Enhancing the Degree of Machine Autonomy in Construction Machines

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Abstract

Construction machine manufacturers have traditionally focused on improving deficiencies, comfort, and safety to enable machine actuators to perform various tasks under different conditions. However, human operators still predominantly control these machines directly or remotely, with the operator positioned near the machine exposing the human operators to risks and hazards associated with operating heavy machinery on a construction site. This thesis investigates the idea of increasing the degree of machine automation in various stages, ranging from assisted to semi-automated systems. Different methods are implemented using the example of the 3-ton compact construction machine BROKK 170.

Regarding the assistance system, this thesis presents a novel data-driven approach for task space control and virtual fixture-based control within the realm of teleoperation. The goal is to enhance efficiency and alleviate the cognitive load on the operator. This achievement is facilitated by an effective data-driven modeling technique that captures the hydraulic construction machine's inherent nonlinearity. Furthermore, the proposed methods incorporate an advanced simulation tool into the control pipeline, aiming to tackle the prevalent limitations often linked with data-driven approaches. These limitations encompass managing the unpredictable behavior of the system during its initial training phase and addressing the need for a substantial amount of training data.

In the context of the semi-automated system, this thesis introduces a shared control methodology that involves the human operator in the control process, enabling an interactive definition of abstract task goals. This approach serves to mitigate the cognitive demands placed on automated systems. Concurrently, human operators benefit from the automated systems' capacity for precise control and coordination of multiple joints, ensuring operational safety and efficiency. In this thesis, the effectiveness of the developed approach is showcased through its application in the deconstruction process. A comparison is drawn between the off-the-shelf teleoperated approach and the newly developed method.

Furthermore, this thesis rigorously examines the implementation and performance of cutting-edge communication technologies, notably 5G, within the intricate landscape of challenging environments like construction sites. It particularly accentuates the essential design requirements, drawing a comparative analysis between the expansive capabilities of 5G and the conventional communication technologies. This comparison is carried out in association with the operational dynamics of automated construction machinery, providing a comprehensive evaluation of their interplay within these demanding contexts.

The thesis introduces key technologies that advance construction machine automation. The author believes that exploring the outlined paths will soon make automated construction machines valuable aids in various applications.

Kurzfassung

Die Hersteller von Baumaschinen haben sich traditionell darauf konzentriert, Mängel, Komfort und Sicherheit zu verbessern, um zu ermöglichen, verschiedene Bautätigkeiten unter unterschiedlichen Bedingungen auszuführen. Allerdings werden diese Maschinen immer noch hauptsächlich von menschlichen Bedienern direkt oder aus der Ferne gesteuert, wobei sich der Bediener oft in der Nähe der Maschine befindet und damit den Risiken und Gefahren ausgesetzt ist, die mit dem Betrieb von schweren Maschinen auf der Baustelle verbunden sind. Diese Arbeit untersucht die Idee, den Grad der Maschinenautomatisierung in verschiedenen Stufen zu erhöhen, von assistierten bis hin zu halbautomatischen Systemen. Unterschiedliche Methoden werden anhand des Beispiels der 3-Tonnen-Kompaktbaumaschine BROKK 170 implementiert.

Im Bereich des Assistenzsystems präsentiert diese Arbeit einen neuartigen datengesteuerten Ansatz zur direkten Fernsteuerung im Arbeitsraum und zur Steuerung auf Basis virtueller Vorrichtungen. Das Ziel ist es, die Effizienz zu steigern und die kognitive Belastung des Bedieners zu verringern. Dies wird durch eine effektive datengesteuerte Modellierungstechnik ermöglicht, die die inhärente Nichtlinearität der hydraulischen Baumaschine erfasst. Darüber hinaus integrieren die vorgeschlagenen Methoden ein fortschrittliches Simulationswerkzeug in die Steuerungs-Pipeline, um die häufig damit verbundenen Einschränkungen von datengesteuerten Ansätzen anzugehen.

Diese Einschränkungen umfassen die Bewältigung des unberechenbaren Verhaltens des Systems während seiner anfänglichen Trainingsphase und die Bewältigung des Bedarfs an einer beträchtlichen Menge an Trainingsdaten.

Im Kontext des halbautomatischen Systems führt diese Arbeit eine Steuermethodik ein, die den menschlichen Bediener in den Steuerprozess einbezieht. Dieser Ansatz dient dazu, die kognitiven Anforderungen an automatisierte Systeme zu verringern. Gleichzeitig profitieren menschliche Bediener von der Fähigkeit automatisierter Systeme zur präzisen Steuerung und Koordination mehrerer Gelenke, was die Sicherheit und Effizienz gewährleistet. In dieser Arbeit wird die Wirksamkeit des entwickelten Ansatzes anhand seiner Anwendung im Abbauprozess dargestellt. Es wird ein Vergleich zwischen dem herkömmlichen ferngesteuerten Ansatz und der neu entwickelten Methode gezogen.

Darüber hinaus untersucht diese Arbeit eingehend die Implementierung und Leistung von Kommunikationstechnologien wie 5G in anspruchsvollen Umgebungen wie Baustellen. Dabei liegt der Fokus auf den spezifischen Designanforderungen und einem Vergleich der Fähigkeiten von 5G mit herkömmlichen Kommunikationstechnologien im Zusammenhang mit automatisierten Baumaschinen. Diese Gegenüberstellung erfolgt im Kontext der operativen Dynamik automatisierter Baumaschinen und bietet eine umfassende Bewertung ihres Zusammenspiels in diesen anspruchsvollen Umfeldern.

Die Arbeit stellt Schlüsseltechnologien vor, die die Automatisierung von Baumaschinen vorantreiben. Der Autor ist der Meinung, dass die Erkundung der skizzierten Wege bald automatisierte Baumaschinen zu wertvollen Hilfsmitteln in verschiedenen Anwendungen machen wird.

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Chapter 1

Introduction

The term construction encompasses a vast array of tasks, all geared towards the development of cities, civil infrastructure, and architectural endeavors. These construction activities span from the creation of residential buildings, road networks, tunnels, and bridges to the establishment of energy infrastructure like nuclear and wind power facilities. Undoubtedly, the construction industry plays a pivotal role in our society, given that the efficiency of its projects profoundly influences our daily lives. Nevertheless, despite its profound significance, the extent of robotic automation in the construction sector remains notably lower when compared to other sectors. Inspired by the achievements witnessed in industries like automotive manufacturing, researchers have been actively pursuing the integration of robotic systems into construction sites since the 1970s. However, this initial attempt encountered a multitude of challenges ranging from the unstructured nature of construction environments and the absence of integration strategies for the initial implementation of robotic automation. In Chapter 3, this aspect is detailed by investigating the different approaches for the study of robotics in construction with corresponding challenges and opportunities.

Within the context of on-site construction activities, safety remains a paramount concern for human operators. This concern is made worse by the absence of suitable technology, especially for those operators working in close proximity to construction machinery. To address this issue, one approach to enhance overall on-site construction safety involves increasing the level of autonomy in construction machinery. By doing so, the exposure of human operators to hazardous deconstruction scenarios can be minimized, reducing the necessity for continuous manual control of machinery at the operational level. This objective aligns with the concept of autonomous robots, wherein tasks are executed without direct human intervention. However, the intricate nature of construction sites, characterized by their dynamic and complex environments replete with various variables such as changing conditions and the presence of human workers, introduces additional challenges when compared to controlled manufacturing facilities. This complexity represents a significant obstacle in the development of fully autonomous construction machinery. As a result, in Chapter 4, the semi-autonomous approach is presented, which reduces the cognitive burden on the construction robots by allowing the human operators to define the high-level goals and strategic objectives, while the machine handles the lower-level tasks and control aspects, striking a balance between human expertise and machine automation to effectively address the unique challenges of construction sites.

In contrast to the production industry, the construction industry presents a unique challenge to automation due to its dynamic and multifaceted nature. Construction sites are constantly changing through various stages of development, where each stage possesses different dangerous conditions for human workers. To mitigate these risks, teleoperation has become a vital component of construction machinery in the current construction industry. However, the complex nature of these machines, which often have multiple degrees of freedom and require individual levers for remote control on a joint level, requires significant operator training. Even experienced operators may require months of training to coordinate multiple joints to achieve the desired end-effector or tool motion. This can result in decreased productivity and reduced local accuracy and work efficiency. Chapter 5 addresses this issue by introducing methods to increase the degree of machine autonomy. Especially, these methods utilize the effective data-driven modeling technique that captures the inherent nonlinear characteristics of hydraulic construction machinery. Additionally, the proposed methods incorporate an advanced simulation tool into the control process to address common limitations associated with data-driven approaches. These limitations include managing the unpredictable behavior of the system during its initial training phase and fulfilling the requirement for a substantial amount of training data. In the realm of deploying automated construction machinery to construction sites, establishing a reliable communication infrastructure with low latency and high bandwidth is paramount. Chapter 6 delves into a thorough examination of implementing an on-site 5G network specifically tailored for the construction sector. It outlines the strategic deployment of this network and demonstrates the potential and feasibility of 5G technology within the domain of automated construction machinery.

In Chapter 7, a comprehensive summary of the key findings and significant outcomes obtained throughout the research is provided. This chapter not only serves as a culmination of the study's primary results but also delves into the prospects for future research directions to push the boundaries of knowledge even further. Figure 1.1 also visualizes the overall structure of this thesis.

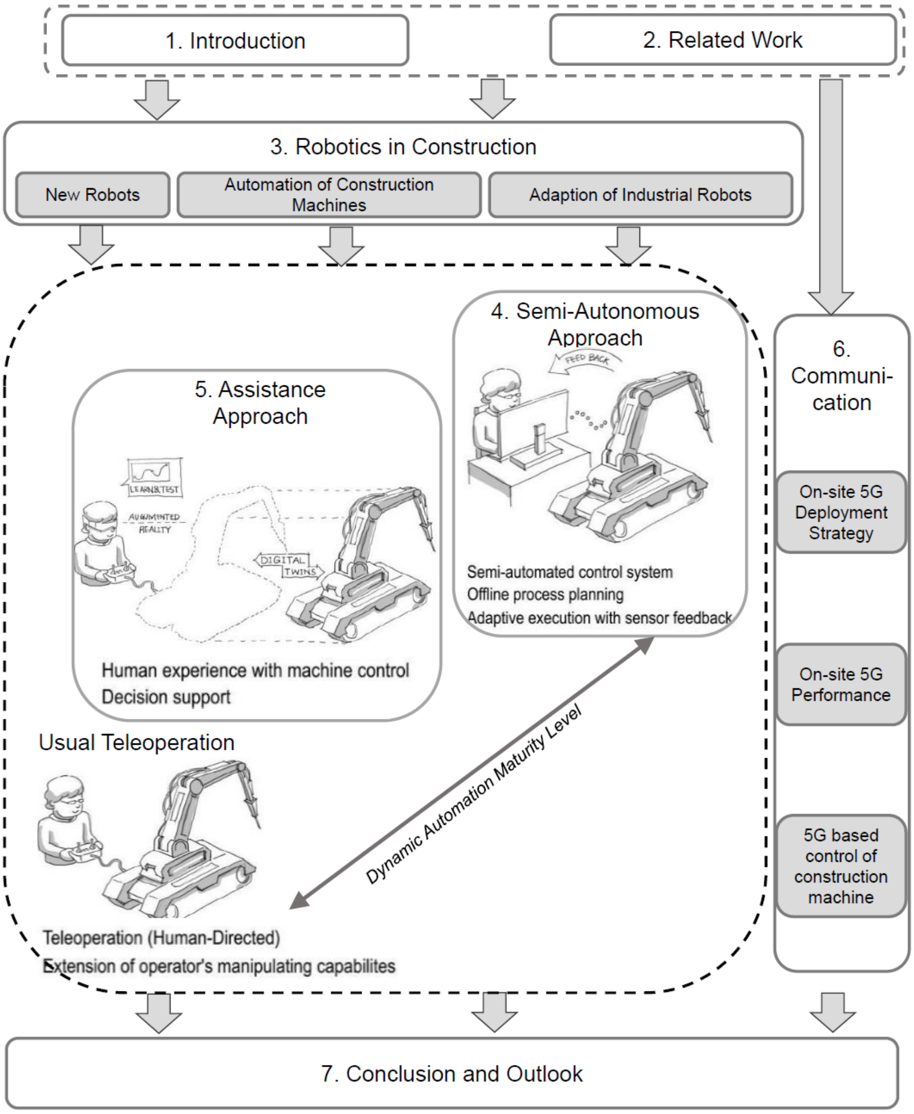


Figure 1.1: Overview of the thesis

Chapter 2

Related work

2.1 Robotic Automation in Construction

Taking inspiration from achievements across various industries, especially the automotive sector, researchers have been intrigued by the idea of integrating robotic systems into construction sites since the 1970s. In construction, tasks often involve repetitive processes that can be divided into smaller operational units like digging, loading, and bricklaying. While automating individual tasks might seem limited when considering the entire construction project, it's actually a step towards achieving fully automated construction sites. As a result, the initial focus of pioneering research groups from Japan was to create robots specialized in performing specific tasks within this repetitive range [1]. However, introducing these first robotic systems to construction sites encountered numerous challenges, largely due to the disorderly nature and tough working conditions inherent in such environments.

Therefore, construction machine manufacturers have traditionally focused on improving deficiencies, comfort, and safety to enable machine actuators to perform various tasks under different conditions. However, human operators still predominantly control these machines directly or remotely, with the operator positioned near the machine. Control is typically achieved using individual joysticks or levers at the joint level. Operating these machines effectively requires significant training due to their multiple degrees of freedom and complex coordination of multiple joints. Even experienced operators require months of training, leading to reduced local accuracy and decreased work efficiency [2]. Furthermore, the proximity to the machine exposes workers to risks and hazards associated with operating heavy machinery on a construction site.

In the historical context of construction machinery manufacturing, there has been a longstanding focus on the enhancement of deficiencies, comfort, and safety parameters. This emphasis has been aimed at enabling machine actuators to execute a set of tasks across diverse environmental conditions. Nonetheless, the preeminent modality of control for these machines remains human intervention, whether in direct physical proximity or via remote operation. Control over these machines is conventionally established through the manipulation of individual joysticks or levers situated at the joint level. Proficiently operating these machines necessitates a considerable investment in training due to their possession of multiple degrees of freedom and the intricate choreography required for coordinating the movements of numerous joints. Even experienced operators must undergo months of training, a phenomenon that correlates with diminished local precision and a reduction in overall work efficiency, as substantiated by the findings presented in [2]. Furthermore, the proximity of human operators to the machinery introduces a distinct set of challenges, namely the exposure of workers to the inherent risks and hazards associated with the operation of heavy machinery within the confines of a construction site.

In the pursuit of introducing automation within the realm of construction sites, researchers have advanced a proposal centered on the integration of industrial robots. One notable exemplar of this concept is the Robotic Facade Disassembly and Refurbishment System (RFDRS), as expounded in [4]. This system introduces a robot-assisted deconstruction methodology, harnessing motion programming to mechanize the intricate process of disassembling multi-layered facade structures. However, it is crucial to recognize that conventional industrial robots, equipped with electrically actuated manipulators, confront a set of inherent limitations. These constraints include a relatively low payload-to-weight ratio and a susceptibility to vibrations and impacts, as elucidated in [5]. Consequently, the application scope of such systems remains constrained to specific domains of work due to these intrinsic limitations associated with industrial robotic platforms.

2.2 Enhancing Autonomy in Heavy-Duty Construction Machinery

The concept of increasing the degree of machine autonomy within the existing domain of heavy-duty construction machinery has drawn significant interest among researchers [6]. The utilization of modern control algorithms to facilitate the autonomous execution of tasks within the field of robotics holds substantial potential for enhancing the efficiency and automation of construction sites, as highlighted by research in [7, 48, 9]. However, it is vital to acknowledge that in highly unstructured environments, there exist inherent limitations to the efficacy of autonomous approaches. The presence of incomplete or imprecise information stemming from unfamiliar objects or unforeseen circumstances can perturb the decision-making process, rendering it challenging for robots to adapt to these evolving scenarios. In the context of construction sites, where the environmental dynamics are in a constant state of flux and multiple variables must be considered, the robustness and adaptability of robots assume even greater significance. Furthermore, the intricate non-linear nature of hydraulic construction machinery poses a formidable challenge in the development of precise controllers.

Consequently, the notion of employing teleoperation support, as opposed to complete autonomy, has gained notable attention within the research community. In this context, Rosenberg introduced the concept of virtual fixture-based assistance systems, as outlined in [2]. These systems entail the augmentation of sensory data with supplementary information, with the aim of enhancing situational awareness and alleviating cognitive workload during teleoperation. Since the inception of collaborative control in teleoperation, numerous alternative approaches have emerged. For instance, in the work referenced as [10], the authors confine the robot's movement within predefined restricted zones generated through a streamed point cloud. Similarly, within the context of robotic surgery, the adoption of virtual fixtures has been employed to assist surgeons by augmenting the rigidity of surgical instruments when they approach areas that should remain untouched, as described in [73].

While prior studies have demonstrated the efficacy of virtual fixtures in enhancing system performance, limited research has been dedicated to their application in the domain of construction machinery. The dynamic and ever-evolving nature of construction sites, marked by frequent alterations in task conditions and objectives, poses a substantial challenge. A pre-established set of virtual fixtures can swiftly become impractical and constraining. Moreover, the provision of precise information regarding system dynamics often proves indispensable for effectively guiding operators through the utilization of virtual fixtures.

2.3 Communication Technologies on Construction Sites

Given the dynamic nature of construction sites, most construction machines operate as mobile devices, relying on wireless transmission of control signals from the control device. Robust wireless communication between these devices is imperative for ensuring safe control. A crucial aspect for effective machine control involves establishing stable, low-latency communication, coupled with data transmission capabilities that maximize bandwidth to improve visual feedback quality [54]. While WiFi and Fourth-Generation (4G) mobile networks have been utilized in recent years for tasks like monitoring hazardous areas, alerting workers in risky situations, and gathering on-site data, these technologies only partially meet industry demands. They notably lack in addressing bandwidth and time-critical communication needs comprehensively. In response to these challenges, Fifth-Generation (5G) technology has emerged as a promising solution tailored to meet the specific requirements of the construction industry [84].

In the existing literature, on-site communication, despite its pivotal role, has been relatively overlooked. A handful of available studies acknowledge communication technology as a significant challenge within the realm of automated construction machinery [89, 54]. Moreover, some works propose diverse concepts for integrating 5G technology into construction tasks [90]. However, these endeavors primarily offer theoretical frameworks and broad overviews, lacking empirical validation derived from real-world experiments conducted using on-site 5G networks. While the foundational concepts delineated in these studies hold undeniable value, their practical applicability remains constrained due to the absence of implementation and testing in real construction scenarios. Construction sites diverge significantly from traditional factory settings, characterized by their non-stationary and continually evolving nature. This dynamism results in constantly shifting operating environments. Factors such as the building's structure, materials, and on-site facilities like containers, access roads, or storage areas can induce signal blockages, shadowing, or reflections. These sites may be linear or punctual and are subject to natural environmental elements such as dust, vibration, and humidity. As a consequence, insights, expertise, and established practices from other environments, such as conventional factories, cannot be seamlessly transferred to construction sites.

2.4 Research objectives

Considering the evident gaps in current research, this thesis aims to achieve multiple objectives. Firstly, it seeks to formulate a systematic approach for the progressive transformation of a heavy-duty construction machine into an intuitively programmable robot. The primary aim is to establish a computational framework that not only eliminates the need for direct human presence in close proximity to the construction machine and workspace but also integrates human input into the automated construction process. This approach strives to surpass exclusive dependence on either teleoperation or complete autonomy. Instead, it seeks to combine the efforts of both modes, aiming to address tasks in an semi-automated manner. This is achieved by integrating the analytical capabilities of the human operator to assess the situation and objectives alongside the robot's proficiency in generating precise movements.

Objective 1: Progressive transformation of heavy-duty construction machines into a robot.

- *Challenge:* Highly unstructured environments, which lead to inherent limitations to the efficacy of autonomous approaches.
- *Proposed Solution:* Merge human analytical skills with robot precision for autonomous task handling.

Previous research on the automation of construction machinery proposes using simple model-free linear controllers, such as PI or PID controllers, for controlling hydraulic actuators. However, this approach necessitates the error-prone parameter tuning of the controller. Also, the performance can not be guaranteed if the disparity between nominal and actual system behavior increases. One commonly used approach to address this is the model-based controller. However, severe advanced control approaches like sliding mode and backstepping-based adaptive controllers have limited performance when models are imprecise. Also, there are unavoidable modeling uncertainties in hydraulic systems. While adapting hydraulic circuits is an option to reduce nonlinearities, it is often not feasible due to the required resources. Thus, modeling or canceling out these dynamics is generally challenging for control approaches. This thesis introduces a data-driven approach to address the challenge of constructing the nonlinear model of the hydraulic construction machine. It achieves this by analyzing operational data gathered from real-world operations.

