to undesired interaction with the VE.

Unlike the first case, there is no single feature that can be introduced to the VEs to make the throwing action more robust. However, if we take a closer look at the pattern of movement, we can see that there are differences of pattern between moving the object around the VE and throwing it.

In such cases, machine learning classification methods might be an alternative to the original moving or throwing rule-based algorithm shown in the Figure 5c.

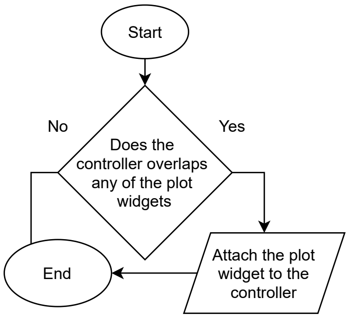
The Replay system was used to annotate all of the attempts to throw or move the interactive plot. The overall workflow of this annotation method using the replay system was previously shown in Figure 4. The data showed that across the 26 participants, there were 89 throw attempts, out of which 23 failed attempts ($\approx$ 25.8%).

The resulting data was used to train a classifier of *ensemble bagged trees* type to predict the user throwing or moving action. Table II shows the results of using classifier in comparison with the original rule-based algorithms, using the classifier the number of failed throw attempts was reduced to 6 ($\approx$ 6.7%).

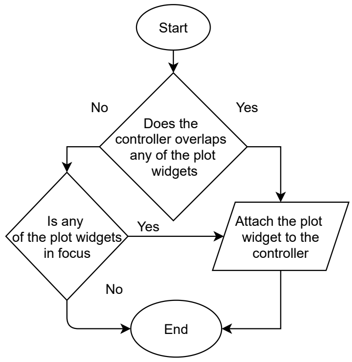
Figure 6 shows the confusion matrix of the result of the training with 5-fold cross-validation. While the trained classifier has a high overall recognition accuracy of approximately 95% and a throw action accuracy of approximately 93%, it introduced an undesired effect of classifying eight move actions as thrown, reducing the accuracy of the move action to approximately 95%.

VI. Discussion

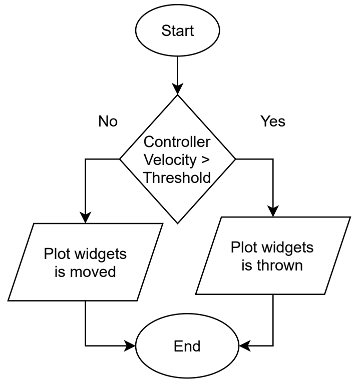
The replay and annotation system enabled us to explore the potential of using a data-driven approach to analyze and improve user interaction in VR. While the two studied cases are relatively simple, the same method and tools can be applied to



(a) Original rule-based algorithm defining grabbing the interactive plot widgets interaction.



(b) Improved rule-based algorithm defining grabbing the interactive plot widgets interaction.



(c) Original rule-based algorithm defining moving/throwing the interactive plot widgets interaction [16].

Fig. 5. Different algorithms for interactions in a VE.

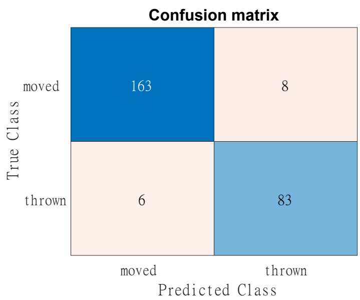


Fig. 6. The confusion matrix of the classifier results using 5-fold cross-validation .

Table II. Moving-Throwing objects interaction algorithms comparison

Algorithm	Total throw attempts	Failed throw attempts
Original rule-based algorithm which is shown in Figure 5c	89	23 (≈ 25.8%)
Classifier of *ensemble bagged trees* type	89	6 (≈ 6.7%)

more complex and cluttered environments with more elaborate interaction behaviours.