Objective 2: Integration of the dynamic model into control approaches

- *Challenge:* Modelling the dynamics of construction machinery is especially complex due to the nonlinear hydraulic systems.
- *Proposed Solution:* Employ data from real operations to analyze and model the nonlinear characteristics.

Construction sites are known for their unpredictability, with constant changes and unexpected hurdles. To tackle these challenges, methods like reinforcement learning (RL) are increasingly used, offering a way for robots to learn in a data-driven manner. RL involves learning through trial and error, adjusting control strategies to optimize tasks based on given criteria. It automates this learning process, optimizing control strategies from sensor data to specific actions, making operations more agile and effective. However, RL often demands extended periods of interaction with the system, sometimes causing erratic behavior and safety risks during training. Applying these methods directly to construction machines is complex and unsafe. This thesis proposes a solution by incorporating a simulated environment, making it easier to adapt to changes and handle dynamic situations more smoothly.

Objective 3: Utilization of data-driven techniques to program the construction machine with less efforts.

- *Challenge*: Implementing data-driven techniques often requires extensive hours or days of operational data. This process typically leads to the emergence of chaotic behavior during the training phase.
- *Proposed Solution*: Train in the simulated environment and deploy the result to the real world. By integrating the data-driven dynamic model from Objective 2, the simulation to reality gap is also minimized.

An effective teleoperation or automated control of construction machinery heavily relies on a reliable communication infrastructure that offers stability, minimal delay, and high data transfer rates. In recent years, WiFi and 4G mobile networks have been utilized to enable robust machine-to-sensor communication. However, while these technologies partly address industry needs, they have limitations, especially regarding bandwidth and the urgency of data transmission. Recognizing these challenges, the emergence of 5G technology presents a promising solution tailored to meet the specific demands of the construction sector. In this study, we present a comprehensive framework for implementing on-site 5G technology in construction, covering its deployment, utilization in a practical scenario, and showcasing the advantages it offers.

Objective 4: Establishment of a robust and high-performance wirless communication network at a construction site.

- *Challenge*: The current WiFi and 4G networks lack the capacity to fulfill the complete requirements for stable wireless communication with the automated construction machines
- *Proposed Solution*: Verifying on-site 5G networks via real-world experiments involving full-scale construction machines, demonstrating the potential and feasibility of 5G technology within the realm of automated construction machinery.

According to the aforementioned objectives, this thesis is partitioned into multiple parts, where severe parts are based on published and peer-reviewed publications. Chapter 3 provides a comprehensive exploration of the strategies and difficulties related to the integration of robotic systems within construction sites. This encompasses an in-depth analysis of identifying and categorizing different types of construction robots, along with their associated opportunities and challenges. The subsequent chapter delves into the development of a programmable robot derived from off-the-shelf construction machinery. It outlines a systematic methodology for establishing a programming interface and discusses techniques and outcomes in automating the perilous deconstruction task, which involves incorporating human operator input into the control process. Chapter 5 elaborates on techniques to enhance teleoperation through data-driven methodologies and simulation capabilities. Chapter 6 studies the comprehensive framework for implementing on-site 5G network within the construction sector starting by detailing the strategic deployment of a 5G network and showcasing the potential and practicality of 5G technology in the context of automated construction machines.

Chapter 3

Robotics in Construction

In this chapter, the existing approaches for enhancing the degree of autonomy on construction sites are investigated, where the overall goal lies in developing robotic systems in the unique environment of construction sites to reduce the burden of human workers and increase the efficiency and productivity of construction processes. The corresponding challenges and opportunities are also introduced, respectively.

3.1 Overview and Opportunity

Construction refers to a vast array of activities crucial for shaping cities, crafting civil infrastructures, and bringing architectural visions to life. From the creation of homes, roads, tunnels, and bridges to the development of sophisticated energy infrastructure like nuclear and wind power plants, construction projects stand as the backbone of societal progress. Despite their undeniable impact, the incorporation of robotic automation within the construction domain lags behind compared to other industries. Human labor still predominantly drives these tasks, presenting a persistent challenge in enhancing the efficiency and advancement of these projects [12].

Taking cues from the success seen in industries such as automotive manufacturing, researchers have devoted attention to integrating robotics systems into construction sites since the 1970s. Within construction tasks, repetitive actions like excavation, material handling, and assembly are commonplace. While automating a singular task may seem like a small step within the grand scope of a construction endeavor, it serves as a crucial milestone toward achieving fully automated construction sites. This pursuit stems from the urgent need to revitalize productivity in an industry that has faced stagnation since the 1970s [85].

Initially, efforts were focused on developing specialized robots for individual tasks, aiming to streamline these repetitive processes [1]. However, the introduction of robotics to construction sites unraveled complexities due to the dynamic and unstructured nature of these environments. Unlike controlled manufacturing facilities, construction sites are in a constant state of flux as projects progress through various phases. Adapting to these changes becomes a challenge for construction robots, further complicated by the presence of multiple variables, including the ever-present human workforce. Implementing safety and health regulations tailored for factory settings becomes a multifaceted task within the dynamic setting of construction sites. The paramount priority remains the safety and well-being of the workers in integrating construction robots, and establishing new standards will profoundly influence their future deployment.

Building upon these challenges, a paradigm shift emerged, pivoting from replicating manual actions to restructuring on-site environments and construction processes for automated production [14]. This approach involves embedding robotic technology right from the design phase, influencing not just the end result but the very process of construction itself. The fundamental idea revolves around reevaluating and redesigning construction subprocesses to align them with robotic capabilities. This paradigm shift aims to analyze and remodel traditional human-centric construction processes, optimizing them for automation and facilitating a more effective integration of robotic systems into the construction industry.

The field of robotics in construction explores these challenges and opportunities specific to construction sites, aiming to alleviate the burden on human workers while concurrently enhancing the efficiency and productivity of construction processes. This exploration seeks to achieve the following objectives:

- To identify and categorize the types of construction robots and to discuss their chances and challenges

- To understand the idea of reconsidering and redefining construction processes through the logic of robotic capabilities

3.2 Construction Robots

Current methods in construction robotics can be categorized into three main groups: the automation of construction machinery, the modification of industrial robots, and the creation of novel construction-specific robots.

3.2.1 Automation of Construction Machines

At construction sites, machinery contends with various environmental elements, including fluctuating weather conditions involving humidity, temperature variations, and the presence of dust and debris. Moreover, these sites commonly engage in heavy-duty tasks, demanding actuators that are sturdy, exceedingly reliable, and resistant to substantial forces. This preference often leans towards hydraulic systems due to their robustness. Thus far, construction machine manufacturers have concentrated their efforts on enhancing functionality, comfort, and safety to enable machine actuators to perform a spectrum of tasks across diverse conditions.

Despite ongoing advancements, construction machines primarily operate under the direct control of human operators or via remote control methods where the operator remains in close proximity to the machine. As this technology has evolved gradually over several decades, most machines are controlled at the joint level, utilizing individual joysticks or levers. Mastering the control system demands extensive training for operators due to the machines' multiple degrees of freedom (DoF). Coordinating these multiple joints to achieve the desired motion with the machine's end effector or tool necessitates complex skills. Typically, this proficiency requires months of training, and even seasoned operators struggle to attain high precision and efficiency. Consequently, this results in diminished local accuracy and reduced work efficiency [2]. Furthermore, the proximity of operators to the machines exposes them to various risks and hazards inherent in operating heavy machinery at a construction site.

Enhancing machine autonomy has captivated researchers' interest since the 1990s. The pioneering work by Stentz et al [3]. in 1998 introduced an autonomous system designed for loading trucks in excavation sites. Subsequent studies, such as those by Melenbrink [5], have demonstrated that sophisticated control algorithms can be implemented without extensive hardware modifications. Recent advancements, highlighted in works by Hutter et al. [7], showcase the integration of hydraulic cylinders, new valve systems, and various sensors like encoders and pressure sensors into commercially available excavators to achieve autonomy. Similarly, numerous research endeavors, as indicated by Lee et al. [6], have utilized personal computers equipped with controller area network (CAN) modules to communicate with existing bus systems in excavators, facilitating the deployment of efficient autonomy algorithms. Nevertheless, the unresolved aspect of additional complexities, such as integrating automated construction machines into construction projects while adhering to safety regulations, remains a subject for future assessment.

3.2.2 Adaptation of Industrial Robots

Although significant strides have been made in industrial robotic technology for stationary production processes within controlled factory settings, construction sites have posed persistent challenges for industrial robotic automation over the past few decades. Fundamentally, the construction domain differs from product assembly and manufacturing in two distinct aspects:

- While in the manufacturing industry, mass products with large output numbers are typically concerned, buildings are one-of-a-kind products, considering individual local conditions (site, soil, design, etc.). Thus, very high adaptability is required for adopting robot-assisted approaches on construction sites.
- In the manufacturing industry, fixed assembly lines are a proven standard so that industrial robots can be placed in one position while products move along the production lines. In con-

> trast, products at construction sites, i.e., buildings, are set in one place, and robots move along the products. At the same time, the workspace of robots keeps changing as the building grows, which complicates the robotic approaches involved with localization and environmental perception. These reasons have prevented the direct adoption of industrial robots for on-site work where the workers are most stressed and accidents frequently happen [19]. Thus, the majority of approaches proposed to customize classical industrial robots to cope with the harsh construction environment partially.

One challenge linked to employing industrial robots in construction pertains to the ever-evolving workspace. Construction tasks entail varying workspaces, shifting from floor to floor and building to building. Stationary industrial robots, with their fixed bases, confront limitations in adapting to this dynamically changing construction environment. Moreover, these robots are typically bulky, costly to transport, and laborious to install on-site, raising doubts about their economic viability (refer to Fig. 3.1). Conversely, commercially available mobile systems equipped with industrial manipulators encounter mobility constraints in construction sites encompassing unpaved outdoor spaces, obstacles, uneven terrains, or stairs [20]. Academic research often focuses on indoor environments [21, 22]. While caterpillar tracks can facilitate movement on non-level or soft ground [23], challenges persist regarding precise movements and power supply efficiency on high-friction terrains.

Construction site tasks often demand high payloads, yet the electrically actuated manipulators of conventional industrial robots suffer from a low payload-to-weight ratio, rendering the system susceptible to vibration and impact damage [5]. This limitation hampers the system's applicability for specific tasks like bricklaying or drilling. Alternatively, more robust construction machines rely on hydraulic drive

Figure 3.1: An industrial robot KR240 R2700 with a fixed base from KUKA with a customized end effector. The heavyweight (~1100 kg) complicates the on-site application of the robot

systems, capable of handling heavier payloads and enduring greater impulsive loads. However, their precision falls significantly short of electrically actuated robots. Precision in movement holds paramount importance in automated construction, yet challenges such as nonlinearities in actuator dynamics [6] impede precise movement control in hydraulic systems.

One strategy to circumvent these limitations involves amalgamating hydraulic and electric manipulators to craft a macro-micro robotic system. Notably, existing construction machines, such as aerial lift systems or tower cranes, have been augmented with industrial robots as end effectors to interact with the environment [24, 25]. Real-world applications, such as SAM [26] or Hadrian X [27], have emerged in recent years, showcasing the potential for large-scale robotic construction on-site.

3.2.3 Development of New Construction Robots

Numerous robotic systems are under development tailored explicitly for diverse construction tasks, ranging from cable robots to humanoids. Across these varied approaches lies a shared objective: augmenting productivity and enhancing safety levels at construction sites. The target tasks for these robotic systems typically involve labor-intensive or hazardous activities, alleviating the burden on human workers. For instance, Montazeri et al. [28] and Taylor et al. [**?**] engineered hydraulically driven manipulators integrated into the base of a teleoperated demolition machine, facilitating robotic utilization in disassembling nuclear facilities. Similarly, an innovative cable-driven robot designed for cleaning high-rise glass facades was developed [30].

As the demand for more sustainable building components surges, the weight and complexity of these components increase, presenting a mounting challenge in on-site handling. Addressing this, Iturralde et al. [31] devised a cable-driven parallel robot, while the work from [32] introduced a tracked mobile platform-based robot. Mobile robotic platforms, owing to their adaptability, are gaining prevalence in construction tasks, leveraging diverse sensors like laser scanners, cameras, and even unmanned aerial vehicles (UAVs) [33] for inspection and monitoring duties.

Diverse strategies in integrating automation into construction sites center on assistive robotic devices designed to directly aid human workers. Exoskeletons, for instance, have the potential to combine the physical prowess of a robot with the cognitive abilities and expertise of a human operator [34]. Another avenue involves augmented reality technology, overlaying design data onto the operator's real-world view, providing task-specific information through 3D graphical overlays, aiding in communicating assembly instructions, and training users on intricate construction equipment [35].

Advancements in sensing, dynamic modeling, and human-robot interaction have propelled humanoid robotics as a noteworthy area in construction automation [36]. Although current humanoid robots are yet to reach a level suitable for on-site utilization, the potential for construction automation is vast. As these technologies mature, humanoid robots could assist human operators in critical scenarios, offering alternative approaches in construction procedures.

As research progresses in sensing, dynamic modeling, and human-robot interaction, construction robotics has emerged as a predominant field in both academia and industry. The development of construction robotic technology necessitates alignment with end-user needs and challenges. In the context of construction site applications, factors like ease of control and reliability hold paramount importance. Close collaboration between construction robotics developers, industry stakeholders, system providers, and construction workers becomes imperative to maximize user acceptance levels and solve real-world challenges in robust and accessible ways.

3.3 Construction Process

3.3.1 Robotic Systems in Construction: Challenges and Chances

The primary inquiry when envisioning the evolution of novel robotic systems revolves around their practical utilization at construction sites. Specifically, it pertains to how the construction processes and these robotic systems can harmonize to seamlessly integrate this new technology into the construction industry [14]. The integration of new technology into construction processes has been a historical trend in architectural engineering and construction. Innovations like elevators, cranes, tuned mass dampers, and wind tunnel testing have facilitated the construction of progressively taller skyscrapers throughout the twentieth century. The essence of construction robotics lies in fostering the next wave of technological advancements to enhance the speed, safety, and efficiency of construction endeavors. However, significant challenges persist in the realm of robotic systems and automated construction sites:

The pivotal role of sensor systems in autonomous systems cannot be overstated. Internal sensor systems monitor internal states like forces, pressure, or velocity, while external sensor systems gather information about the surrounding environment. Particularly in construction sites where an array of obstacles coexist with human workers (see Fig.3.2), accurate and dependable perception of the working environment stands as a critical concern for successful robot deployment.

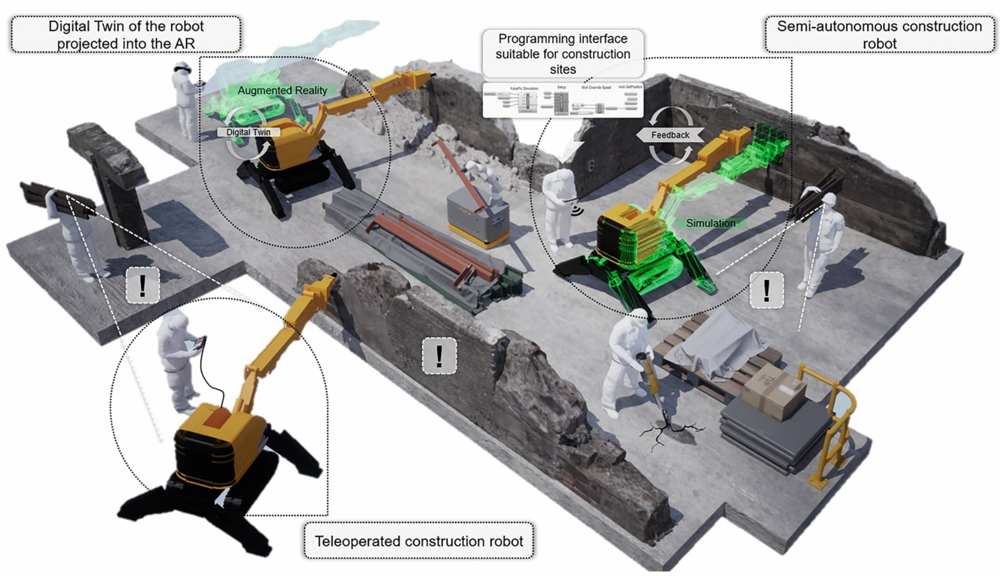


Figure 3.2: Illustration of a scenario on a construction site where robots with different autonomy levels execute tasks alongside human workers. For such a scenario, a comprehensive interaction approach between robots and human workers is required from a safe, automated construction site standpoint

Although object recognition and scene analysis have seen considerable advancements, primarily driven by strides in artificial intelligence [37, 38], comprehending a construction scene encompassing diverse objects and evolving conditions (such as rain, dirt, and dust) in real-time to avert potential accidents remains a substantial challenge. The pivotal question arises: How can the construction process adapt to enhance the efficacy of environmental perception processes?

This challenge of integrating sophisticated sensor systems into the dynamic environment of construction sites isn't solely about technological prowess. It's a fusion of technical innovation and adaptability within an inherently multifaceted setting. Construction sites are not static environments. They are bustling with ever-evolving activities, varying conditions, and human interactions. Thus, the effective integration of sensor technologies demands a multifaceted approach.

It requires not only the advancement of sensor capabilities but also their seamless integration into the fluidity of construction processes. Balancing technological sophistication with practical adaptability becomes imperative to ensure these systems don't just function in isolation but become integral components harmonizing with the intricacies of real-world construction environments. This necessitates a collaborative effort involving engineers, technologists, construction professionals, and researchers to bridge the gap between technological innovation and on-site practicality.

Another critical aspect involves acknowledging the human element. Studies consistently emphasize how the conditions, accuracy, and fatigue of human operators significantly affect overall performance [39]. As a result, the predictability of a construction process involving human operators becomes uncertain. Thus, optimizing this process to complement the operational capacities of robotic systems becomes crucial in improving human conditions. Safety within operations involving robots requires attention to two primary scenarios: ensuring the safe functioning of robotic systems within their tasks and managing the interaction between human workers and robots.

The former scenario focuses on maintaining the safe operation of robots concerning their assigned tasks. For instance, task-specific forces can potentially damage the robot if inaccurately estimated, leading to tool breakage or actuator damage. This necessitates an advanced sensor system paired with an appropriate algorithm. Conversely, the latter scenario revolves around the safety of construction workers interacting with robots. This involves studying the regulations governing human-robot interaction in shared work environments. Addressing this interaction involves adapting the construction process to mitigate risks associated with human workers operating alongside robots.

The shift from single-task to multi-task construction robots signifies a move toward automated systems collaborating on a larger scale. Concepts like swarm systems, common in warehouse fulfillment centers, are now being adapted for construction sites. Integrating interconnected construction robots has the potential to revolutionize construction methodologies, impacting tasks from assembling intricate components to managing large, heavy elements. However, this evolution necessitates robust network infrastructure on construction sites for effective data communication among interconnected robotic systems. Moreover, the construction process must exhibit high adaptability to accommodate the diverse capabilities of on-site robots, which may vary from project to project.

The shift towards multi-task construction robots and their integration into complex on-site operations signifies a transformative leap in the construction industry. It redefines the traditional boundaries of construction methodologies, paving the way for a collaborative environment where human expertise synergizes with robotic efficiency. This evolution isn't merely about adopting new technology but entails a fundamental reimagining of construction processes. The potential impact spans across construction tasks of varying scales, from streamlining intricate assembly procedures to revolutionizing the handling of massive structural components. However, the realization of this evolution requires a holistic approach. It involves not only the technological advancement of robotic systems but also a reconfiguration of construction site infrastructure and practices. This entails fostering a dynamic and adaptive construction ecosystem that can seamlessly accommodate the diverse functionalities of interconnected robotic systems, thus reshaping construction practices. Such a transformative shift demands collaborative efforts, bringing together engineers, technologists, construction experts, and stakeholders to steer this evolution towards a future where human-robot collaboration in construction becomes the norm, augmenting efficiency, safety, and innovation in the industry.

3.4 Future Directions for Research

The degree of automation in the construction industry remains low compared to other manufacturing, automotive, and aerospace production sectors. The massive potential for innovation has increased interest in adopting existing robotic solutions into the construction industry and/or developing new domain-specific robotic solutions. Previously discussed challenges require further research and development to address the gap between design and engineering information and automated production technology.

The majority of digital information generated by architects and engineers is currently not reaching the construction site due to the lack of a closed digital process chain, mainly caused by the transition between digital and analog construction phases (see Fig. 3.3). Current conventional construction machines are exclusively human-mechanically controlled without leveraging the digital information generated from other computer-controlled or aided processes.