We have shown that this system allows testing alternative algorithms without recording new data by replaying an experiment with a newly introduced algorithm (alternative to the one used when recording the experiment). However, this newly introduced algorithm will invalidate the long-term sequences of actions taken by the user as the user's action after experiencing these alternative algorithms is unknown. Therefore we should limit our analysis to isolated activities throughout the recorded experiment, not the complete sequence of activities.

VE interaction algorithms are not the only factor in the immersion level of VE. Design elements such as haptic and visual feedback significantly impact the VE immersion level as well. Therefore the effect of introducing these alternative algorithms on other factors of immersion must be examined. Examining the case of grabbing or moving interaction and its impact on other immersion factors reveals some limitation of using machine learning classifiers to replace rule-based methods. Due to the nature of the models generated by machine learning methods, providing users with a description of the machine learning model is far more complex than rule-based algorithms. For example, using the original rule-based algorithms shown in Figure 5c., it is possible to add a visual indicator to the VE that shows the user if the threshold velocity has been reached. However, in the case of the machine learning model using such indicators is not possible.

VII. Conclusions

Creating VEs that can adapt to users varying abilities remains one of the challenges towards truly immersive VR. We presented a replay and annotation system that enables the use of data-driven methods as an alternative for the classical rule-based algorithms used in VR. Two examples of the system being used successfully on data collected from a VR study were presented. First, the system was used to identify, classify and gain insight into users object grabbing action in the VE. From this learned insight, an alternative algorithm was introduced that improved the rate of success of grabbing action by approximately 23%. In the second example, the system was used to train an ML classifier that can predict users throwing/moving action with a high 95% accuracy.

We envision that methods similar to what we have presented in this paper will help to establish a new generation of data-driven VEs that can reuse data collected from experiments effectively.

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Publication 3

Reference

S. Alsaleh, A. Tepljakov, M. Tamre, V. Kuts, and E. Petlenkov, “Digital twin simulations based reinforcement learning for navigation and control of a wheel-on-leg mobile robot,” in ASME International Mechanical Engineering Congress and Exposition, vol. 86649.

Abstract

Hybrid mobile robots are able to function in a number of different modes of locomotion, which increases their capacity to overcome challenges and makes them appropriate for a wide range of applications. To be able to develop navigation techniques that make use of these improved capabilities, one must first have a solid grasp of the constraints imposed by each of those different modalities of locomotion. In this paper, we present a data-driven approach for evaluating the robots’ locomotion modes. To do this, we formalize the problem as a reinforcement learning task that is applied to a digital twin simulation of the mobile robot. The proposed method is demonstrated through the use of a case study that examines the capabilities of hybrid wheel-on-leg robot locomotion modes in terms of speed, slope ascent, and step obstacle climbing. First, a comprehensive explanation of the process of creating the digital twin of the mobile robot through the use of the Unity gaming engine is presented.

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DIGITAL TWIN SIMULATIONS BASED REINFORCEMENT LEARNING FOR NAVIGATION AND CONTROL OF A WHEEL-ON-LEG MOBILE ROBOT

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ABSTRACT

Hybrid mobile robots are able to function in a number of different modes of locomotion, which increases their capacity to overcome challenges and makes them appropriate for a wide range of applications. To be able to develop navigation techniques that make use of these improved capabilities, one must first have a solid grasp of the constraints imposed by each of those different modalities of locomotion. In this paper, we present a data-driven approach for evaluating the robots' locomotion modes. To do this, we formalize the problem as a reinforcement learning task that is applied to a digital twin simulation of the mobile robot. The proposed method is demonstrated through the use of a case study that examines the capabilities of hybrid wheel-on-leg robot locomotion modes in terms of speed, slope ascent, and step obstacle climbing. First, a comprehensive explanation of the process of creating the digital twin of the mobile robot through the use of the Unity gaming engine is presented. Second, a description of the construction of three test environments is provided so that the aforementioned capabilities of the robot can be evaluated. In the end, Reinforcement Learning is used to evaluate the two types of locomotion that the mobile robot can utilize in each of these different environments. Corresponding simulations are conducted in the virtual environment and the results are analyzed.

Keywords: Reinforcement learning; digital twins; mobile robots; machine learning; simulation

NOMENCLATURE

DRL Deep Reinforcement Learning
DT Digital Twins
MDP Markov Decision Proccess
RL Reinforcement learning
R The long-term cumulative expected reward value
r_t The instantaneous reward at step time t
γ The a discount factor (0,1] of future reward

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INTRODUCTION

Mobile robots are built and deployed for a diverse range of tasks, including planetary exploration, safety and resource operations, industrial manufacturing, and last-mile package delivery. Researchers have proposed a variety of potential locomotion mechanisms for mobile robots [1], each optimized for navigation in a particular sort of environment. For example, wheeled robots are energy efficient and simple to control in environments with even terrains such as paved roads and indoor environments, whereas legged robots have greater obstacle navigation capability making them suitable for unstructured and rough terrain environments at the expense of increased energy consumption and increased control complexity.

Due to the fact that real-life applications require the robot to navigate a mixture of rough and smooth terrains, researchers have presented a variety of hybrid locomotion concepts which lead to the robot operating in different locomotion modes to adapt to its surroundings. The problem of determining the optimal operational mode for these robots requires using prior information about the capabilities and limitations of each mode. This requirement limits the application and adds complexity to the navigation strategies of the hybrid locomotion mobile robots. Since [2], outstanding achievements have been made by applying deep reinforcement learning algorithms to a variety of applications, including video games, energy management systems [3], and robotics from both manipulation and navigation perspectives [4, 5]. In several cases, these RL techniques have even outperformed humans [6, 7, 8].

Contribution

Motivated by those recent developments in reinforcement learning and the emergence of Industry 4.0 technology, we propose a data-driven method for evaluating the performance of hybrid mobile robots by formalizing this problem as a reinforcement learning task applied to a digital twin simulation of the mobile robot. The proposed method investigates the application of the DT concept to develop a collection of testing environments for evaluating the robot's capabilities in a variety of operation modes and with a variety of task sets using deep reinforcement learning algorithms. The overall schema for the prospered method is detailed in Fig. 1.

More specifically, we use a general purpose reinforcement learning simulation tool to create a digital twin of a Hybrid Wheel-on-Leg mobile robot developed at the School of Engineering at Tallinn University of Technology [9] that will be trained on a set of three predefined tasks to determine abilities of the robot's locomotion modes to solve these three tasks.

The tasks are used to assess the robot's ability to rapidly reach a known target position, ascending an increasing steep slope, and climb over steps of increasing height. All tests are conducted on the robot in two operational modes, with the environment structured in such a way that the analysis of results can be used to asses the operational mode of the robot to accomplish the three distinct sets of tasks.

Outline

The structure of the paper is as follows. Prior work in hybrid locomotion robots and deep reinforcement learning which serve as motivation behind this work is presented in Section 1. Next, the proposed DT and RL framework is detailed in Section 2 where a use case of a digital twin based implementation of the hybrid mobile robot is described. The three tasks that are used to assess the robot's abilities are presented in Section 3. The results of the experiments are presented and discussed in Section 4. Finally, conclusions are drawn in Section 5.

1 RELATED WORK

Different configurations of hybrid locomotion robots have been introduced by researchers. For example, in [1], a leg-wheel hybrid robot is introduced with the capacity to modify the morphology of wheels so that it can function in two different modes: full-wheel and half-circle wheel, where the second mode can be used as a two degrees of freedom mode for navigation, allowing the robot to navigate with greater flexibility. A novel, transformable, four-legged robot was introduced in [10]; this reconfigurable robot can operate in both circle-wheeled and wheel-legged modes. The robot's multi-mode operation provides it with additional obstacle negotiation capacity, which is particularly useful for search and rescue missions in difficult terrain.