Such data loss represents a massive bottleneck in the continuous flow of the digitized information chain. In the near future, we may experience construction sites where human operators and construction machines with different autonomy levels from teleoperation to fully automated machines collaborate in data exchange and physical operation, as shown in Fig. 3.2. To achieve reliable robot-based construction automation, adequate data about the design to be built, the status of construction progress, and sensor information to evaluate the dynamic construction environment must be available to the robot systems in real-time.

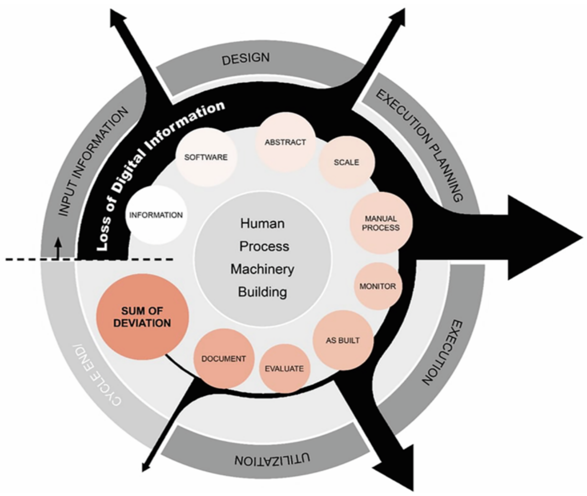


Figure 3.3: Loss of digital information during the building life cycle [41]

Since conditions and parameters for construction tasks vary from one project to another, the appropriate autonomy level of robotic systems will be adaptively defined by the building process and local circumstances. This implies that robotic systems must be able to flexibly adjust the level of autonomy and operating type on-site as needed (see Fig. 3.2). For instance, in a refurbishing task, the temporary dependencies such as crowded environments by human workers can set rigid boundaries for autonomous operation. The spatial dependencies such as hazardous environments can constrain the on-site operation. Robotic systems in a dynamic environment like a construction site need to fulfill the spatiotemporal requirements of on-site construction tasks.

Moreover, to meaningfully increase the overall productivity of construction sites, multiple robotic systems and sensors from different vendors with varying levels of autonomy, including conventional construction machines and human workers (Fig. 3.2), have to work in a well-structured and comprehensively coordinated system. The development of a holistic approach that considers different types and states of machines, local job-site conditions, on-site field workers, and the overall construction project is a future research direction with enormous potential.

3.5 Conclusion and outlook

The integration of robotics into the construction industry is poised to bring about transformative changes, offering opportunities to enhance efficiency, safety, and productivity. The exploration has unveiled the three primary categories of construction robots: automation of construction machines, adaptation of industrial robots, and development of construction-specific robotic systems. As we navigate the challenges and prospects within each category, it becomes evident that addressing issues related to autonomy, environmental perception, and human-robot interaction is essential. Future research directions should prioritize the establishment of closed digital process chains, adaptive autonomy levels for robots, comprehensive coordination of diverse machines, and the optimization of human-robot collaboration.

Chapter 4

Semi-autonomous approach for controlling the construction robot

In the previous chapter, three ways for integrating robotics into construction sites are identified: the automation of construction machinery, the adaptation of industrial robots, and the development of new construction-specific robots. In this research, the primary focus centers on the first approach due to its numerous advantages over the other approaches:

- Most of the construction tasks are heavy-payload processes. The machinery used for the process must be very dependable, durable, and resistant to force. Hydraulic machines are a better fit in this situation than electric machines, such as industrial robots, which have a limited payload and are generally error-prone in outside conditions (dirt, humidity, etc.).
- Hydraulic construction machinery has consistently proven its

ruggedness across diverse scenarios. Creating a novel construction robot tailored for the dynamic construction site environment is a formidable undertaking that demands significant dedication and effort.

- Many modern construction machines are already using electrified commands to interact with the control system and the actuators, which serves as a fundamental requirement for integrating various automated approaches.

Within this chapter, the techniques for transforming a commercially available construction machine into a robot capable of being controlled via a semi-autonomous approach. The content in this chapter, encompassing both text and figures, has been reproduced from the following peer-reviewed paper. In this paper, the first author conceptualized the ideas, conducted experiments, and carried out the scientific writing, while the second author reviewed the original draft and contributed as the scientific supervisor:

Lee, H.J., Brell-Cokcan, S. Towards controlled semi-autonomous deconstruction. *Construction Robotics* (2023). https://doi.org/10.1007/s41693-023-00111-9

4.1 Abstract

The automation of deconstruction processes presents unique difficulties due to the harsh working conditions involved. In this research, we aim to address these limitations by advancing the teleoperated machine, BROKK 170, towards a developed semi-autonomous concept. We propose a framework for robot-assisted deconstruction, exploring the communication and sensing systems of the prototype deconstruc-

tion robot, along with its capabilities. Additionally, field tests are conducted to evaluate the performance of the proposed approach in real-world scenarios. The potentials and limitations drawn from these initial results are discussed.

4.2 Introduction

The (de-)construction industry is the most significant waste stream of any other business [42]. There is a clear need to increase resource efficiency and decrease the environmental effect of the (de-)construction industry. This growing interest in deconstruction has captured the attention of industry and researchers alike. However, the process of deconstruction faces significant challenges in managing dust and hazardous pollutants in a cost-effective manner that also prioritizes employee safety. The (de-)construction industry has been associated with a poor track record in employee retention, partly due to the sector's high incidence of catastrophic accidents. In fact, among all sectors, (de-)construction has the third-highest incidence of such accidents, with 10 out of every 100,000 (de-)construction workers affected [43].

Despite societal issues, there is currently limited automation for the deconstruction process [44], which is challenging due to multiple variables, including changing weather conditions in outdoor activities. Heavy-duty operations require actuators with robustness, high reliability, and the ability to withstand substantial force. Significant efforts are required to develop a robotic system for these kinds of operations in outdoor environments. Consequently, (de-)construction machines are still directly or remotely controlled by human operators, with the operator standing near the machine [80].

Figure 4.1: Conventional teleoperation, where the human operator directly stands on the deconstruction scene

4.2.1 Related Works

Construction machine manufacturers have traditionally focused on improving deficiencies, comfort, and safety to enable machine actuators to perform various tasks under different conditions. However, human operators still predominantly control these machines directly or remotely, with the operator positioned near the machine, see Fig. 4.1. Control is typically achieved using individual joysticks or levers at the joint level. Operating these machines effectively requires significant training due to their multiple degrees of freedom and complex coordination of multiple joints [46]. Even experienced operators require months of training, leading to reduced local accuracy and decreased work efficiency [2]. Furthermore, the proximity to the machine exposes workers to risks and hazards associated with operating heavy machinery on a construction site.

To introduce automation in deconstruction sites, researchers have proposed integrating industrial robots. One such system is the Robotic Facade Disassembly and Refurbishment System (RFDRS) [4], which employs a robot-assisted deconstruction approach with motion programming to automate the dismantling of multi-layered facade structures. However, traditional industrial robots with electrically actuated manipulators face limitations, such as a low payload/weight ratio and vulnerability to vibration and impact damage [5]. Consequently, the application of such systems is restricted to specific types of work due to these inherent limitations of industrial robots.

Here, the idea of enhancing the level of machine autonomy in existing heavy-duty construction machinery has captured the interest of researchers [6]. One notable study by Lampinen et al. focuses on upgrading an industrial breaker boom with a visual perception system, enabling it to break rocks autonomously [47]. However, the system's effectiveness relies heavily on autonomous components, particularly the vision system, which required 4733 rock photos from a field test for rock detection. They reported a success rate of 34% for rock cracking.

Given the existing challenges and needs in the deconstruction process, there is a growing demand for alternative approaches to enhance machine autonomy. Currently, no robotic platform fully meets the requirements for controlled deconstruction, to the best of our knowledge. While autonomous solutions in similar construction tasks have demonstrated various potential benefits [48], we argue that adopting a systematic approach toward a semi-autonomous approach is a necessary step toward further development of the deconstruction process. Considering the dynamic nature of the task, where the hammering target continuously changes over time, a fully autonomous robot should be capable of understanding its surroundings and reasoning the best suitable hammering target accordingly. By integrating human operators into the control process and allowing them to interactively define the target positions for hammering, the cognitive load on robots can be reduced on deconstruction sites. At the same time, the robot can convert the target hammering position into precise control and coordination of multiple joints, ensuring both the safety and efficiency of operations. This work builds upon this aspect of the semi-autonomous approach.

4.2.2 Contributions

Here, a semi-autonomous deconstruction concept is proposed as a progressive approach to ensure safe and controlled deconstruction processes. Unlike conventional teleoperation methods that require the operator to control each joint continuously, our proposed semi-autonomous concept allows the operator to control the deconstruction machine using a high-level goal, i.e., a desired hammering point. By specifying this desired point, the appropriate joint motions are generated according to different states, such as moving the hammer toward the target or activating the hammering action. In this way, this approach eliminates the need for operators to micromanage the deconstruction machine. At the same time, controllability and safety are ensured by pre-visualizing the planned motion and eliminating the operators from the direct proximity of the deconstruction machine and scene.

This work presents each component of our proposed system, along with the limitations we encountered during the development process and their corresponding solutions. The paper is organized as follows: First, we propose a list of basic hardware adaptations to convert an off-the-shelf teleoperated deconstruction machine into a programmable robot. Second, we provide a systematic overview of the information

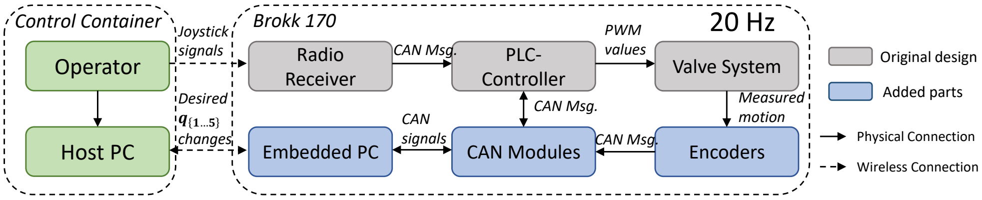


Figure 4.2: Schematic system overview of the core modules of adapted BROKK 170. The green components are executed from a safe control container, whereas the others are executed onboard BROKK 170. The components added to the original design are depicted in blue.

flow between each component. Next, we introduce the planning and control algorithms employed to achieve the required capabilities for robot-assisted deconstruction. We highlight the capabilities of our proposed system through a demonstrator in Section 4 and outline the lessons learned from the initial field test and plans for addressing the identified limitations. In Section 5, we draw essential conclusions.

4.3 System Overview

In the following subsections, we describe the overall concept of the semi-autonomous approach, followed by the hardware description and the required modification.

4.3.1 Concept of Operations

The main goal of developing a semi-autonomous deconstruction system is to enhance operator safety by minimizing their direct exposure to hazardous deconstruction scenes and reducing the need for constant manual control of the machine at the joint space level. This

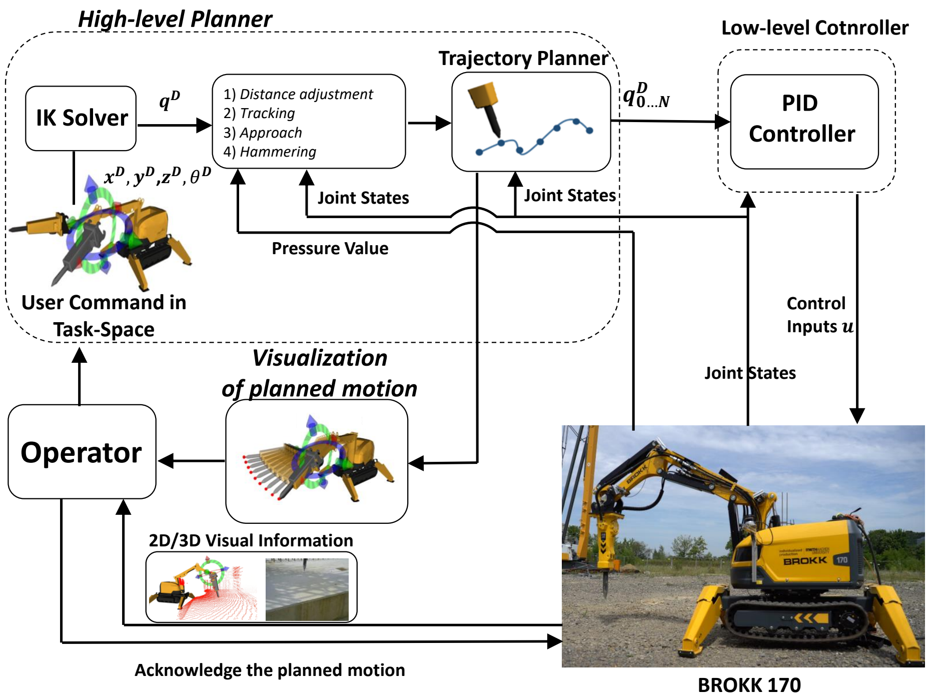


Figure 4.3: Based on the captured visual information of the workspace, the operator defines the desired pose for the hammer, which is converted to the corresponding control inputs by the trajectory controller. The planned motion gets visualized to the operator and is only executed when the operator acknowledges it.

objective aligns with the concept of autonomous robots, where tasks are performed without human intervention. However, the challenging nature of construction sites, which are dynamic and complex environments with numerous variables like changing conditions and human presence, presents additional complexities compared to controlled manufacturing facilities. As a result, our proposed solution focuses on allowing the human operator to define high-level goals for the deconstruction robot. By doing so, we aim to alleviate the cognitive burden on the robot while improving safety and overall system robustness. The control concept in detail is further explained in Section 4.4.

4.3.2 System Description

This section provides a description of the hardware configuration of the BROKK 170 construction machinery, along with the necessary modifications for the proposed work. The BROKK 170, like other modern construction machines, utilizes components such as actuators and sensors, which are connected to the machine control unit (MCU) through a Controller Area Network (CAN) bus. When the operator sends commands using the control device, such as joysticks, specific CAN messages are generated and forwarded to the Programmable Logic Controller (PLC) controller, where they are then translated into corresponding Pulse-Width Modulation (PWM) signals with specific voltage levels. The power electronics receive these signals and drive the mechanical components of the machine. Figure 4.2 illustrates the original hardware architecture (in grey) and the additional hardware added (in blue).

To enable operators to program the deconstruction machine for the semi-autonomous deconstruction process interactively, a communication link is established using an embedded PC, Jetson AGX Xavier. This embedded PC is equipped with a CAN bus controller and acts as a bridge, saving filters and forwarding incoming CAN bus messages to the controller of the BROKK 170. This setup expands the original connection between the control device (i.e., radio receiver) and the controller, as shown in Fig. 4.2. With this configuration, the machine can be teleoperated using the original joystick signals and also receive signals computed by algorithms deployed on the Host PC in program mode. These computed signals enable optimized and controlled motions. The embedded PC communicates wirelessly with the host PC, exchanging machine states and visual information of the remote workspace. This wireless communication facilitates the interactive programming of the deconstruction machine and enables semi-autonomous operation by exchanging information between the embedded PC and the host PC.

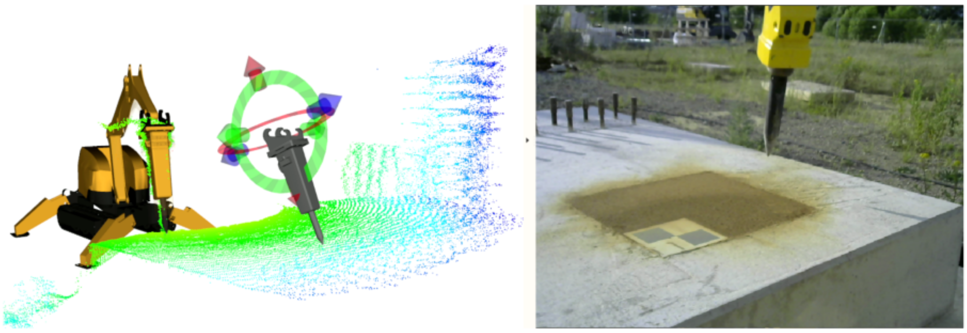


Figure 4.4: Captured visual information of the workspace.

To ensure operator safety, this study avoids direct proximity between the operator and the deconstruction machine and scene. Instead, the operator observes the remote workspace using visual sensors, which capture 3D point clouds and 2D images, respectively. The lack of depth perception in 2D visual information presents challenges in accurately perceiving the spatial relationships and distances within the scene, see Fig. 4.4. To address this issue, we employ the use of 3D visual sensor. By leveraging 3D visual information, operators can infer depth information, reducing the cognitive load they experience and minimizing potential errors in their understanding of the environment.

The captured data is transmitted wirelessly to the operator using WLAN with the 802.11ac standard. Due to data size limitations and the constraints of the wireless network, the framerate is limited to 2 Hz for 3D information and 25 Hz for 2D information. The overall system architecture, shown in Fig. 4.3, provides an overview of the components and their interactions in the proposed semi-autonomous deconstruction system.

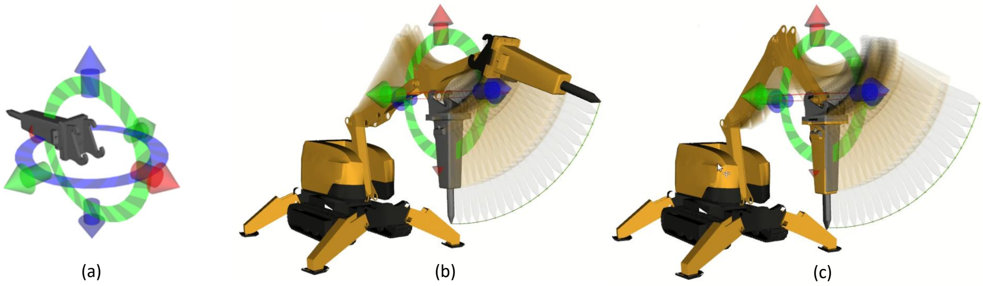


Figure 4.5: a) Interactive hammer model; b) According to the desired pose of the hammer, the trajectory planner generates the corresponding joint motions; c) Only after acknowledgment from the operator the planned motion is forwarded to the real machine.

4.4 Control Methods

This study introduces a flexible interface enabling the operator to dynamically set or adjust various task parameters during runtime, ensuring successful execution. These parameters may include goals or trajectories for the controller, object locations, or poses. The proposed approach follows a shared control methodology, where both the operator and the robot can simultaneously control different signals rather than relying solely on teleoperation or full autonomy. By employing shared control, the operator can define higher-level goals, thereby reducing their workload for reasoning. This approach is particularly well-suited for dynamic work environments such as construction sites, where the work conditions continuously change. This work mainly focuses on empowering the operator to control the robot using high-level goals, such as the desired hammering point. As opposed to manually controlling every joint-level command of the robot, the defined high-level goals are automatically converted into different joint motions based on the state machine aligning with the principles of shared control.

4.4.1 High-Level Control

The high-level planner is responsible for converting these task-level robot commands into the corresponding operation modes based on an event-triggered state machine. Here, the current state of the machine, i.e., the pressure value, the current, and the desired task space pose of the hammer, are considered to define the transition between the states.

Defining the hammering target

In this study, we utilized the RVIz program to implement interactive markers. These markers serve as visual controls that enable users to engage with a robot in a fully immersive 3D environment. This environment encompasses real-time feedback on the robot's status and utilizes various 3D sensory data, such as laser scans and RGB-D point clouds. Users can easily interact with these markers by manipulating them with the mouse. Each marker offers the ability to control up to six degrees of freedom, including both position and orientation. Additionally, developers have the flexibility to associate custom shapes with these markers, allowing for representations like tools or the robot's end-effector. For instance, Figure 4.5 showcases an interactive marker exemplified by a hammer-shaped model. Notably, we specifically focus on the position and orientation of the robot, denoted as $\mathbf{x}^D = x, y, z, \theta$, while disregarding roll and yaw angles. This decision is driven by the robot's limited motion within a fixed-base position, eliminating the need for base movement. As depicted in Figure 4.5, the operator defines the desired pose for the hammer by actively interacting with its corresponding model.