Machine learning in general provides attractive means for implementing intelligent, digital twin based environments [11]. What concerns the navigation of wheeled mobile robots, machine learning approaches have been investigated in multiple studies. In [12], *deep imitation learning*, a supervised learning approach, was effectively applied to the issue of mapless navigation control of mobile robots using direct LIDAR sensors and relative target position with excellent results. Such systems require the annotation of data by humans, on the other hand, by utilizing the availability of advanced simulation environments [13] Reinforcement learning became a viable solution for the navagation of mobile robots. In [14], an obstacle navigation system based on deep reinforcement learning was employed to drive the Turtulebot 3 mobile robot. The algorithm was initially trained through simulation, during which the author proposed the usage of discrete action space instead of a continuous action space, considerably reducing training time. RL was also applied on legged robots in, e.g., [15]. To teach a legged robot to leap and navigate in a low gravity environment, the authors used a deep reinforcement learning technique.

Similar approaches were are also used on hybrid locomotion robots with different configurations; for example, consider

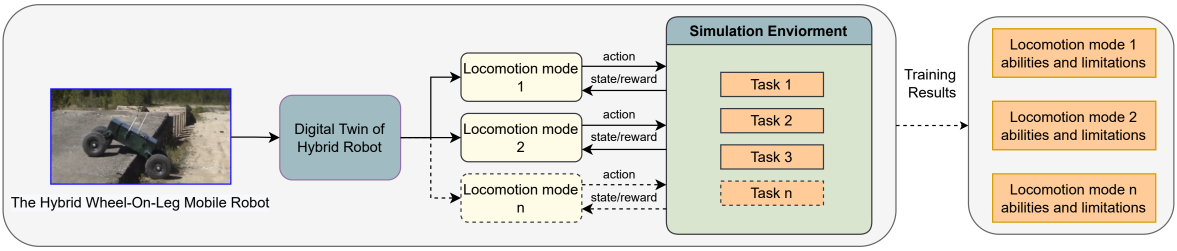

FIGURE 1. Overall Reinforcement learning Digital Twin method for evaluating hybrid mobile robots' locomotion modes. The picture of the hybrid mobile robot is courtesy of the School of Engineering at Tallinn University of Technology.

an obstacle avoidance navigation control of a leg/wheel robot described in [16] where a model-predictive control system that works for both robot operating modes was developed and implemented. The authors of [17] utilized deep reinforcement learning with proximal policy optimization (PPO) to teach a crawl-type robot the ability to climb stairs using a mix of visual (camera) observation and robot posture. As a result, the robot learned to climb stairs.

An interest towards developing methods for the selection of the locomotion method can be observed in the research community. In [18], the authors stressed the need to develop new action planning methods for hybrid multi-modal mobile robots, in which action planning can take into account how well a robot performs in each mode of operation and in different types of terrain, and they devised a method for finding the best routes using environment topology and specifications. In [19], a 2D occupancy map constructed based on priority information that provides the maximum jump height, as well as a state machine that selects the jumping action when such obstacles are met, are applied for quadrupedal jumping across confined obstacles.

These methods necessitate the use of knowledge about the capabilities of the robots beforehand to be able to make the decision regarding the selection of the locomotion mode. In our work, we propose a data-driven methodology using RL and DT towards acquiring and evaluating such knowledge.

2 DIGITAL TWIN AND REINFORCEMENT LEARNING

The wheel-on-leg hybrid robot that is shown in Fig. 2 is capable of operating in two different modes of locomotion. In the first operational mode, the legs of the robot are locked, and the robot is driven only through the torque that is applied to its wheels. In the second operational mode, however, the robot is given the ability to rotate both the wheels and the legs simultaneously. To create a digital twin that is capable of operating in the same locomotion modes as the physical counterpart, the Unity Engine and the ML-agents framework [20] were used. This made it possible to use reinforcement learning to evaluate the different

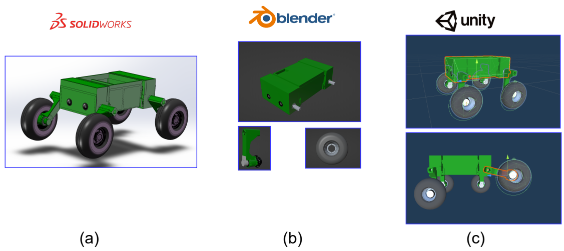

FIGURE 2. The Digital Twin creation process: (a) original SoildWorks assembly (b) exported subassemblies in Blender (c) Digital twin in Unity 3D.

locomotion modes. The procedure of creating a digital twin is shown in Fig. 2 and can be summarized as follows:

1. Convert existing SolidWorks assemblies of the target robot to OBJ files which are compatible with Unity.
2. Utilize a hierarchical set of rigid bodies, joints, and collision components to recreate the robot within Unity.
3. Create programmable sensor and motor functionality, using custom and built-in scripts.

SolidWorks software was used to create the original 3D model of the hybrid robot, where the robot is composed of numerous subassemblies for each physical component. The first step involved exporting the SolidWorks subassemblies for the vehicle's main body, legs, and wheels as OBJ files.

Blender software, on the other hand, was used as a bridge between Unity and Soildworks to modify the OBJ files, such as reducing the number of vertices and setting an appropriate pivot points for each subassembly, to make re-creating the vehicle easier in the following steps.

After importing the OBJ files for all of the components, the robot is modeled using a hierarchical parent-child approach, with the main body serving as the parent for all four legs that are located in relative coordinates to the main body and the wheels as child objects of the legs. If the pivot points are selected correctly, as described previously, the process is quite simple to follow.

At this point, the robot is only a visualization of a digital twin of the robot. To achieve physical interaction with the unity environment, component definitions must be used to define the robot's behavior, which will be simulated using the Unity "Physix" engine. The first component is the rigid body, which was added to the robot's main body and each of its four legs. We define properties such as the mass of the body part in this component which will be used by the Physix engine during the simulation. Each wheel was fitted with the built-in wheel collider component. This wheel component enables torque to be applied independently to each wheel while also managing the interaction with the surface.

To enable the Physix system to detect and handle collisions, the Mesh collider component was also added to the wheels and robot's body. Finally, the legs' motorized function is applied via a coded script that rotates the legs at the pivot point where they are connected to the mobile robot's main body.

The final step in this process is simulating the sensors which will be used as observations for the reinforcement learning training. First, the robot posture and velocity are extracted by accessing the internal states in the previously added rigid body components. Second an array of laser range finders competent which comes built-in with the ML-Agent Framework is used to for sensing the environment.

In the context of mobile robots navigation using reinforcement learning, the robot is defined as an *agent* and everything outside the robot is considered to be the *environment*. The agent-environment interaction process can be described as an Markov Decision Process (MDP) where the agents goal is to learn how to select the best action A based on the state of the environment S ,towards receiving the maximum reward value from the environment R.

While the agent receives an immediate reward feedback at each time step, the goal of reinforcement learning is to maximize the cumulative reward value over time, rather than to maximize the short-term reward. Thus, the goal is formulated such that the cumulative reward R_t is to be maximized according to (1):

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}, \qquad (1)$$

where R the long-term cumulative expected reward value, r_t the instantaneous reward at step time t and γ is the a discount factor $(0,1]$ of feature reward. Research works have proposed numerous methods for solving such MDP, to evaluate our case study we have selected to use Proximal Policy Optimization (PPO) [21]. PPO is a policy gradient DRL method that can be used for environments with either discrete or continuous action spaces. The method aims to optimize π_θ—a neural network function approximate which maps the state of the environment S to the action taken by the agent A. Table 1 shows the observations and actions used for the training of the mobile robot in both locomotion modes. While this method is known to have a good balance between simplicity, and efficiency making it a good candidate for our use case, the same approach can be used using other reinforcement learning methods.

TABLE 1. The reinforcement learning observation and action space for both locomotion modes of the mobile robot.