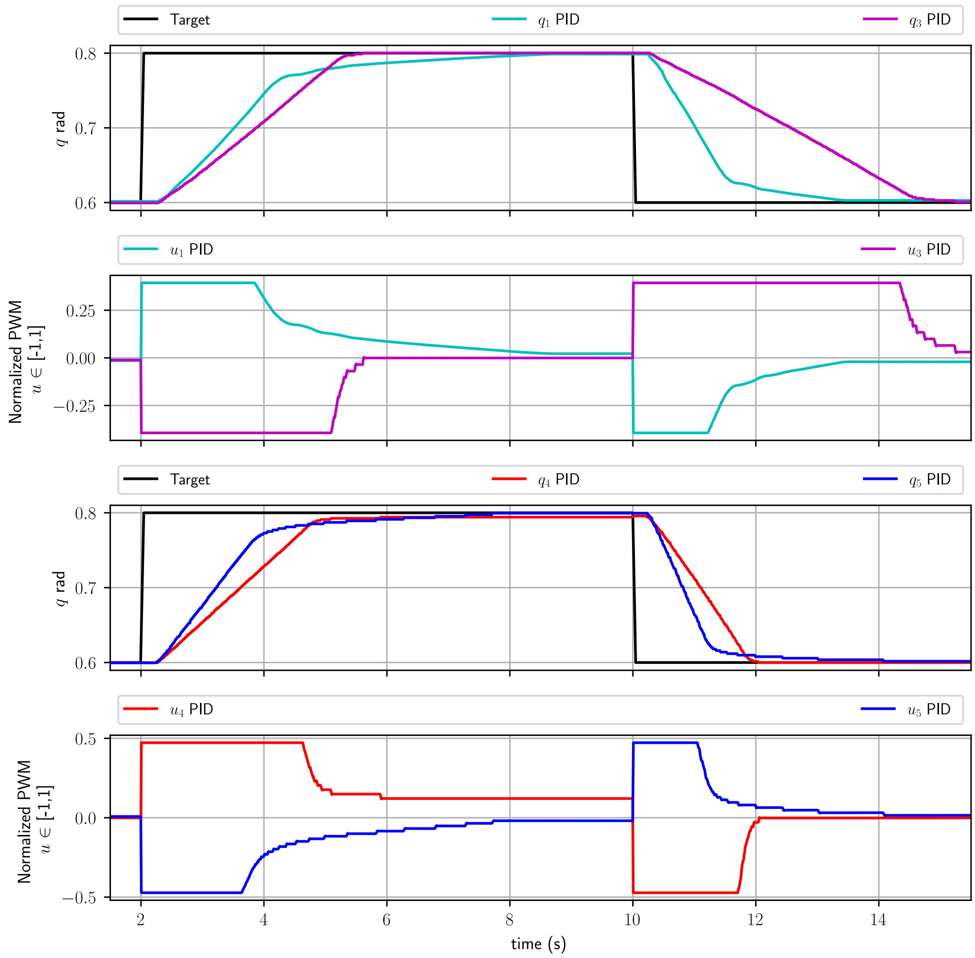


Figure 4.6: A snippet of the step response from 0.6 rad to 0.8 rad and the corresponding PWM signals

Planning the Hammering

In our study, we utilize a predefined order logic consisting of four states: *distance adjustment*, *tracking*, *approach*, and *hammering*. It is important to note that the base of the system remains fixed throughout the task.

The BROKK 170 manipulator is a hydraulic serial link manipulator with five revolute joints. Among these joints, the second joint, denoted as q_2, is mechanically coupled to q_3. The manufacturer has designed q_2 to modify the manipulator's reach and implemented a communication protocol to ensure its independent control from the other joints. This raises the question of when to utilize q_2 and when to utilize the other joints, based on a desired goal pose $\mathbf{x}^D = [x^D, y^D, z^D, \theta^D]^T$ defined by the user.

In our approach, we first check the distance between q_2 and x^D for the desired goal pose $\mathbf{x}^D$. Through experimental analysis, we determined that if this distance falls within the range of $[1.7m, 2.4m]$, the goal position is within the reachability of the BROKK 170. In the initial *distance adjustment* mode, only q_2 is actuated until the distance to the goal falls within this range. Once the distance criterion is met, the system transitions to the next mode, *tracking*.

In the *tracking* mode, a trajectory is planned that includes a constraint on q_2 to maintain its current position and prevent its utilization. This constraint ensures that a trajectory in the joint space $\mathbf{q}^D_{i...N}$ is defined, which brings the hammer to the desired $\mathbf{x}^D$ without involving q_2. The planned trajectory is first visualized to the operator and then tracked by the low-level controller in the *tracking* phase. Monitoring the states of $q_{1,3,4,5}$ and comparing them with the final trajectory waypoint $\mathbf{q}^D_N$ allows for a smooth transition from the *tracking* phase to the *approach* phase.

The hammer mechanism of the BROKK 170 is hydraulically powered, with piston movement in the cylinder generating the hammering action. During the hammering operation, the chisel attached to the hammer moves back and forth for approximately 15 cm, indicating its ability to press against a surface. The objective of the *approach* state is to position the hammer in close proximity to the target object's surface and press the chisel against it, ensuring effective impact during hammering. The pressure in the main hydraulic pump increases when the hammer encounters resistance from the surface while pressing down. Therefore, the pressure value from the main pump serves as a trigger to transition to the next stage, *hammering*. Specifically, when the pressure exceeds 100 bar while the hammer is moving in the negative z direction, the movement is halted, and the subsequent *hammering* state is initiated.

Maintaining an appropriate distance between the chisel and the target object's surface is crucial for successful hammering. During the hammering process, the surface is demolished, causing the distance between the chisel and the surface to automatically increase. However, if the distance becomes too large, the chisel may not effectively impact the surface. To address this, the joint q_5 of the robot manipulator is gradually rotated towards the surface's direction (assuming the surface is located below the hammer) to maintain a small distance during the *hammering* state.

In the current setup, the decision on when to start and stop the hammering operation is made intuitively by a human operator who observes the remote workplace through captured visual information. Once the target point is properly hammered, the operator can define a new goal pose by repositioning the interactive hammer model, which subsequently triggers the *distance adjustment* state to resume the task.

Trajectory Planner

In the context of trajectory planning, we further elaborate on the *tracking* aspect. We aim to plan and accurately track a trajectory to position the hammer at the desired task space goal $\mathbf{x}^D$. To achieve this, we first convert the defined desired pose $\mathbf{x}^D$ into the corresponding joint angle values $\mathbf{q}^D$ using an inverse kinematic solver [6]. Using the computed

$\mathbf{q}^D$, the trajectory planner generates waypoints from the current joint configuration. The desired changes between these waypoints are then converted into control inputs, specifically PWM values, through the implementation of a low-level controller.

To generate collision-free trajectories, we employ the motion planning framework MoveIt! [49]. This framework utilizes the rapidly exploring random tree (RRT) method from the open motion planning library (OMPL) [50] to sample the current and desired end poses and construct search trees. The generated trajectories are created and smoothly interpolated using a quintic-polynomial spline. To facilitate closed-loop control, we implement a control system based on the ROS (Robot Operating System) control framework. The main control loop of the system operates at a predefined interval of 20 Hz.

Within each control loop iteration, the control system updates sensor information, such as joint states from the robot, and computes commands for each joint to guide the robot toward the desired pose defined by the operator. Before the computed joint commands are forwarded to the low-level controller for conversion into actual motions, the operator has the opportunity to observe the defined hammer goal position and the corresponding manipulator motions. Once the operator is satisfied with the planned motions, they can be executed as actual motions.

Low-Level Control

The objective of the low-level controller in this research is to determine suitable control inputs, specifically PWM values for the valve system, based on the given actual and desired joint states. While analytical control techniques such as sliding mode control [51] and adaptive controllers [52] have been proposed for similar hydraulic applications, their implementation can be challenging due to the lack of accurate machine models. Most manufacturers do not provide comprehensive descriptions of their machines and the underlying system dynamics, making it difficult to generate an analytical model.

In this work, a Proportional-Integral-Derivative (PID) controller is employed for the low-level controller. The controller gains are adjusted primarily to prevent joint overshoot and avoid unintended collisions with the environment. The PID controller is chosen due to its simplicity and robustness, as it does not rely on accurate system models. By appropriately tuning the controller gains, the control inputs are optimized to achieve the desired joint movements.

4.5 Experimental Results

The experiments are designed first to evaluate the performance of the low-level controller using pulse tests. Then the trajectory tracking performance in the task space level is evaluated, where a position trajectory is computed by considering the desired hammer pose from the operator. After that, we show the performance of the implemented framework within a deconstruction task.

4.5.1 Pulse Test

The pulse tests are conducted to assess the performance of the low-level controller under various conditions, such as movements towards and against gravity in different directions. In these tests, the pulse time is set to 8 seconds. The PID gains are manually tuned by gradually increasing their values and comparing the system's performance. During this manual tuning process, special attention is given to avoid

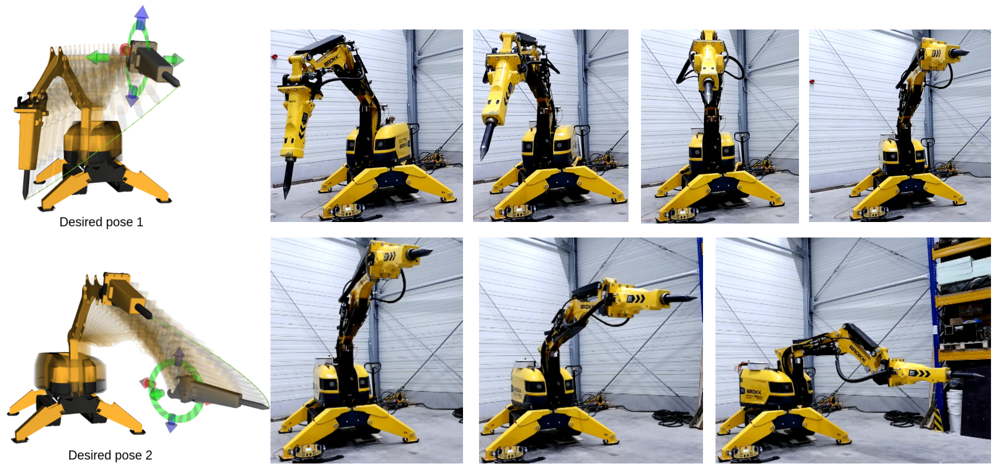


Figure 4.7: Desired poses 1 and 2 for the tracking test in the task space level and the snapshots from the real machine.

overshoot, as safety is a crucial concern when the machine's movement exceeds the target and encounters unexpected structures.

The overall tracking performance can be observed in Figure 4.6. While the implemented PID controller produces satisfactory results in terms of overshoot and rise time during the pulse tests, the differences in settling and rise time observed in two different rotation directions, i.e., towards and against gravity, indicate the nonlinear behavior of the system. This nonlinearity should be further investigated in future research to better understand its impact and refine the control approach.

4.5.2 Tracking Performance at the task level

The objective of this experiment is to assess the tracking performance of the implemented framework at the task level. To accomplish this, the BROKK 170 starts from a given initial pose $\mathbf{x}_s = [p_{xs}, p_{ys}, p_{zs}, \theta_s]^T$ = [1.96, -1.17, 1.69, 1.04]^T and moves towards the predefined end-effector

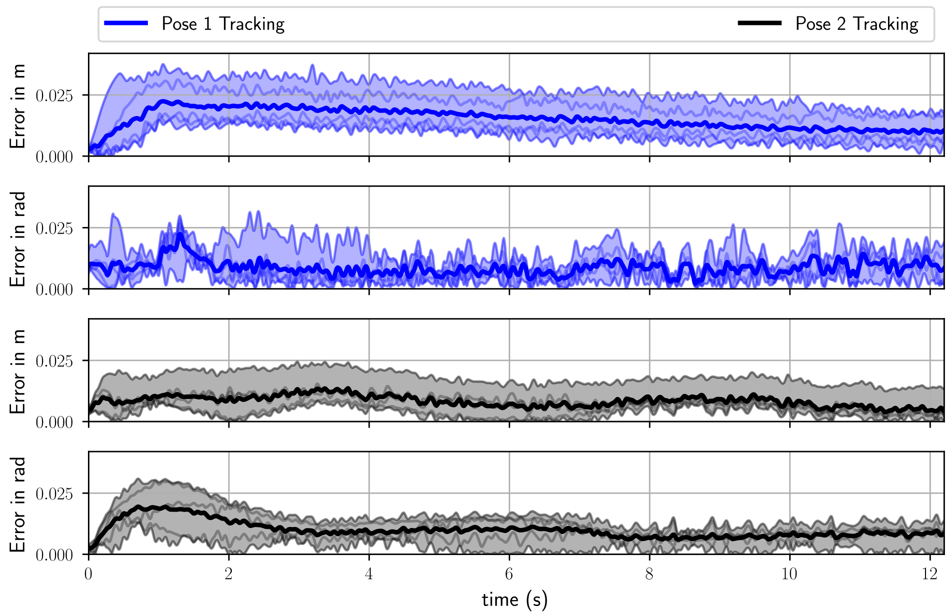


Figure 4.8: Tracking result in the task space level for the desired poses 1 and 2.

pose x_{d1} = [2.47, 0.01, 2.12, 0.38]^T. Subsequently, the robot proceeds from x_{d1} towards the desired pose x_{d2} = [1.84, 1.16, 1.78, 0.11]^T. This trajectory is repeated five times to evaluate consistency.

Figures 4.7 and 4.8 show that for the first desired TCP pose x_{d1}, the system achieved a position error of 2.5 cm and an orientation error of 0.02 rad. The tracking error decreased for the second pose x_{d2}, particularly as joints moved towards gravity. In x_{d1}, joints rotated from q_s = [2.10, 0.64, 1.13, 0.60, 2.01] to q_{d1} = [1.55, 0.64, 1.06, 1.30, 1.56], and for x_{d2} from q_{d1} to q_{d2} = [1.01, 0.64, 0.60, 0.78, 0.35]. Joint q_4 rotated positively in x_{d1} and negatively in x_{d2}, exhibiting faster response when rotating negatively, which led to a slightly larger tracking error for x_{d1}. Nonetheless, tracking errors remained small for both poses.

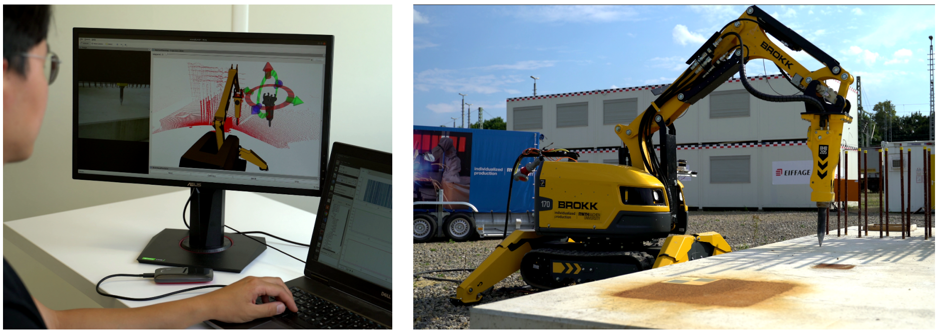


Figure 4.9: The operator in the control container monitors the remote site with 2D and 3D visuals (Left), views the machine's status, and uses an interactive hammer model to set the desired pose (Right).

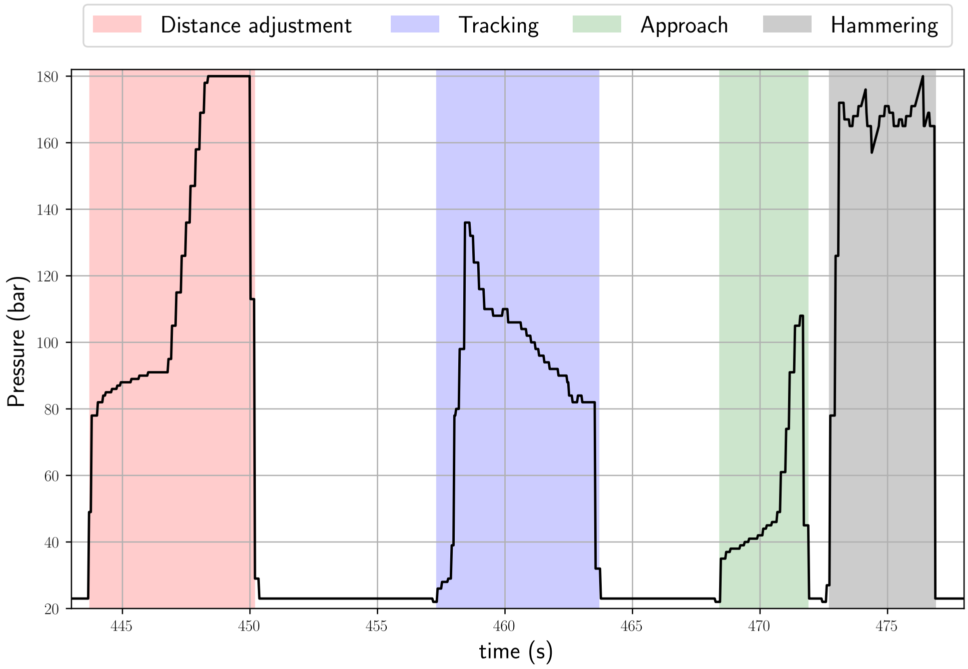


Figure 4.10: Pressure value profile from an individual hammering attempt. First, the joints are actuated in a disjointed manner to adjust the distance (q_2) and track the desired hammer pose ($q_{1,3,4,5}$). The manipulator moves down to press the chisel (green). Afterward, the hammering follows (grey).

4.5.3 Field Deployment

In order to demonstrate the system's performance, the BROKK 170's base is positioned in front of a concrete structure, and the manipulator carries out the deconstruction process using the proposed method. During this process, the operator interacts with the interactive hammer model, utilizing the visual information provided, see Fig. 4.9 to define the desired hammering target. The control container is situated at a distance of approximately 20 meters from the deconstruction site.

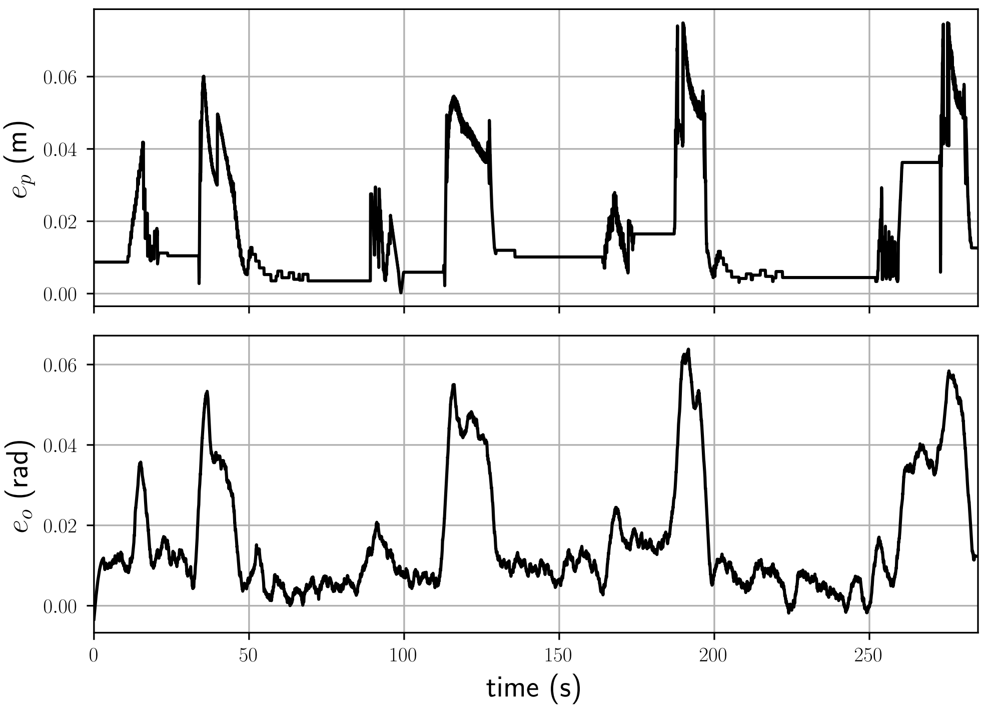


Figure 4.11: A snippet of task space level tracking performance during the deconstruction.

4.5.4 Experimental Results

The proposed system exhibits promising capabilities in achieving accurate deconstruction of structures in a semi-autonomous manner while prioritizing human operator oversight and safety throughout the process. Figure 4.10 provides a depiction of the pressure profile, offering insights into the transitions between different states. It is worth noting that the human operator retains the ability to modify planned movements or acknowledge actions, leading to idle states between each pre-defined state. For example, in the *approach* state, the pressure value gradually increases until the hammer tip makes contact with the object's surface, resulting in a sharp rise in pressure. Once the pressure value surpasses the threshold of 100 bar, the state transitions from *approach* to *hammering*.

Figure 4.11 illustrates that the tracking error remains minimal throughout the deconstruction experiment, indicating accurate tracking performance. As illustrated in Fig. 4.12 and 4.13, the proposed semi-autonomous deconstruction method offers a solution to mitigate the dust and risks associated with human proximity to heavy machinery in deconstruction sites while simultaneously increasing safety and accuracy by integrating the human operator into the control loop. Notably, the integration of the human operator's reasoning capability in defining the deconstruction target along with the pre-visualization of the planned motion for the operator, contributes to enhancing the controllability and safety of the deconstruction process.