Locomotion mode	**Observations**	**Actions**
Skid steering (Wheels only)	An arrays of sparse laser range finders; vehicle pose and velocity; target relative location.	Wheels motors.
Hybrid steering (Wheels and legs)	An arrays of sparse laser range finders; vehicle pose and velocity; target relative location; legs rotation.	Wheels motors; Legs motors.

3 EXPERIMENTAL SETUP FOR THE CASE STUDY

The first operational mode of the hybrid robot is achieved by locking the legs and allowing the robot to control just the torque given to the wheels, whereas the second operational mode allows the robot to rotate the legs in addition to the wheels. By altering its center of gravity, this hybrid operation attempts to enable it to clear obstacles and steep slopes. Three task environments were created to assess three distinct qualities of these operational modes: the robot's speed in reaching a known goal; the robot's ability to traverse slopes; and the robot's ability to climb step obstacles:

1. Reaching the target on a flat surface;
2. Ascending Slopes;
3. Climbing steps.

We now describe each scenario in more detail.

3.1 Reaching a Target On a Flat Surface

The agent's first task, as illustrated in Fig. 3, is to reach a static target with a known location. While this is seemingly a trivial task, there are multiple operating modes involved in it

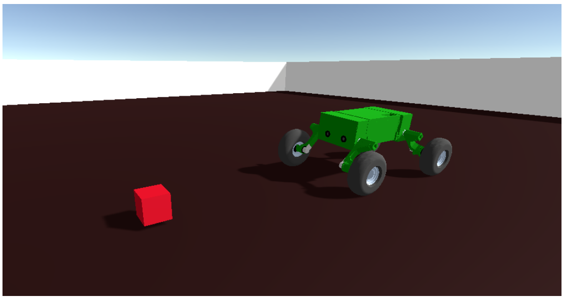

FIGURE 3. Target Reaching Task Environment.

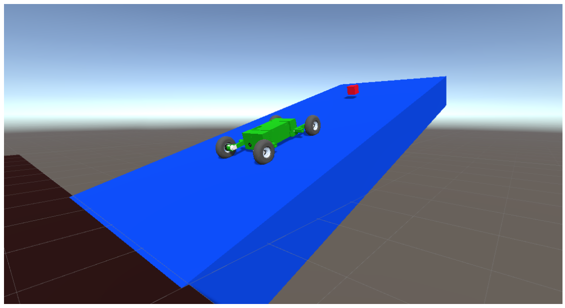

FIGURE 4. Ascending Slopes Task Environment.

which require some consideration from the side of implementing the RL technique.

For the first operating mode, the robot must learn how to apply a skid steering mechanism to a navigator in order to navigate the course by employing a variety of torques on each wheel independently.

While in the second operation mode, it must learn two behaviours in order to reach the destination successfully:

1. Adjust the leg angles such that the wheels are in contact with the ground.
2. Use the skid steering method to drive and rotate the robot.

In this first task, the reward R consists of two components:

1. Each step rewards the robot based on its movement: a positive reward is given for progressing toward the target and a negative reward is given for moving away from the target. This reward is linearly scaled according to the robot's initial distance from the target and is capped at $+10$ points when the robot reaches the target.
2. The second component of the reward is given only after the robot reaches the target and is dependent on the amount of time (simulation steps) that took the robot to achieve the target.

As a result, in this first test setting, the robot's speed capability to be evaluated is directly related to the cumulative amount of reward R_t collected during each episode, where higher reward indicates higher speed for that operation mode.

3.2 Ascending a Slope

The robot must complete this task by reaching a goal positioned at the end of a slope, as illustrated in Fig. 4. When the robot hits the objective a predetermined number of times, the angle of the slope increases, making the slope steeper. The robot must successfully reach the goal 100 times before the slope angle is increased by 0.5 degrees. The reward in the second task is defined and quantified in a similar way to the first task. This choice of reward shaping and incremental increase of the slope angle enables one to use the overall cumulative reward for the evaluation the robot performance. When the maximum inclination of the slope that the robot can ascend is reached for each operation mode, the robot's earned reward decreases significantly throughout training. As the robot is unable to ascend the slope it will not earn the maximum possible reward.