4.5.5 Lessons learned from the field test

In this demonstration, we created a hardware and software framework to build and test the system. The successful completion of this demonstration was essential in evaluating the chosen framework and gaining valuable knowledge to enable robots to assist in deconstruction tasks in challenging environments like construction sites, which can be unstructured, cluttered, and dynamic. The conducted experiments demonstrate that it is possible to enhance the level of machine autonomy and improve controllability during the deconstruction process. However, as expected in any field test, we have identified several areas that need improvement and further investigation.

In this work, a fine-tuned PID controller was utilized to convert the desired joint states into the corresponding PWM values. Although the experiments show promising results, the performance can not be guaranteed if the disparity between nominal and actual system behavior increases during the dynamic deconstruction process. Here, more advanced control approaches need to be investigated.

The semi-autonomous approach presented in this study exhibits a limited depth of deconstruction, as illustrated in Fig. 4.13. This limitation arises from the dynamic nature of the deconstruction process. With each hammering attempt, the structure's surface undergoes continuous changes, necessitating dynamic adaptation of the hammer's orientation and position to maximize its impact. While a human operator positioned directly in front of the workspace can observe and promptly adjust the manipulator configuration during hammering in conventional teleoperation, the proposed method lacks this adaptiveness. Investigating and enhancing the adaptiveness of the approach in future research work is thus planned.

The integration of robotics technology in the construction industry presents promising opportunities for improving on-site operations and the collaboration between human workers and robots, as demonstrated in the conducted experiments. However, a crucial requirement for the successful implementation of such emerging technologies is stable and low-latency communication between the human operator and the robot, ensuring minimal data transmission delays. In our experiments, the remote workplace was captured using visual sensors and streamed to the operator through WLAN. Here, the continuous streaming of captured visual information over WLAN was found to be a limitation due to the resulting point cloud data size, even after resolution and scan area reduction, reaching several tens of megabytes. This highlights the need for a more robust wireless communication solution. While established compression techniques exist [53], their application often requires computation time, particularly when performed on embedded PCs. This poses a critical challenge, considering that the human operator heavily relies on spatial awareness of the remote workplace. One potential solution to address this challenge is leveraging the 5G mobile networking standard. However, the utilization of 5G for wireless communication in construction sites remains largely unexplored. One significant obstacle in existing research gaps is installing a 5G network on-site. Unlike many industrial production environments, the workspace in construction sites undergoes continuous infrastructure changes. For example, the workspace evolves in building projects as the structure is constructed. Therefore, the efficient deployment of a 5G network on-site and its effective integration with the control of construction machines is further investigated in Sec. 6.

4.6 Conclusions

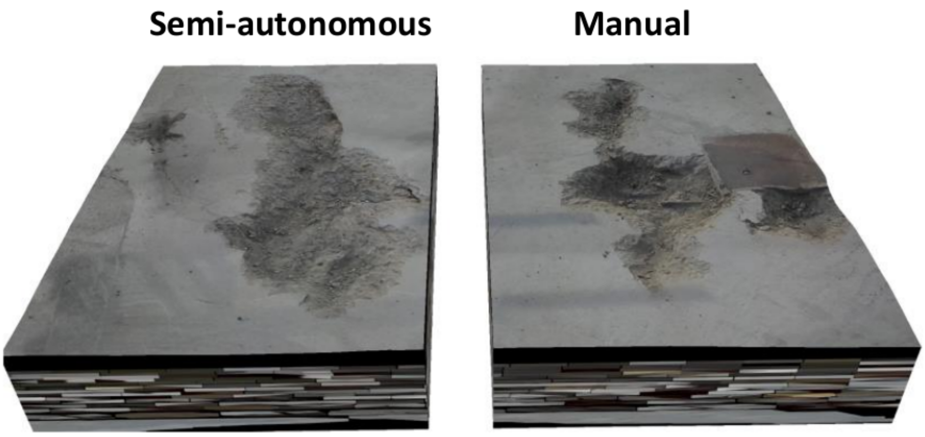
This paper introduces a semi-autonomous approach for deconstruction tasks, wherein a commercially available machine is further enhanced for the proposed work. Equipped with visual sensors, the machine enables the human operator to monitor the workspace remotely. The operator can define the desired hammering point through the interactive placement of a dummy hammer. A trajectory-tracking controller is developed to achieve precise control at both the joint and task levels. Prior to execution, the planned motion is visualized to the operator, allowing for the possibility of pre-planning and further optimization. Experimental results demonstrate the capability of the proposed approach for semi-autonomous deconstruction. However, the initial field test reveals both potential benefits and limitations.

The presented approach offers the potential to enhance worker safety by reducing the need for direct proximity between human operators and the machine or workspace, thus mitigating associated risks and hazards on the construction site. Additionally, verifying and adjusting the planned motion as needed can significantly improve the controllability of the deconstruction process. Traditional teleoperation techniques struggle with precise control of construction machines due to their complex degrees of freedom, requiring extensive training and experience. Visualizing the planned motion and enabling motion optimization for heavy-duty construction machines enhances overall process safety and efficiency, particularly when precision is required in the task.

Future research directions include investigating methods to enhance adaptiveness during hammering attempts, considering the continuously changing surface of the structure throughout the process. Additionally, exploring the potential of leveraging 5G technology will be pursued. Furthermore, the current work focuses on the hammer as the primary tool, and thus the aspect of material reuse has not been extensively addressed. Future investigations will involve replacing the hammer with a wall saw to explore the controlled dismantling of structures while preserving elements and materials for potential reuse.

Figure 4.12: Snapshots of the manual teleoperation (Top) and the semi-autonomous approach (Bottom) for deconstruction.

(a) Snapshot of the deconstructed area.



(b) Deconstruction results reconstructed in 3D.

Figure 4.13: Deconstruction results

Chapter 5

Assistance methods for teleoperated construction robot

The content in this chapter, encompassing both text and figures, has been reproduced from the following peer-reviewed papers. In these papers, the first author conceptualized the ideas, conducted experiments, and carried out the scientific writing, while the second author reviewed the original draft and contributed as the scientific supervisor:

- Lee, H. J., Brell-Cokcan, S. (2023). Task Space Control of Hydraulic Construction Machines Using Reinforcement Learning. arXiv preprint arXiv:2307.09246.

- Lee, H. J., Brell-Cokcan, S. (2023). Reinforcement Learning-based Virtual Fixtures for Teleoperation of Hydraulic Construction Machine. arXiv preprint arXiv:2306.11897.

5.1 Task Space Control of Hydraulic Construction Machines Using Reinforcement Learning

5.1.1 Abstract

Teleoperation is vital in the construction industry, allowing safe machine manipulation from a distance. However, controlling machines at a joint level requires extensive training due to their complex degrees of freedom. Task space control offers intuitive maneuvering, but precise control often requires dynamic models, posing challenges for hydraulic machines. To address this, we use a data-driven actuator model to capture machine dynamics in real-world operations. By integrating this model into simulation and reinforcement learning, a control policy for task space control is obtained. A 3t hydraulic construction machine, Brokk 170, serves as the platform for implementing the proposed approach. Through a series of experiments, the framework's validity is established by comparing it against a well-established Jacobian-based approach.

5.1.2 Introduction

Unlike the manufacturing industry, the construction sector poses unique challenges to robots due to its dynamic and diverse characteristics [44]. Construction sites constantly undergo changes throughout different stages of development, each presenting distinct hazardous conditions for human workers [54]. To mitigate these risks, teleoperation has become a crucial component of construction machinery in today's construction industry [80]. However, the complex nature of these machines, which often have multiple degrees of freedom (DoF) and require individual levers for remote control at the joint level, necessitates extensive operator training. Even experienced operators may need several months of training to effectively coordinate multiple joints and achieve the desired end-effector or tool motion. As a result, productivity decreases, local accuracy is reduced, and work efficiency is compromised.

Despite developing intelligent robotic systems equipped with advanced control and planning algorithms to address the challenges of unstructured construction sites and provide automation benefits, their autonomy is often constrained to highly unstructured environments. The reason behind this limitation lies in the impact of incomplete and inaccurate information regarding unfamiliar objects or unforeseen situations, which can significantly affect the decision-making process of robots and undermine their capacity for autonomous operation. To surpass the limitations faced by autonomous robots in unstructured environments, ongoing research aims to enhance operator capabilities through teleoperation systems that integrate automation techniques [56], such as virtual fixtures [46] or task space control [57].

Task space control enables the robot to manipulate its actions and interactions with the environment intuitively and efficiently, considering its multi-DoF nature. When the robot model is accurately known, task space control is well-established and offers various alternatives for resolution, including resolved-motion rate control, resolved-acceleration control, and force-based control [58]. However, constructing a dynamic model of a construction machine presents significant challenges due to various factors. The intricate mechanical structure of the machine and the complex interactions among its numerous components, such as hydraulic actuators, linkages, and sensors, make it difficult to model the system's dynamics accurately. Furthermore, the presence of nonlinearities like friction, backlash, and hysteresis adds further complexity to the modeling process, requiring advanced techniques to address these effects effectively [6]. In [48], the authors presented achievements in automating an excavator. However, a PI-controller was utilized as a low-level controller, underscoring the need for further research to integrate more sophisticated control strategies that account for the inherent complexities of the machine's dynamics.

To address these challenges and enable effective task space control, we propose a framework utilizing a data-driven approach based on reinforcement learning (RL). By integrating a data-driven actuator model that establishes a mapping between system states and corresponding control signals, this framework avoids the need for a lower-level controller. Instead, the framework directly produces the relevant control signals essential for achieving efficient task space control. In this approach, an agent is trained in a dynamic simulator and directly deployed in the real world. It is important to note that during the initial training phase, the agent may exhibit unpredictable behavior, which can raise safety concerns, particularly when dealing with heavy-duty machines. To overcome this issue, the task space control policy is learned through simulation and can be seamlessly applied to the real machine without requiring any parameter adjustments or post-processing. To the best of our knowledge, the application of general learning approaches to achieve task space control with a full scale of construction machines has not been adequately addressed.

5.1.3 System Description

The Brokk 170 consists of linkage and actuator systems that are connected to a mobile base, while the base itself is considered to be locally fixed throughout the study. In modern construction machinery like the Brokk 170, several electronic components are integrated into

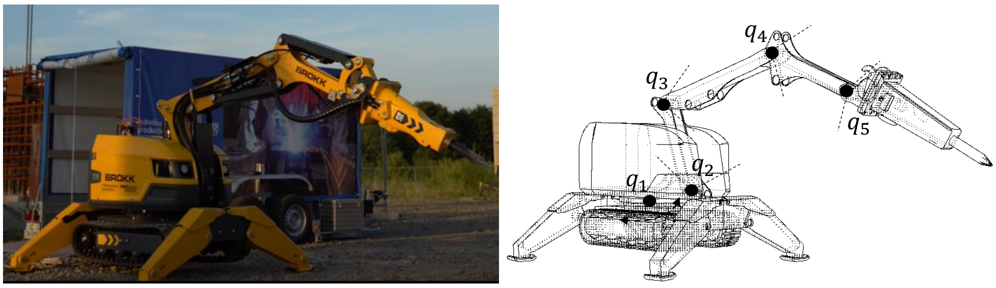
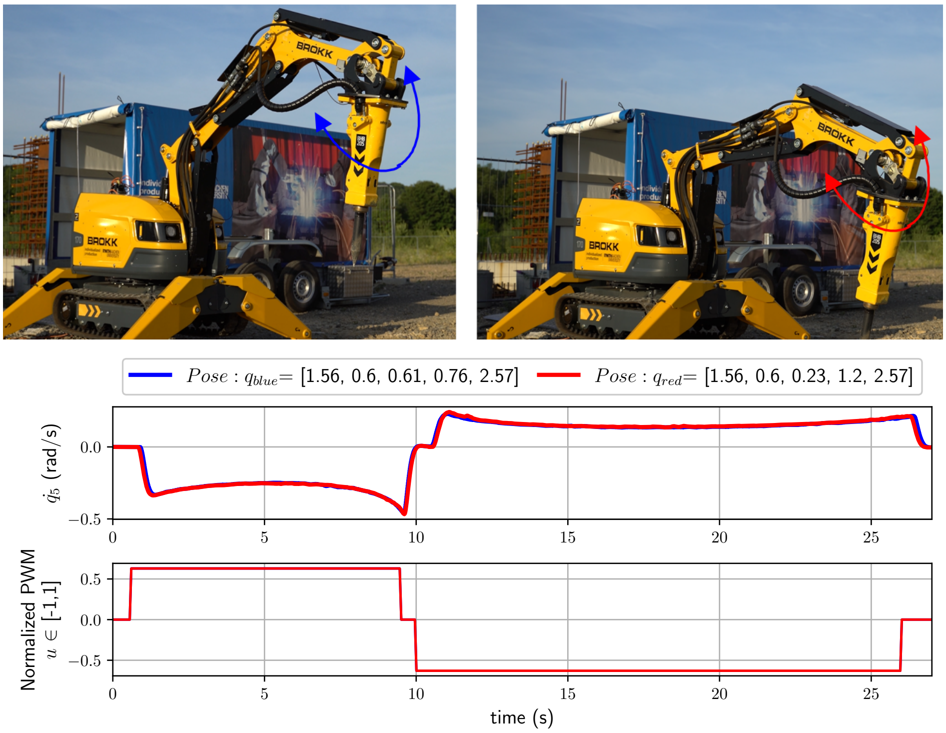


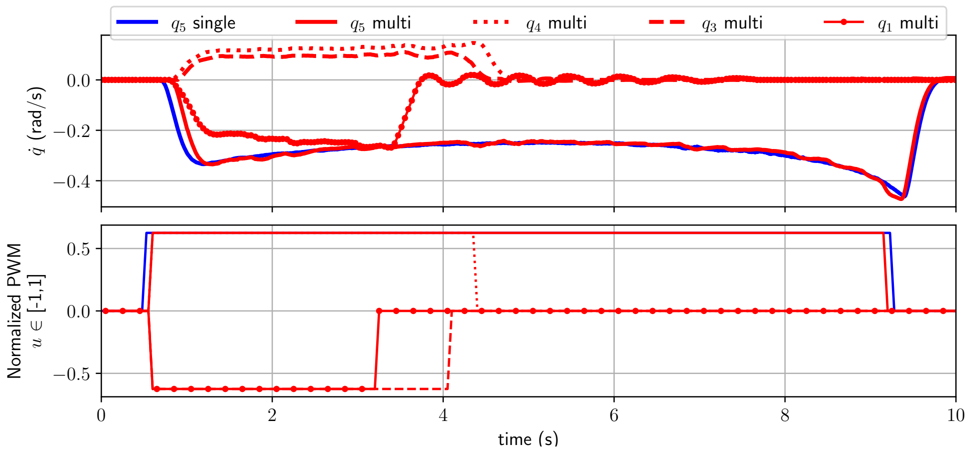
Figure 5.1: Brokk 170 (Left) and the geometric representation in the joint space (Right).

the system, including sensors. These components are connected to the machine control unit (MCU) through a Controller Area Network (CAN) bus. When the operator sends commands using a control device such as joysticks, specific bus messages are generated and translated into Pulse-Width Modulation (PWM) signals with designated voltage levels. These PWM signals are then transmitted to specific power electronics responsible for driving the machine's mechanical components. Each joint of the Brokk 170 is equipped with an absolute multiturn encoder IFM RM9000, which enables accurate tracking of the joint motion. A controller IFM CR711S and an embedded PC Jetson AGX Xavier are utilized to facilitate communication between the host PC and the MCU. The MCU, which is responsible for controlling the machine's valve system, operates at a frequency of 20Hz as specified by the manufacturer. In this work, instead of directly producing the PWM duty cycle from the joystick movement, the different joystick movements are converted into task space goals. These specified task space goals are then translated into corresponding PWM values for each joint in the host PC and wirelessly transmitted to the MCU through the controller, which has the CAN bus interface.

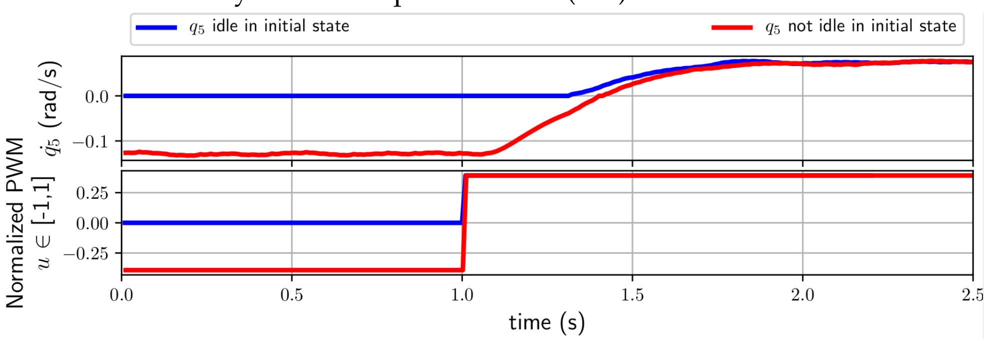
Brokk 170 is a hydraulic serial link manipulator consisting of five revolute joints. It is important to note that the second joint, denoted as q_2, is physically connected to q_3 (refer to Fig. 5.1). According to the manufacturer's specifications, q_2 is intended exclusively for adjusting the reach of the manipulator. To ensure the proper functioning of the machine, the manufacturer has established a communication protocol that restricts the rotation of q_2 in conjunction with other joints. Therefore, in this study, the focus is solely on implementing task-space control using joints q_1, q_3, q_4, and q_5 while disregarding the involvement of q_2 in the control process.



(a) Velocity profiles of q_5, when commanded pwm_5 values of 80 and 175 at different joint configurations of the machine.



(b) Velocity profiles of q_5 were compared when actuated individually (blue) and simultaneously with multiple actuators (red).



(c) Velocity profiles of q_5 and the corresponding pwm_5 normalized in [0,1].

Figure 5.2: Primary experiment tests results.

5.1.4 Method

Reinforcement learning (RL) revolves around the iterative process of collecting data through trial and error, automatically adjusting the control policy to optimize a cost or reward function that represents the task at hand [59]. This approach offers a fully automated means of optimizing the control policy, encompassing everything from sensor readings to low-level control signals. It provides a flexible framework for discovering and refining skills to solve complex tasks. However, RL typically demands extensive interaction time with the system to learn intricate skills, often requiring hours or even days of real-time execution [60]. Moreover, during the training phase, machines may exhibit sudden and unpredictable behavior, raising safety concerns, particularly when dealing with heavy-duty tasks.

To effectively train construction machines in handling complex tasks, our proposed methodology leverages advanced physics simulation technology. This involves training the machines in a simulated environment and transferring the acquired skills to human operators for real-world scenarios. By employing this approach, we mitigate the risk of unpredictable machine behavior during initial training stages and reduce the need for extensive real-world training data. However, the success of this methodology hinges on effectively bridging the reality gap between the simulated and real-world systems. To address this challenge, we incorporate the concept of a data-driven actuator model [61], which helps reconcile the disparities in system dynamics between the simulation and real-world environments.

Data-driven Actuator Model

In this work, we aim to train a control policy that directly outputs the control signals for task space control. The question arises of how different the machine behaves in the simulation, where the control policy is trained, from the real machine, when the same control signals are applied. As mentioned earlier, to minimize the difference in the mapping behavior between the system states and the control signals, we apply the data-driven actuator model. In this section, we introduce the required preliminary tests and the training procedure.

The selection of input and output sets in the network significantly influences the performance of predictions. In this study, we conduct experimental investigations to understand the factors that affect the mapping behavior between the control input (PWM) and joint velocity. These initial experiments also serve as a fundamental guideline for identifying the machine's relevant characteristics in relation to the proposed data-driven control approach, which is typically not provided by manufacturers.

Cylinder Movement Direction

The manipulator is inherently affected by gravity. If the joint rotates towards gravity, the according rotational speed is typically larger than rotating in the opposite direction. In this experiment, q_5 was rotated with the same PWM signal but a different sign (i.e., u_5= 80 and u_5= 175, respectively) throughout the actuation range. Here $u_5 \in$ [0,127] corresponds to the rotation into the positive direction and u_5 $\in$ [255,128] into the negative direction. The corresponding rotational speed $\dot{q}_5$ is reported in Fig. 5.2a. We conducted this test multiple times from different postures of the machine, as shown in Fig. 5.2a. As expected, the velocity was larger when rotating towards gravity with the minimum value around -0.47 $\frac{rad}{s}$. In contrast, in the other instance, the maximum velocity was around 0.24 $\frac{rad}{s}$. The different joint configurations did not have any impact on the velocity profile.