3.3 Climbing a Step

The hybrid robot capacity to climb steps is one of the reasons behind its design. The third test environment was created with the purpose of assessing the steps climbing ability of the robot. The robot must complete this task by reaching a goal positioned at the end of a step of varying height, as seen in Fig. 5. As with the second task, the step height will be increased as the robot hits the target a specific number of times. The threshold is set to 100, which means that the robot must successfully complete the task for each step height before the step height is increased by 0.05m. The third task's reward is defined in the same way as the first and second tasks. Similarly to the previous task, this environment and reward shaping design allow us to utilize the overall cumulative reward to evaluate the robot's performance. The robot's received reward during training will drop significantly when the maximum height of the step that the robot can climb is reached for each operation mode. As the robot is unable to climb the step it will not earn the maximum possible reward.

4 EXPERIMENTAL RESULTS AND DISCUSSION

An overview of the hybrid mobile robot different locomotion modes results and evaluated capability is shown in Table 2.

The results shown in Fig.6-a indicate that initially there is a speed difference between the two robots —the first mode the robot was able to reach the goal with fewer simulation steps than the second locomotion mode— As illustrated in Fig.7-a, the robot in the second mode was eventually able to learn a policy re-

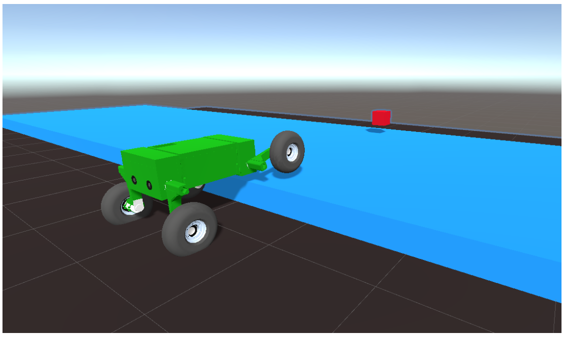

FIGURE 5. Climbing Step Task Environment.

TABLE 2. Overview of the mobile robot performance in different locomotion modes.

Task	First mode, skid steering (Wheels only)	Second mode, Hybrid steering (Wheels and legs)
Target Reaching On Flat Surface	Maximum speed= 1.64 m/s.	Maximum speed= 1.69 m/s.
Ascending Slope	Maximum ascended slope=18.5 degrees.	Maximum ascended slope=24 degrees.
Climbing Step	Maximum climbed step=0.3 m.	Maximum climbed step=0.8 m.

sulting in a higher speed than the first mode. The robot reached maximum speed of approximately 1.6 m/s (about 5.76 km/h).

The drop in the collected reward for both locomotion modes in the slope ascending task shown in Fig.6-b indicates the point at which the slope steepness increased and the robot's previously learned policy must be updated before the robot is able to ascend the new slope. Fig.7-b shows that the robot reached a terminal steepness of 18.5 degrees after 1.2M steps in the first operation mode, and 24 degrees after 5.45M steps in the second operating mode.

Finally, in a similar way the dropout in reward shown in Fig. 6-c illustrates the point at which the step height has increased where the robot's previously learned policy must be updated before the robot can climb the new step height. Fig.7-c shows the robot reached a terminal step height of 0.3 m after 400 k steps in the first operation mode, and 0.8 m after 4.8M steps in the second operating mode.

In the simulation of all three tasks, it was observed that while the robot was operating in the first mode, it learned to reach the target faster than when it was operating in the second mode. This is expected behavior, as the second mode of operation increases the control complexity by requiring the robot to control both the wheels and legs. As demonstrated in Fig. 6, the robot in the first locomotion mode reached the target in each one of the tasks in approximately 110K, 90K, and 60k steps, respectively, while the robot in the second mode completed the same tasks in 500k, 280K, and 190k steps.