Coupled Dynamics

In general, coupled dynamics occur in hydraulic actuators if the fluid pump cannot deliver the requested fluid flow. In other words, the data collection process must be designed to sufficiently capture the coupled dynamics by simultaneously actuating multiple cylinders in the presence of the coupled dynamics. Thus, this test was conducted to analyze whether the system's behavior changes when numerous joints are actuated. Through this work, the maximum value for PWM is restricted to about 65 $\%$, i.e., 80 and 175, respectively. The reason for this is that the manipulator's impulsive movement with multiple joints actuation at full speeds can possibly cause the overturning of the machine or undesired collision with the environment. Thus, for the test, q_5 was rotated along its actuator range with u_5= 80. At the second time, the q_1, q_3 and q_4 were also simultaneously rotated with u_1= 175, u_3= 175 and u_4= 80, respectively, while u_5= 80 was applied to q_5 like the first test. The result in Fig. 5.2b shows that the difference is marginal and neglectable.

Past Movement

Brokk 170 used in this work has a slow system reaction, as shown in Fig 5.2c. As a result, the system's previous states often influence the next state, i.e., even if the same PWM signal is transmitted to the same system, the resulting velocity profile varies depending on the system's prior and present velocity. Fig. 5.2c clearly shows this behavior. Here, the same PWM signal is sent to q_5 at $1s$. In the first test, q_5 starts from

Table 5.1: Inputs/Outputs of the data-driven actuator model

Inputs	
Joint Positions	$q_i^{t-0.6s}$,$q_i^{t-0.55s}$, $\cdots$, q_i^t
Joint Velocities	$\dot{q_i}^{t-0.6s}$,$\dot{q_i}^{t-0.55s}$, $\cdots$, $\dot{q_i}^t$
Control Signals	$\dot{u_i}^{t-0.6s}$,$\dot{u_i}^{t-0.55s}$, $\cdots$, $\dot{u_i}^t$
Output	
Joint Velocity	$\dot{q_i}^{t+0.05s}$

its idle state, not moving. The response time is roughly $400ms$ in this case. When q_5 is already moving, the response time is faster with approximately $100ms$. As this result clearly shows, the past states play a vital role in accurately describing the correlation between u and $\dot{q}$, particularly before $\dot{q}$ converges.

Methods of Training

Based on the primary experiment results from the previous section, the set of network input and output is defined, as listed in Table 5.1. To collect the training data that captures the actuator's behavior in different directions and speeds, PWM signals are generated in a sine waveform. Here, the sine wave's frequency and amplitudes are randomly modified. The generated PWM signals are applied until the corresponding joint reaches its minimum or maximum, where the joint then returns back to the home configuration. Then the next sine wave is generated. The data collected during the return is not included in the training data.

We collect the dataset during $1h$ for each actuator separately at 20 Hz ($5h$ for all the actuators) as the coupling dynamics are found to be insignificant (see Fig. 5.2b). By collecting the training data separately for each actuator, we can reduce the risk of collision between the machine and the environment, as the other actuators can be moved to a safe configuration and held still while obtaining the data from one actuator. The generated PWM signals are set to be larger than the dead zone to partially compensate for the dead zone, estimated to be roughly 7% of the maximum. Also, the PWM duty cycle is limited to 65% of its maximum due to safety.

The nonlinear relationship between the given PWM and the resulting joint velocity is modeled using a multi-layer perceptron (MLP), which consists of two hidden layers with 32 units, a ReLu activation function, and a linear output layer with a sigmoid activation function. All the input and output data are normalized. The model is trained using the mean squared error (MSE) loss function and Adam optimizer, where the loss converges after around 0.75h for each model.

Learning the task-space control policy

Brokk 170 utilized in this study possesses a total of five degrees of freedom (DoF), out of which four DoF are employed for task space control, as mentioned in the previous section. In this work, the robot's base is considered to be fixed. Consequently, the task space can be defined as $\mathbf{x} = (x, y, z, \theta)$, where $\mathbf{x}$ represents the position and orientation in the task space. However, when tracking a goal in the task space with the joint configuration $\mathbf{q} \in \mathbb{R}^4$, the robot may encounter challenges in accurately following the goal. Therefore, in this study, we do not track the orientation component θ in order to demonstrate the performance of the implemented task space controller. By omitting the orientation tracking, we can focus on evaluating the performance of the task space control without additional errors arising from the limited robot configuration and kinematics.

To address the nonlinear dynamics of the actuators and achieve optimal control inputs, we employ RL, as it allows for learning through

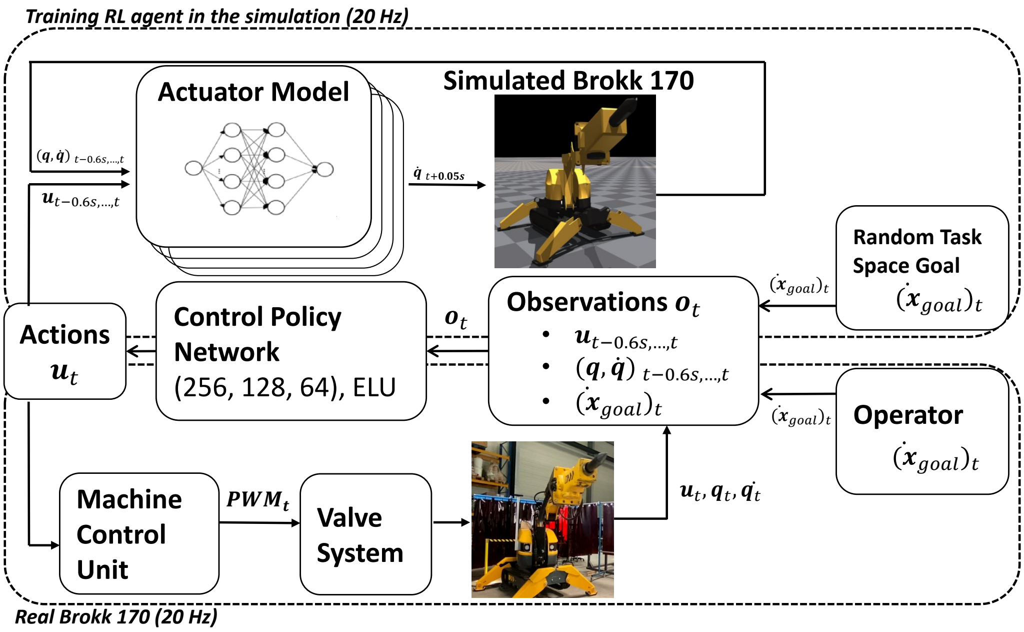


Figure 5.3: Overview of the proposed system.

trial and error. In our approach, we integrate a real-world data-driven actuator model into the RL environment, enabling the RL agent to effectively handle input delays and nonlinear dynamics, thereby optimizing the coordination of the joints.

Observation

At every time step t, the agent is provided with an observation that encompasses various details about the current state of the environment. These details include information like the present and target velocity of the end-effector, as well as the requisite data for the actuator network, see Fig. 5.3. It is assumed that the kinematics of Brokk 170, specifically the joint position and link lengths, are already known. Therefore, utilizing only the joint values is sufficient for determining the position and velocity of the end-effector through forward kinematics.

Rewards

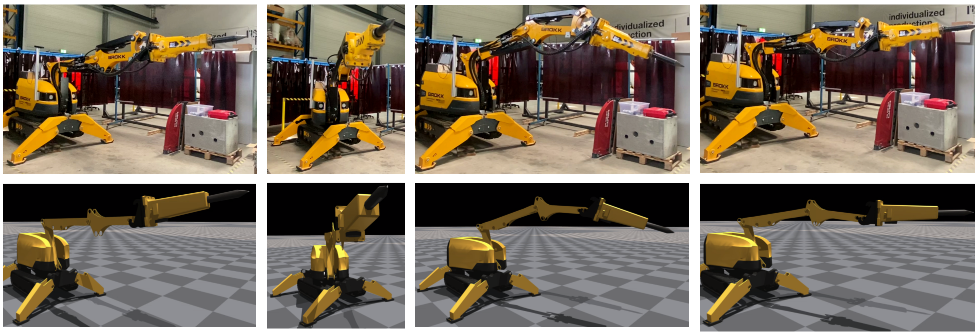
A reward function is utilized to guide the learning process and encourage the desired behavior in the control policy. Typically, this function incorporates penalties for actions that lead to undesired behaviors, such as collisions with the environment (in this case, the ground). However, considering the nature of construction machines that are intended to manipulate the environment for construction purposes, no additional penalty is implemented in this context. The reward function is designed such that the agent utilizes joints $q_{1,3,4,5}$ to control the end-effector velocity v_t^{ee} according to the desired velocity v_t^d:

$$r_t = 1/(1 + \|v_t^d - v_t^{ee}\|_2) \tag{5.1}$$

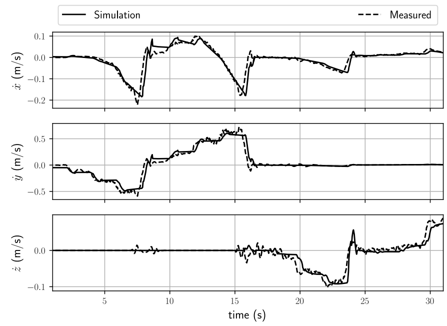
At every time step t, the reward r_t is calculated and accumulated throughout each episode. This approach ensures that the agent is inherently motivated to promptly track the desired velocity, aiming to maximize the overall reward.

Training Procedure

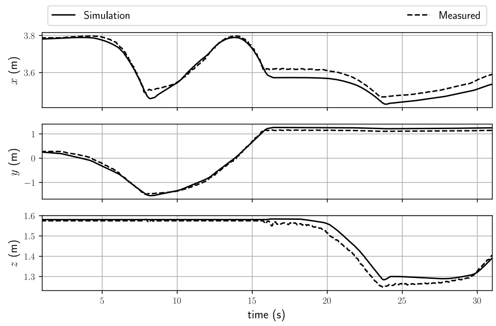
To effectively train the agent, maintaining a high sampling rate is essential for learning the tasks at hand. We used the IsaacGym simu-



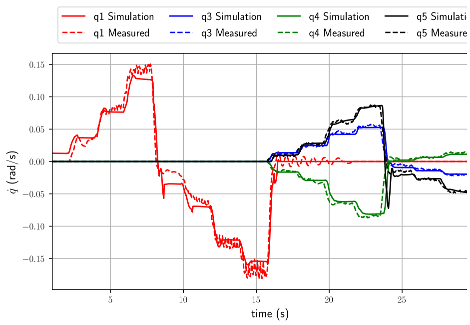
(a) Snapshots from the experiments, where the same sequence of control signals are applied to the real machine (top) and the simulation (bottom)



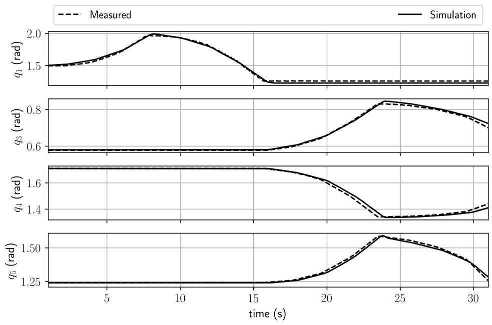
(b) Velocity difference in the task space



(c) Position difference in the task space



(d) Velocity difference in the joint space



(e) Position difference in the joint space

Figure 5.4: Comparison between the simulated and the measured movement.

lator [62], a specialized environment for policy learning with a parallelized physics engine on a single GPU, enabling rapid sampling and

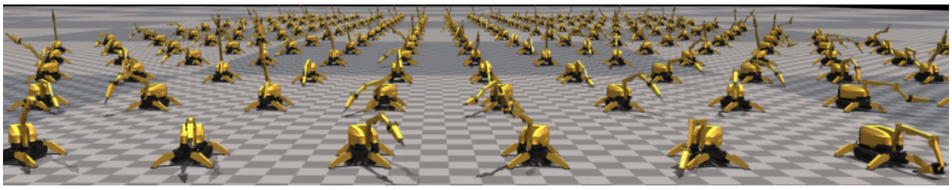


Figure 5.5: Parallel simulation environment with 256 agents to train a control policy for task space control

improved learning. After each episode, we randomly reset the initial arm configuration to introduce diversity in starting positions, enhancing adaptability. If the episode exceeds the maximum length, we terminate it. In cases where the initial arm configuration intersects with the ground after the reset, the episode is immediately terminated without rewards.

For task space control policy training, we employed the Proximal Policy Optimization (PPO) algorithm [63]. We used the PPO implementation by Makoviichuk et al. [64], supporting GPU-accelerated training with parallel environments in Isaac GYM. To address noise from machine vibrations, we added uniformly sampled white noise to $\mathbf{q}$ and $\dot{\mathbf{q}}$ controlled by a scaling factor. The noise maintains a consistent maximum amplitude of 5% throughout episodes. Two multilayer perceptron (MLP) neural networks approximate the value function and policy. These networks have three hidden layers with 256, 128, and 64 units, respectively, using Exponential Linear Unit (ELU) activation and linear output. Training the control policy occurs at 20 Hz on a system with an Intel Core i7-9850H CPU, 16GB RAM, and an NVIDIA Quadro RTX 3000 GPU. To expedite the training process, all observations and actions are standardized by applying a normalization technique using mean and standard deviation. Also, 256 agents are employed in parallel, as shown in Figure 5.5. The training process takes around 2.5 hours to converge.

Jacobian based Task Space Control

To evaluate the performance of the trained policy, we compare it with a well-established method based on the pseudo-inverse Jacobian matrix [57], which we briefly introduce in this section:

$$\dot{\mathbf{q}}_t = \mathbf{J}^{+}(\mathbf{q}_t)(\mathbf{x}_{goal} + \mathbf{K}\mathbf{e}_t) \tag{5.2}$$

,where $\mathbf{J}^{+}$ represents the pseudo-inverse of the Jacobian [65], $\mathbf{K} \in \mathbb{R}^{3x3}$ is a positive definite gain matrix and $\mathbf{e} \in \mathbb{R}^{3x1}$ is the remained velocity error. In this work, $\mathbf{J}^{+}$ is defined by introducing the weighted least squares method [66] and damped least square method [67] to handle the joint limit and singularity problem, respectively:

$$\mathbf{J}^{+} = \mathbf{W}^{-1}\mathbf{J}^{T}(\mathbf{J}\mathbf{W}\mathbf{J}^{T} + \lambda^{2}\mathbf{I})^{-1} \tag{5.3}$$

,where the diagonal matrix $\mathbf{W} \in \mathbb{R}^{5x5}$ is utilized to penalize the joint motion when a joint approaches its hardware limit. The elements of $\mathbf{W}$ are adjusted to impose suitable penalties based on the proximity of each joint to its limit. Additionally, the damping factor λ is employed to restrict the robot's motion when it approaches a singularity, preventing undesired behavior.

5.1.5 Experimental Evaluation

The objective of this study is to develop a task space control policy in simulation that can be directly deployed on a real machine without any modifications. This requires minimizing the gap between the simulation and the real-world performance (referred to as the Sim2Real Gap). To achieve this, we first assess the effectiveness of a data-driven actuator model integrated into the simulation. Subsequently, we demonstrate the performance of the trained task space control policy on a real-world Brokk 170 machine.

Sim2Real Gap

The purpose of this experiment is to evaluate the disparity between the behavior of a simulated machine and a real machine, both in terms of task space and joint space. To achieve this, Brokk 170 was initially set to a specific pose defined by the joint configuration vector $\mathbf{q}_s = [1.5, 0.5, 0.58, 1.71, 1.24]$, see Fig. 5.4a. A predetermined sequence of control signals, spanning a duration of 30 seconds, was applied to the joints of the robot. This control signal sequence was intentionally designed to induce diverse changes in joint angles and simultaneous actuation of multiple joints. In order to assess the performance of the simulation, the same control signal sequence was also applied to the simulated Brokk 170. The control signals from the predefined sequence were applied at a frequency of 20 Hz throughout the experiments. Similarly, the joint angle and velocity values, as well as the end-effector position and velocity, were recorded at the same frequency of 20 Hz.

The experimental results are depicted in Figure 5.4. Notably, in the simulation, the error accumulated over time due to the reliance on predicted joint angle values for subsequent predictions. However, despite this accumulation, the discrepancy between the simulation and the real machine, both in the joint and task space, remained reasonably small. This outcome suggests that the integrated data-driven actuator model effectively captures the underlying nonlinear effects of the hydraulic system.

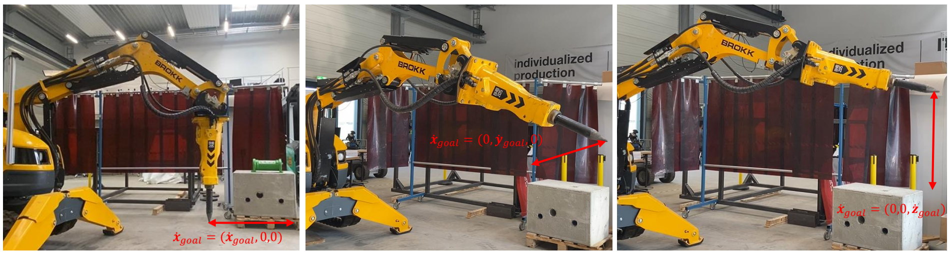
Task Space Control

In this experiment, we assess the effectiveness of the trained policy for task space control by directly deploying it onto the Brokk 170 machine without any additional tuning. The control policy is designed to generate control signals based on the desired goal velocity in task space. It operates in the background at a frequency of 20 Hz and communicates with the machine control unit (MCU) responsible for controlling the actuators.

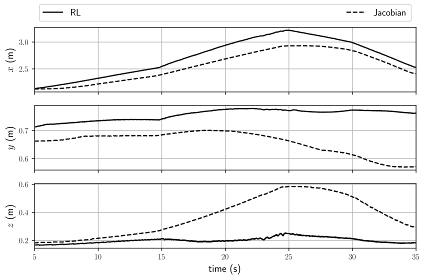
In order to assess and contrast these two distinct approaches under identical conditions, a predetermined velocity sequence in the task space was applied to both the trained control policy and the Jacobian-based controller. This experiment encompassed three distinct velocity sequences: one in the x-direction, one in the y-direction, and one in the z-direction, as illustrated in Fig. 5.6. For the case of movement in the x-direction, the velocities of y and z were set to zero (Fig. 5.6c), ensuring that only the x position would experience an increment while the y and z positions remained stationary.

The results depicted in Figure 5.6b demonstrate this expected behavior of the RL agent, where the y and z positions remain stationary. In contrast, the Jacobian-based method significantly fails to maintain the stationary positions of y and z, as evident from the figure. This discrepancy can be attributed to the observations presented in Figure 5.6d. After Equation (3) computes the desired joint motions to move the end-effector according to $\mathbf{x}_{goal}$, the resulting $\dot{\mathbf{q}}_t$ is converted into PWM signals that actuate the joints. Various advanced control methods, such as backstepping-based adaptive controllers [68], can be utilized for this low-level control task. However, these controllers typically rely on accurate dynamic models of the system. The performance accuracy of such controllers heavily depends on the precision of the model employed. Consequently, in practice, PID controllers are often employed for this low-level control task, as in the present work. However, due to the nonlinearity of the hydraulic system, the fine-tuned gains of the PID controller yield varying results depending on the direction of movement and the velocity amplitude. Figure 5.6d clearly depicts how the PID gains perform well when q_4 moves in the positive direction. However, around $t = 25$ s, when the direction changes, the performance deteriorates.

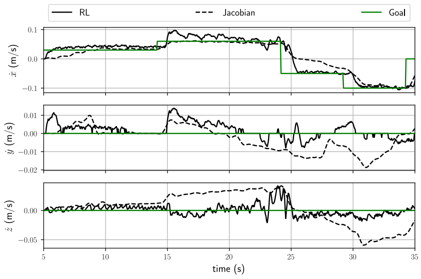
In contrast, the trained RL agent directly outputs control signals in the form of PWM signals, as shown in Figure 5.3. During the training process, the RL agent explores and learns the relationships between control signals and resulting end-effector velocities, enabling robust velocity tracking, as illustrated in Figures 3c, 3f, and 3h. As previously mentioned, the damped least square method is employed to address the singularity problem, aiming to dampen the robot's motion using a damping factor λ when it approaches a singularity. Typically, λ is determined based on a constant k and the current manipulator configuration [67]. However, this damping effect can impede accurate task space control [65]. By reducing the damping effect through a lower value of the constant k, the system often exhibits jerky movements near the singularity, particularly when the arm is almost fully extended, as illustrated in Figure 5.6a. The resulting jerky movements are also evident in the position and velocity profiles, as shown in Figures 5.6e and 5.6f at $t = 18$ s when k is reduced from 0.1 to 0.05. In contrast, the RL agent demonstrates a more robust performance, which can also be verified in case of movement in z-direction, see Fig. 5.6g and 5.6h.