These findings suggest that it is possible to acquire information about the capabilities and limitations of hybrid robot locomotion modes; however, this knowledge will be constrained by the task set utilized during training and the accuracy of the DT and simulation environment.

5 CONCLUSIONS

In the present paper, a digital twin and reinforcement learning method was proposed as a data-driven approach for evaluating the abilities of hybrid mobile robots under different locomotion operation modes.

This concept was illustrated by developing a digital twin of a hybrid wheel-on-leg robot capable of operating in two operation modes. The abilities of the robot in various operation modes were assessed using three independent tasks: speed to complete a stated objective, slope ascending, and step obstacle climbing.

The process of creating the digital twin using the general-purpose gaming engine was detailed. A detailed description of the three tasks that were used to measure the robot's abilities in different modes was given. The results have shown that a careful selection of reward shapes and the increased complexity of the environment tasks made it possible to evaluate the robot's abilities under different modes of locomotion.

In future work, we will address the issue of transferring the learned abilities from the digital twin to the real-life robot and the creation of a set of tasks which is applicable to a wide range of mobile robot configurations.

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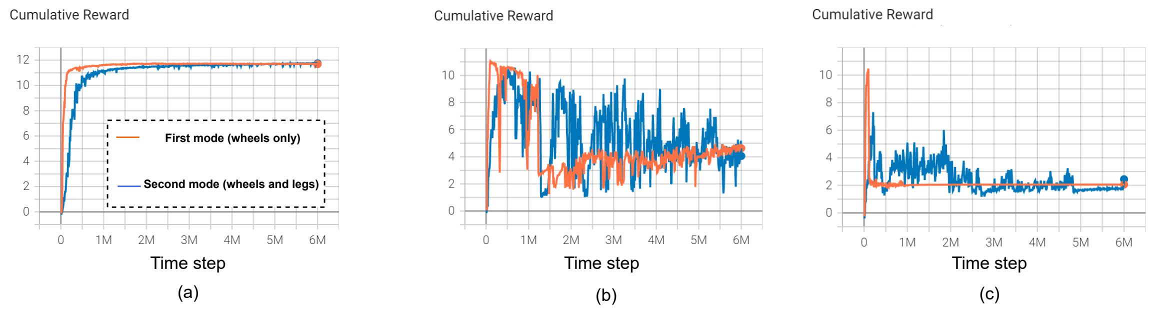

FIGURE 6. The cumulative reward over time steps for the three tasks: (a) reaching a target on a flat surface (b) ascending a slope (c) climbing a step.

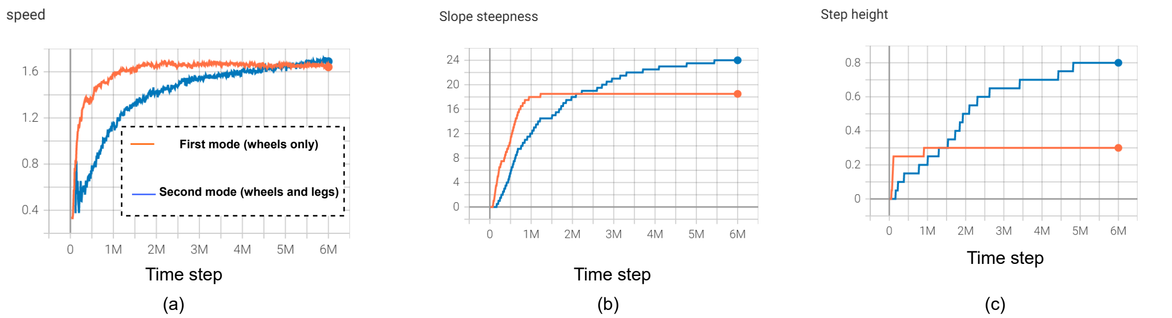

FIGURE 7. The performance metric over time steps for the three tasks: (a) reaching a target on a flat surface (b) ascending a slope (c) climbing a step.

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