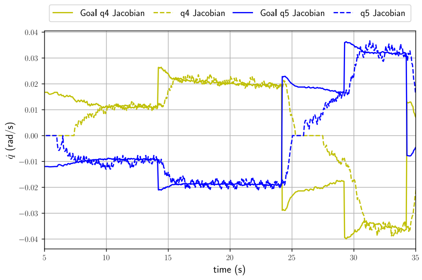
(a) Different start configuration for the task space control test.



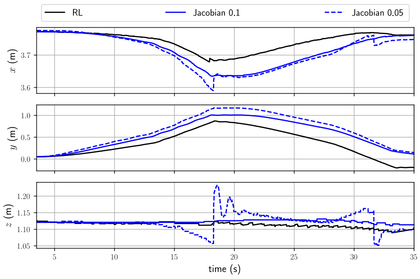
(b) Position profile in the task space



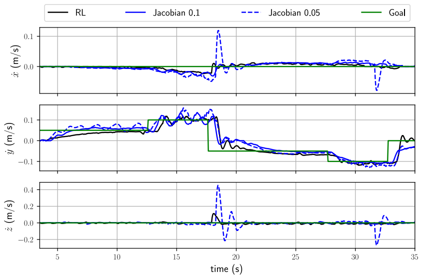
(c) Velocity profile in the task space



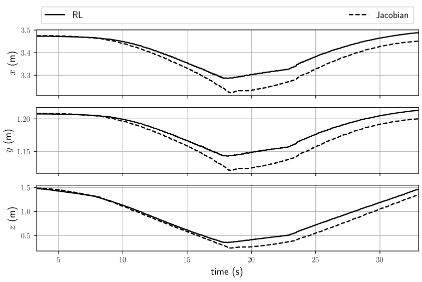
(d) Velocity profile in the joint space



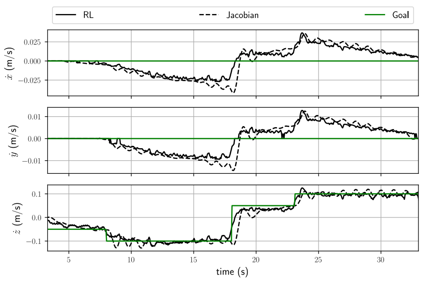
(e) Position profile in the task space



(f) Velocity profile in the task space



(g) Position profile in the task space



(h) Velocity profile in the task space

Figure 5.6: Results during x-direction (b-d), y-direction (e,f) and z-direction (g,h).

5.1.6 Conclusion

This paper introduces a reinforcement learning (RL) framework designed to learn an effective policy for task space control in a simulation environment. The goal is to enable direct deployment of the learned policy to a real construction machine without any modifications. To bridge the gap between simulation and reality, a data-driven actuator model is incorporated during training to capture the machine-specific nonlinearities in the relationship between control inputs and system state changes. The learned control policy takes the desired velocities in the x-, y-, and z-directions in task space as input and directly generates the corresponding control signals. Compared to conventional methods, the RL-based approach has the advantage of not relying on a dynamical model, making it suitable for hydraulic machines where such models are typically unavailable. Additionally, the proposed method outperforms the Jacobian-based approach by eliminating damping effects and the need for a low-level controller.

In the context of teleoperation, an assistance system is proposed, which enables intuitive task space control. This system enhances safety during teleoperation and minimizes tracking errors during task execution, particularly for heavy-duty hydraulic machines, as operators can now directly generate desired motions within the task space, eliminating the need for manual control and coordination of individual joints. The effectiveness of the proposed method is evaluated through experiments conducted on a full-scale hydraulic machine, Brokk 170. In future work, the authors plan to further investigate the impact of the proposed method on mental workload and task efficiency by conducting additional explorations and evaluations involving a larger number of participants.

5.2 Reinforcement Learning-based Virtual Fixtures for Teleoperation of Hydraulic Construction Machine

5.2.1 Abstract

The utilization of teleoperation is a crucial aspect of the construction industry, as it enables operators to control machines safely from a distance. However, remote operation of these machines at a joint level using individual joysticks necessitates extensive training for operators to achieve proficiency due to their multiple degrees of freedom. Additionally, verifying the machine's resulting motion is only possible after execution, making optimal control challenging. In addressing this issue, this study proposes a reinforcement learning-based approach to optimize task performance. The control policy acquired through learning is used to provide instructions on efficiently controlling and coordinating multiple joints. To evaluate the effectiveness of the proposed framework, a user study is conducted with a Brokk 170 construction machine by assessing its performance in a typical construction task involving inserting a chisel into a borehole. The effectiveness of the proposed framework is evaluated by comparing the performance of participants in the presence and absence of virtual fixtures. This study's results demonstrate the proposed framework's potential in enhancing the teleoperation process in the construction industry.

5.2.2 Introduction

In contrast to the production industry, the construction industry presents a unique challenge to automation due to its dynamic and

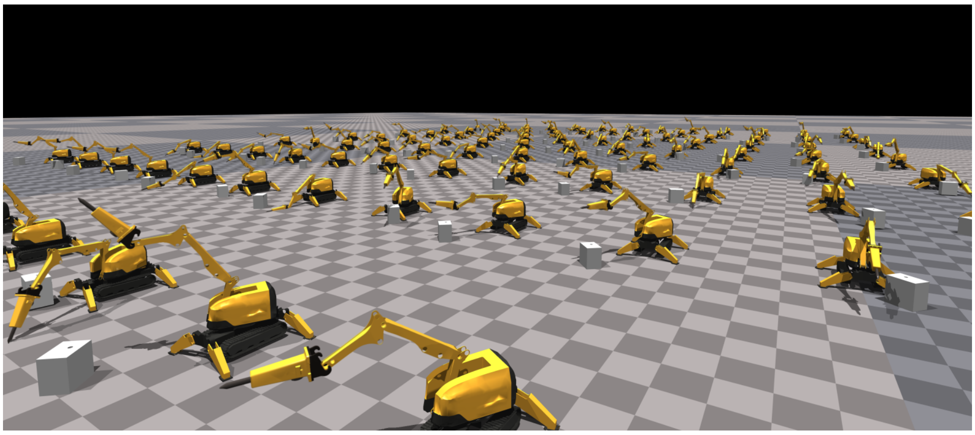


Figure 5.7: Simulation environment with 128 agents being progressed in parallel to train a control policy for the hammer insertion task.

multifaceted nature [44]. Construction sites are constantly changing through various stages of development, where each stage possesses different dangerous conditions for human workers [80]. To mitigate these risks, teleoperation has become a vital component of construction machinery in the current construction industry [81]. However, the complex nature of these machines, which often have multiple degrees of freedom and require individual levers for remote control on a joint level, requires significant operator training. Even experienced operators may require months of training to coordinate multiple joints to achieve the desired end-effector or tool motion. This can result in decreased productivity and reduced local accuracy and work efficiency.

While intelligent robotic systems with advanced control algorithms have been developed to address the challenges posed by the unstructured nature of construction sites and provide numerous benefits associated with automation [6, 48], the autonomy of these robots may be limited in highly unstructured environments. This is because incomplete and inaccurate information about unknown objects or unexpected situations can significantly impact the decision-making process of the robots, compromising their ability to operate autonomously.

To overcome the limitations of autonomous robots in unstructured environments, research is focused on enhancing operator capabilities through teleoperation systems that integrate automation techniques such as virtual fixtures [2]. Virtual fixtures guide a remote manipulator or robot to perform a desired task and can be classified as forbidden-region virtual fixtures or guidance virtual fixtures [69]. These systems reduce operator workload, increase task efficiency, and improve system performance in complex tasks [70]. However, the complex system dynamics of hydraulic construction machines present a significant challenge in this area of research [71]. Analyzing and modeling the system's behavior is often challenging due to its significant nonlinear system dynamics.

To address these challenges, we suggest employing a data-oriented method that leverages data gathered while the machine operates, enabling the capture of its unique attributes. Our method does not depend on a detailed analytical model of the system, time-consuming parameter tuning, or costly hardware adjustments. The machine's data-driven model is seamlessly integrated into a reinforcement learning (RL) framework. This approach empowers RL agents to discover efficient approaches for accomplishing tasks autonomously, without human intervention. The policies generated by these agents can then assist human operators by guiding virtual fixtures.

5.2.3 Related Work

Developing an autonomous robotic system that can effectively operate in unstructured environments is a formidable challenge, owing to the complexity and limitations inherent in such environments. As a result, the interest in teleoperation support as a viable alternative has continued to grow. Among the promising methods of teleoperation support is the virtual fixture-based assistance system, first introduced by Rosenberg [2]. This system enhances situational awareness and mitigates the cognitive load of teleoperation by overlaying supplementary information on sensory data. Since the introduction of Rosenberg's collaborative control concept in teleoperation, numerous other approaches have been proposed [72, 73].

While virtual fixtures have been shown to enhance system performance in previous studies, limited research has focused on applying virtual fixtures to construction machines. The dynamic nature of construction sites, with frequently changing task conditions and objectives, presents a significant challenge. A pre-defined set of virtual fixtures can quickly become impractical and restrictive. Furthermore, precise information about the system dynamics is often necessary to effectively guide operators using virtual fixtures. However, modeling the system dynamics of construction machines is often challenging due to the nonlinearity of their hydraulic circuits, requiring significant effort and resources that are frequently impractical.

Applying data-driven methods in nonlinear construction machines has collected considerable interest among researchers. Notably, researchers have employed neural networks to capture the underlying dynamics of excavators using a supervised learning approach [74], and have trained control policies for grading tasks through a data-driven actuator model in simulation using a reinforcement learning framework [75]. Despite the advancements established in these studies, human operators do not use the knowledge generated about optimizing excavator control. Given construction sites' unstructured and dynamic nature, it can be challenging to implement autonomous approaches for all construction sites. Thus, transferring the knowledge from the autonomous control policies to the operator can be advantageous. This transfer would allow operators to benefit from the optimized movement learned through the autonomous approach and apply this knowledge to subsequent teleoperation tasks.

This study aims to expand upon the conventional data-driven reinforcement learning (RL) approach for training control policies. We propose a framework where RL agents initially learn effective task-completion strategies without human intervention. Subsequently, these learned policies are utilized to teach humans by providing visualized optimized control inputs, including joystick motions, with guidance virtual fixtures. The primary objective of this approach is to introduce a new method for supporting operators in the teleoperation of construction machines by leveraging the latest advancements in data-driven control methods. Specifically, the operator specifies the overarching objective by designing the reward function, and the RL agents generate efficient skills that the operator can learn via the guidance of virtual fixtures. We demonstrate the effectiveness of our proposed framework by conducting hardware experiments on Brokk 170, a hydraulic construction machine in the context of a hammer insertion task, and present the results of our user study.

5.2.4 Method

To facilitate the transfer of knowledge from machines to humans, it is necessary to first train the construction machine to effectively tackle the given task, considering that the task conditions and the construction site undergo constant changes throughout the project. Data-centric methodologies, such as reinforcement learning (RL), have gained significant traction in addressing this challenge, presenting a versatile learning framework for machines. RL involves the accumulation of data through iterative experimentation and automatic fine-tuning of the control policy to optimize the reward function that represents the task [59]. This process can be fully automated, enabling

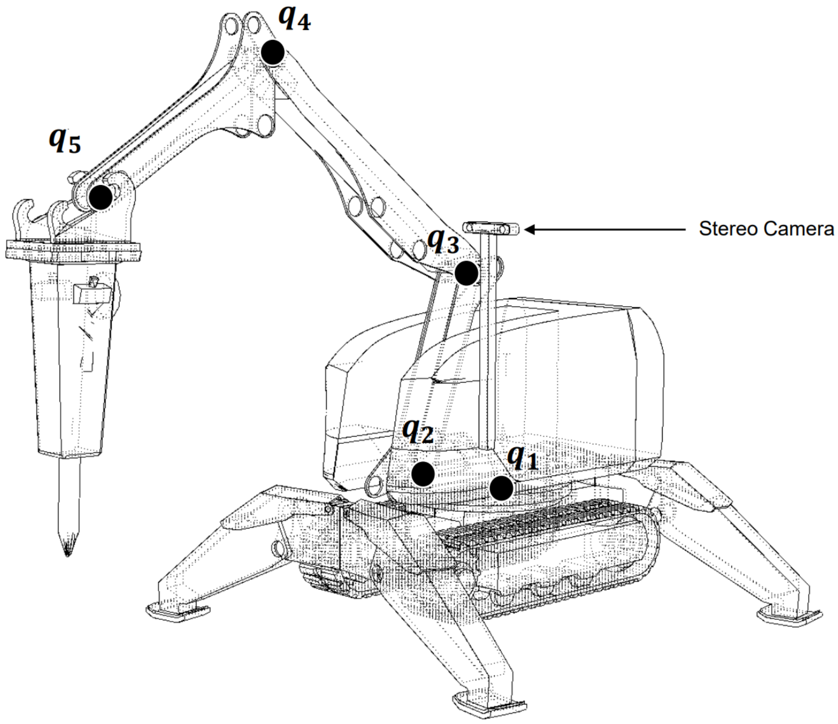


Figure 5.8: Joint configuration of Brokk 170 used in this work.

end-to-end optimization of the control policy, from capturing sensor readings to generating precise low-level control signals, thereby creating a highly adaptable framework for identifying suitable skills to resolve the task at hand. However, RL typically necessitates extensive interaction time with the system to acquire complex skills, often spanning hours or even days of real-time execution [60]. Furthermore, during the training phase, the machine may exhibit abrupt and unpredictable behavior, giving rise to safety concerns, particularly in scenarios involving heavy-duty machinery.

The proposed methodology aims to tackle the challenge of effectively training construction machines to handle intricate tasks by leveraging advanced physics simulation technology. This involves training the machines in a simulated environment and transferring the acquired skills to human operators in real-world scenarios. This approach reduces the risk of unpredictable machine behavior at the beginning of the training and lessens the need for extensive training data. However, its effectiveness depends on successfully bridging the reality gap between the simulated and real-world systems. To address this challenge, this work utilizes the concept of the data-driven actuator model [61] to address the discrepancies in system dynamics between the simulation and real-world environments.

The proposed approach involves steps illustrated in Figure 5.3. Firstly, the actuation is modeled using measurements obtained during the operation of the construction machine. Secondly, a control policy is trained in the simulation for the given task, taking into account the underlying dynamics of the machine in conjunction with the actuator model. Thirdly, a perception pipeline is implemented to estimate the pose of the borehole on the test concrete block. Finally, the trained control policy is applied to the real machine, and the output of the control policy is transformed into virtual guidance fixtures to train human operators in efficiently accomplishing the task.

Data-Driven Actuator Model

This study explores the relationship between control input and system state change in hydraulic machines by utilizing a multi-layer perceptron (MLP) neural network. The MLP has two hidden layers, each with 32 units, and is equipped with a rectified linear unit (ReLu) activation function and a linear output layer. To gather training data that effectively characterizes the behavior of the actuator at varying directions and velocities, we generated PWM signals in a sine waveform. The frequency and amplitudes of the sine wave were randomly adjusted. The resulting PWM signals were applied until the associated joint reached its maximum or minimum position, at which point the joint was returned to its original home configuration. Training data is

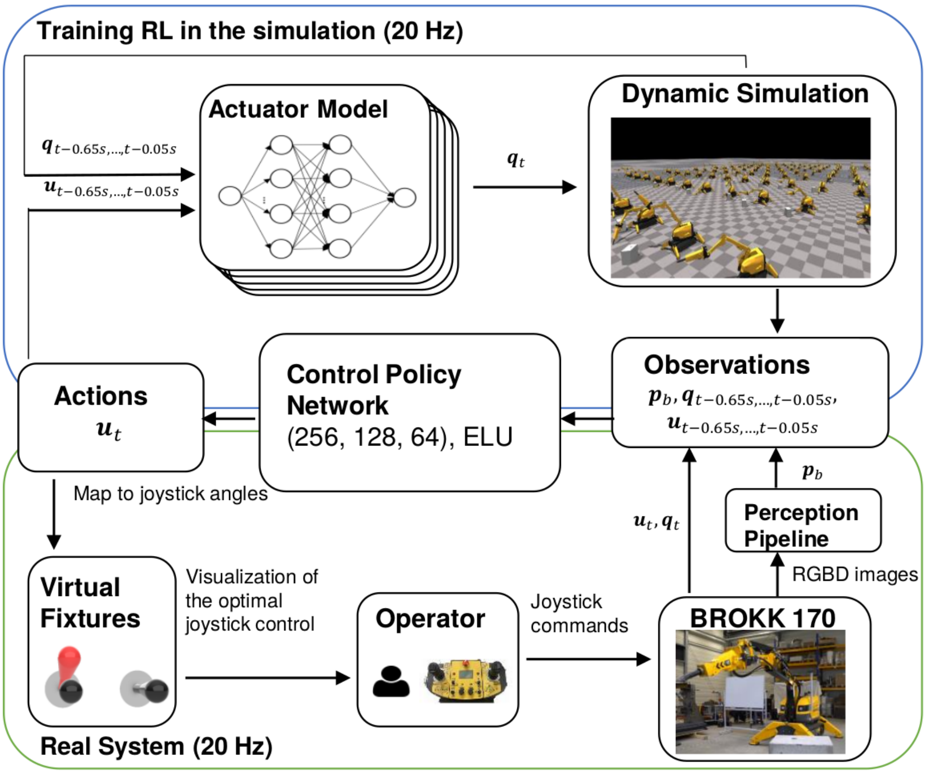


Figure 5.9: The approach starts by training a control policy in a dynamic simulation with the actuator model to minimize the gap between reality and simulation. Here, the actuator model accepts $u_{t-0.65s,...,t-0.05s}$ and $q_{t-0.65s,...,t-0.05s}$ as inputs and generates q_t. This output is subsequently utilized within the dynamic simulation to reproduce a realistic actuator motion. The policy, trained using this actuator model, is then implemented on the physical machine. The resulting output is converted to joystick angles for virtual fixtures to the operator. By following the control policy's computed outputs as a guideline, the operator learns to perform the task optimally.

collected at 20 Hz covering the entire actuation range. The duration of the data collection process is $1.0h$ for each joint. To minimize the risk of collision between the machine and the environment, the training data is collected separately for each joint since the coupling dynamics between joints were found to be insignificant. However, in the case of substantial coupling dynamics, the data must be collected by simultaneously actuating multiple joints to consider the impact of hydraulic

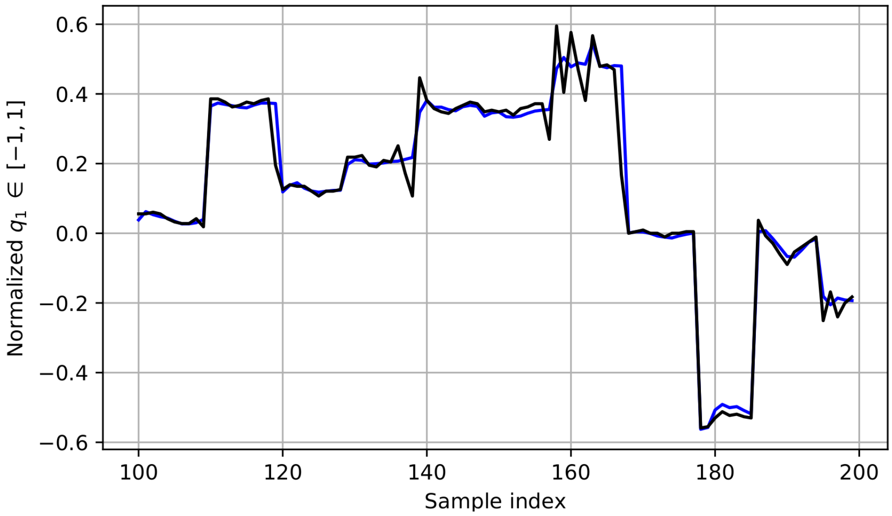


Figure 5.10: Comparison between the collected (black) and predicted q_1 (blue).

coupling. Moreover, the actuator model should incorporate a unified and comprehensive network capable of representing multiple actuators alongside their inherent dynamics, including hydraulic coupling effects.

Here, the input to the actuator model is designed to encompass the entire system delay, which is experimentally determined to be 550ms. Thus, the history of the control input and system state from the preceding 650ms are incorporated into the inputs. The output is the corresponding system state change. To facilitate the training process, all input and output data are normalized. The model is trained using the mean squared error (MSE) loss function and the Adam optimizer. The loss function converges after roughly $1h$ of training time, resulting in $5h$ of total training time for all 5 joints. Fig. 5.10 illustrates the results of the trained actuator model, where the predicted q_1 is directly compared with the collected q_1. The results demonstrate that the trained actuator model can predict q_1 at different speeds with direction changes.

Learning to solve the hammer insertion task

First, we set up the desired task in a simulated environment. Our ultimate objective is to obtain a control policy that can generate control inputs for each of the joints $q_{1...5}$ to insert a hammer into a borehole. It is important to note that joint q_2 cannot be actuated simultaneously with other joints due to the manufacturer-defined design of the machine. Therefore, the control policy must learn how to independently control q_2 and $q_{1,3,4,5}$ to insert an 8 cm diameter chisel into a 10 cm diameter borehole. Furthermore, the trained actuator model is integrated into the simulation to allow the control policy to effectively manage the machine's input delays and hydraulic properties and coordinate the joints optimally. In this task, the borehole's position is detected via a stereo camera. We assume the borehole's orientation is fixed since the concrete block used in this task cannot be tilted during the experiments. Fig. 5.9 provides an overview of the proposed system.

States and Observation

At each time step t, the agent receives an observation s_t that includes information about the current state of the environment, such as the borehole position p^b and the same information that the actuator network requires, as shown in Table 5.2. Providing the agent with a history of past measurements is vital to enable optimal coordination of different joint delays. Additionally, the agent receives the position of the borehole (i.e., the target position). The agent's actions consist of control inputs for each joint provided to the actuator model in the simulation during training or the actual machine during deployment (see Table 5.2). We normalize all observations and actions to accelerate training with an approximate mean and standard deviation. In practi-

Observation	Description	Dimensions
p_b	Borehole position	3
$q_{t-0.65s,\ldots,t-0.05s}$	Joint positions	65
$u_{t-0.65s,\ldots,t-0.05s}$	Control inputs	65

Actions	Description	Dimensions
u_t	Control inputs	5

Table 5.2: Observations and actions of the agent

cal settings, the inferred position of the borehole from stereo cameras is subject to noise. To account for this, we incorporate uniformly sampled white noise to p^b, with a maximum amplitude of 5%. Furthermore, to address potential inaccuracies in the concrete block model, we introduce random variations in the collision geometry of the block by increasing its size by up to 10%. To improve the robustness of our policy and to account for errors in the actuator model, we also introduce noise to the other components q and u. Specifically, we randomly scale the values of q and u by a maximum of 10%, and this scaling factor remains constant throughout a given episode.

Disjoint control

To ensure effective control of the hydraulic machine, teaching the agent the appropriate actions is essential. Since the machine cannot move all joints simultaneously, q_2 must be controlled separately as it is used primarily to adjust the distance to the target object. To facilitate this, we introduce action masks, namely $[0, 1, 0, 0, 0]$ and $[1, 0, 1, 1, 1]$, which restrict the agent's actions to prevent simultaneous movements of all joints. We also encourage the agent to adjust the distance to the target object at the beginning of the operation, following the expert behavior of human operators. Accordingly, an action mask $[0, 1, 0, 0, 0]$

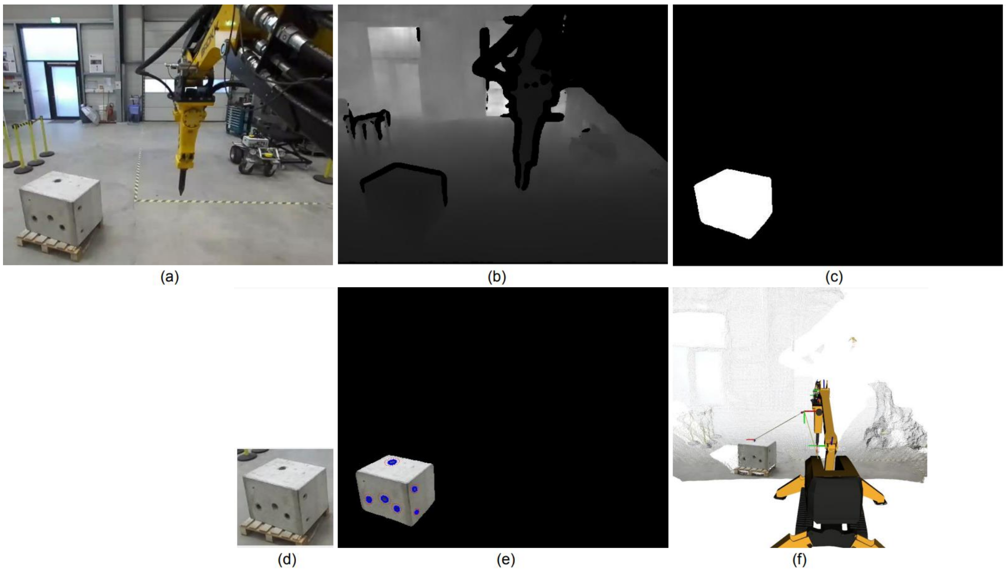


Figure 5.11: Overview of how the borehole position is estimated. First, the concrete block is segmented from the retrieved RGB (a) images using the trained U-net (c). By using the mask of the segmented concrete block, the area around the concrete block is cropped (d). Ellipse-like shapes are detected from the cropped RGB images to ensure that only the target concrete boreholes are considered the final borehole position. The borehole positions are estimated by finding the corresponding depth value from the identified ellipse center point (e). By comparing the normals, only the borehole of the interest is considered (f).

is applied to the computed control input u_t so that only q_2 is actuated until the target object is within a good reachable working area. Since q_1 is solely responsible for rotating the base, the remaining joints, $q_{3,4,5}$, are used for the manipulation task. Empirical analysis has shown that the manipulator has good manipulability over the target object when the distance d_t between q_3 and the target object is within $1.7 \leq d_t \leq 2.4$ meters. Hence, the agent stops actuating q_2 and utilizes $q_{1,3,4,5}$ when $1.7 \leq d_t \leq 2.4$ or the height of the end-effector d_h is below 0.2 meters to prevent collisions with the ground.

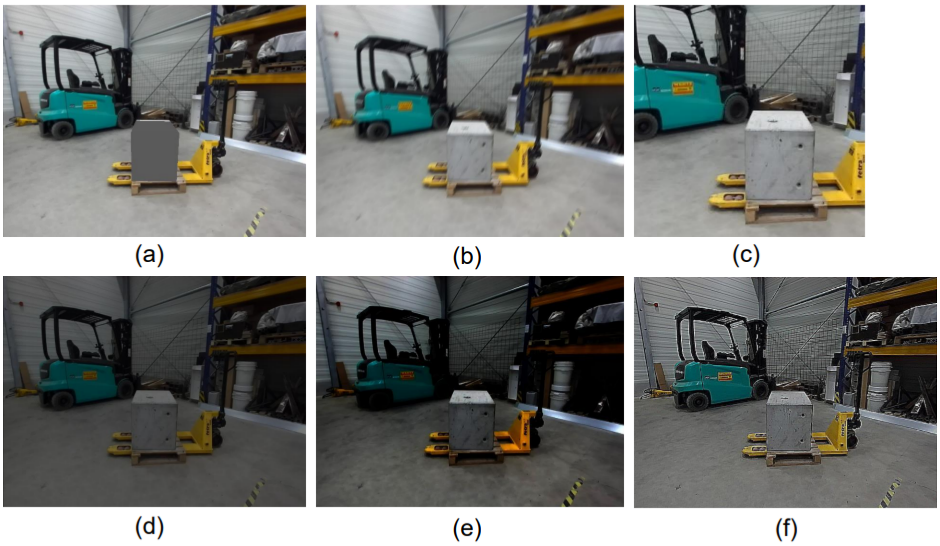


Figure 5.12: Labeled data generated by the pipeline (a). Each labeled data is augmented with blurred (b), cropped (c), light contrast (d), gamma (e), and noise (f) effects. Here, only the data (a) is collected by a hand-carrying RGBD camera.

Rewards

A reward function must be implemented to guide the learning process to achieve a desired behavior in the control policy. This function should impose penalties on actions that result in undesired behaviors, such as collisions with concrete blocks. The reward functions are designed such that the agent utilizes joint q_2 to position the manipulator in a location that facilitates object manipulation while utilizing joints $q_{1,3,4,5}$ to insert the hammer into the borehole. This approach avoids unnecessary collisions with the environment and promotes smooth commands by penalizing significant changes in control actions:

$$
r_t = \begin{cases} r_t^m, & \text{if } 1.7 \geq d_t \text{ or } d_t \geq 2.4 \\ & \text{ or } d_h \geq 0.2 \\ r_t^d + r_t^o + r_t^i - r_t^c - r_t^a, & \text{otherwise} \end{cases} \tag{5.4}
$$

where

$$
r_t^m = \begin{cases} 0.25/(1 + d_t - 2.4), & \text{if } d_t \geq 2.4 \\ 0.25/(1 + 1.7 - d_t), & d_t \leq 1.7 \end{cases}
$$

$$
r_t^d = 1/(1 + \|p_t^b - p_t^{ee}\|_2),
$$

$$
r_t^o = 1/(1 + |1.57 - \theta_t^{ee}|),
$$

$$
r_t^i = \begin{cases} 5(r_t^d + r_t^o), & \text{if } r_t^d, r_t^o \geq 0.9 \text{ and } p_t^{ee_z} \leq 0.7 \\ 0, & \text{otherwise} \end{cases}
$$

$$
r_t^c = \begin{cases} 0.01 f_t^{ee}, & \text{if } r_t^d \leq 0.7 \text{ and } \|f_t^{ee}\|_2 \geq 0 \\ 0, & \text{otherwise} \end{cases}
$$

$$
r_t^a = 0.01\|u_t - u_{t-1}\|_1,
$$

At each time step t, this study's total reward r_t comprises six distinct terms, outlined in equation (5.4). The first term, denoted as r_t^m, encourages the agent to move the manipulator to an optimal position for effective object manipulation. The following two terms, r_t^d and r_t^o, encourage the agent to approach the borehole while aligning the hammer perpendicular to the surface. The estimated borehole depth $p_t^{b_z}$ is reduced by 0.1 m to encourage the agent to move inside the borehole.

The desired hammer orientation for successful insertion is assumed to be $\phi^{ee}, \theta^{ee}, \psi^{ee} = (0, 1.57, 0)$ since the borehole orientation is always parallel to the xy-plane. A successful hammer insertion is rewarded by the term r_t^i, while collisions are penalized by the term r_t^c, but only if the agent is far from the borehole. Contact is detected by measuring the hammer's force value f_t^{ee}. To ensure smooth command execution during operation, the term r_t^a penalizes large changes in control actions. This is important because the agent's commands are transmitted to a human operator in the final stage to assist them, and sudden, significant changes in commands are found to be difficult for the operator to follow.

Training Procedure

To achieve effective training of the agent, a high sampling rate is crucial for learning the specified tasks. In this study, we utilized the IsaacGym simulator [62], a simulation environment designed to enable policy learning with a high sampling rate by parallelizing physics on a single GPU. Following each episode, we randomly set the initial arm configuration and borehole position to enable the trained agent to perform the task from various positions. We terminated an episode prematurely if the machine was at its joint limits or if the maximum episode length was reached. Additionally, after the random reset of the arm configuration and borehole, there were instances where the starting arm configuration intersected with the concrete block. In such cases, we terminated the episode immediately with zero rewards.

To train the control policy for the hammer insertion task, the Proximal Policy Optimization (PPO) algorithm is used [63]. Specifically, the PPO implementation provided by Makoviichuk et al. [64] is used, which supports GPU-accelerated training with parallel environments using Isaac GYM. Two multilayer perceptron (MLP) neural networks approximate the value function and the policy, each with Exponential Linear Unit (ELU) activation in the hidden layers and a linear output layer. The networks consist of 3 hidden layers, with 256 units in the first layer, 128 units in the second layer, and 64 units in the last layer. The control policy is trained at 20 Hz on a computer with an Intel Core i7-9850H CPU, 16GB of RAM, and an NVIDIA Quadro RTX 3000 GPU. The training process takes approximately 3 hours to converge, during which 128 agents are used in parallel to accelerate the training process.

Pose Estimation of the Borehole

In this study, we utilize an RGBD camera to estimate the borehole position observed by the trained agent (see Table 5.2), focusing on the boreholes on the target objects to ensure that the agent only considers those as target points. The workflow is illustrated in Fig. 5.11. Firstly, RGB and depth images are captured using a Zed2i camera. Next, a U-net segmentation network, which utilizes the LabelFusion framework [76], is employed to segment the concrete block from the RGB image [77]. To ensure robustness in different lighting and noise conditions, we also incorporate an additional data augmentation pipeline to generate the different training data sets, as shown in Fig. 5.12. After the concrete block is segmented, the corresponding mask in the RGB image is used to restrict the interest area by cropping the image. We employ an ellipse detection framework from [78] on the cropped RGB image to detect the boreholes. By performing the ellipse detection only on the cropped image, we ensure that only the boreholes from the interest area (i.e., where the target concrete block is detected) are considered the target position. The center point of the detected ellipses is estimated, and the corresponding depth values are retrieved from the depth image. We limit the target borehole to the one on the

xy-plane and filter out the other ellipses by comparing the normal values. Finally, the center point of the final ellipse is considered the target position by the agent and is also visualized by the operator.

5.2.5 Virtual Fixtures

The aim of this work is to generate virtual fixtures that guide a human operator in a hammer insertion task using a trained control policy. The policy takes as input the borehole position and the joint positions and control inputs from the previous 650 milliseconds, as indicated in Table 5.2, and provides the next control inputs, which are scaled to the range of [-1, 1]. Here, the computed next control input is converted into the desired lever angle α_t^d as follows:

$$\alpha_t^d = \alpha_{max} u_t \tag{5.5}$$

where the α_{max} represents the maximum lever angle from the real lever. The left lever is responsible for the q_1 and q_4, whereas the right lever controls $q_{2,3,5}$. As multiple joints need to be controlled with each lever, (2) is extended to represent the desired lever orientation in two different orientations:

$$(l\_\phi^d, l\_\theta^d, l\_\psi^d) = (0, \alpha_t^{d_4}, \alpha_t^{d_1}) \tag{5.6}$$

$$(r\_\phi^d, r\_\theta^d, r\_\psi^d) = \begin{cases} (0, \alpha_t^{d_2}, 0), & \text{if } u_t^{d_2} \neq 0 \\ (0, \alpha_t^{d_3}, \alpha_t^{d_5}) & \text{otherwise} \end{cases} \tag{5.7}$$

Notably, the right lever controls three joints, where q_2 is separately controlled from other joints (see Fig. 5.13). The buttons on the right lever allow the control of q_2 to be switched between the right lever and

Figure 5.13: Control device for Brokk 170. The left lever controls $q_{1,4}$ and the right lever $q_{2,3,5}$. When the right button on the right lever is activated, the right lever controls q_2 and otherwise $q_{3,5}$.

$q_{3,5}$. To facilitate the lever control process, the visualization of the desired lever control is overlaid with the actual lever control, enabling the operator to compare both and more easily mimic the desired lever control (see Fig. 5.14). This approach is designed to alleviate the burden on human operators and reduce the risk of errors by leveraging the knowledge from the obtained control policy to teach an optimized lever control.

5.2.6 Experimental Evaluation

The evaluation of the proposed approach involves a user study to demonstrate the impact of virtual fixtures on performance. The study includes 5 participants who have no experience with the teleoperation of Brokk 170. The study consists of two experiments with and without virtual fixtures, each requiring the insertion of a hammer with a diameter of 8cm into a 10cm diameter borehole located at different positions on a concrete block. To perform the task, the operator uses 2D RGB images and 3D point cloud data provided at 3 Hz (see Fig. 5.15).

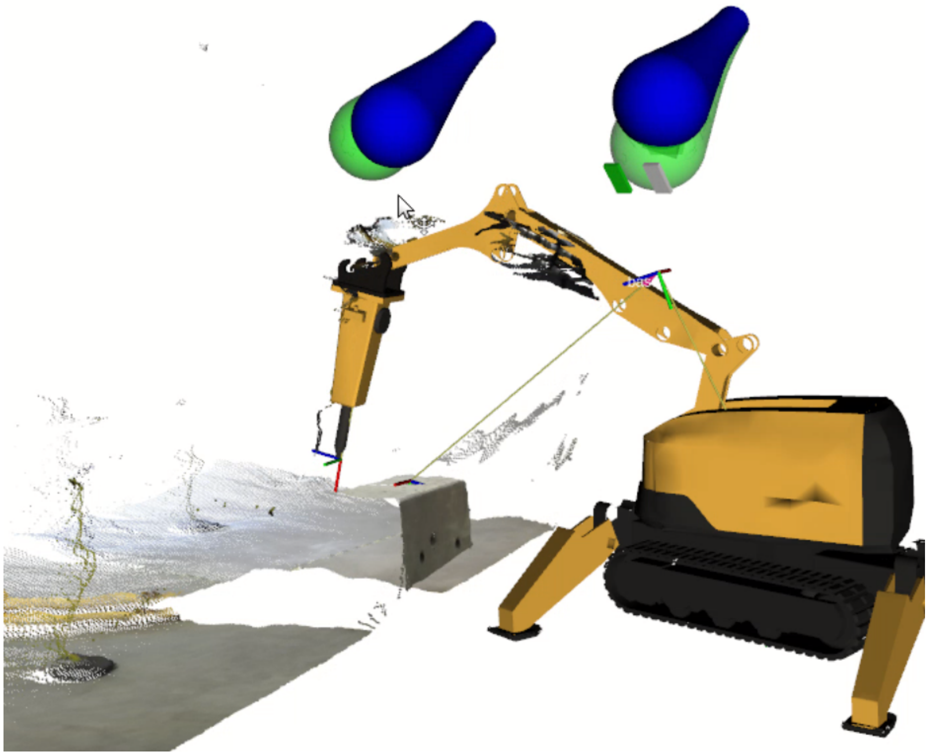


Figure 5.14: The virtual fixtures with the 3D point cloud are provided to the operator. The computed joystick maneuvers from the trained control policy are shown in green, whereas the operator's maneuvers are visualized in blue.

The borehole is detected only once at the beginning of each experiment due to its detection dependency on the manipulator's configuration. The control policy, which computes the optimal joystick maneuver at 20Hz, utilizes the detected borehole position.

In the first experiment, the participants are instructed to perform hammer insertion using virtual fixtures. The detected borehole position is sent to the trained control policy along with the joint positions and control inputs from the last 650 ms. The control policy then calculates the corresponding control input towards the detected borehole position, converted to the corresponding joystick angles. The green joystick visualizes the optimal joystick maneuver from the trained control policy, while the blue joysticks represent the current maneuver. To guide the operator when to use q_2, the color of the buttons on the right joystick is changed to green. The participants perform the same task in the second experiment without the virtual fixtures. Before starting the experiment, each participant is provided with a brief introduction to the teleoperation of Brokk 170 and given 10 minutes of practice time to become familiar with it. To evaluate the system's performance qualitatively, the participants fill out NASA Task-Load Index (TLX) questionnaires [79]. Additionally, the end-effector motion is recorded during the experiment by applying forward kinematics with the joint angle values.

Figure 5.16 illustrates the recorded trajectory of the end-effector during the hammer insertion task, wherein the outcome of a single participant is emphasized to enhance visual clarity. The solid curve corresponds to the virtual fixtures-based experiment, while the dotted curve represents the experiment without virtual fixtures. The star and sphere icons depict the start and end positions of the task, respectively, which vary across participants. The blue trace is used to facilitate the comparison for a particular participant. Moreover, Figure 5.17 presents the mean scores of the NASA Task-Load Index (TLX) questionnaires completed by the five participants in both virtual fixture-based and non-virtual fixture-based experiments.

The user study results demonstrate a notable disparity in the teleoperation of the machine. As depicted in Figure 5.16, the participants struggled to control multiple joints simultaneously and preferred to control them individually. This difficulty was particularly evident in the borehole area, where the participants had difficulty determining the correct joint angles to insert the hammer. However, when presented with visualized virtual fixtures derived from the trained control pol-

(a) (b) (c)

Figure 5.15: Experimental setup with an arbitrary start position (a). Using the provided virtual fixtures, the operator inserts the hammer into the borehole (b). The direct sight into the workspace is limited to emulate the scenario where the operator remotely works in a safe control room (c).

icy, the participants tended to control multiple joints simultaneously, resulting in a more efficient path to the borehole. The computed q_2 motion ensured optimal distance to the borehole, reducing the number of movements required for hammer insertion. This difference is also evident in Figure 5.17. The findings from the questionnaires indicated that the utilization of virtual fixtures resulted in a reduction in mental demands and required effort for the participants. This reduction occurred as the fixtures provided clear guidelines for optimal joystick utilization during teleoperation. However, it should be noted that additional exploration and evaluation involving a larger number of participants are needed to assess the impact on mental burden comprehensively.

5.2.7 Conclusions

This paper presents an RL-based framework that can efficiently learn the hammer insertion task in a simulation environment. To minimize the simulation-to-reality gap, we use a data-driven actuator model

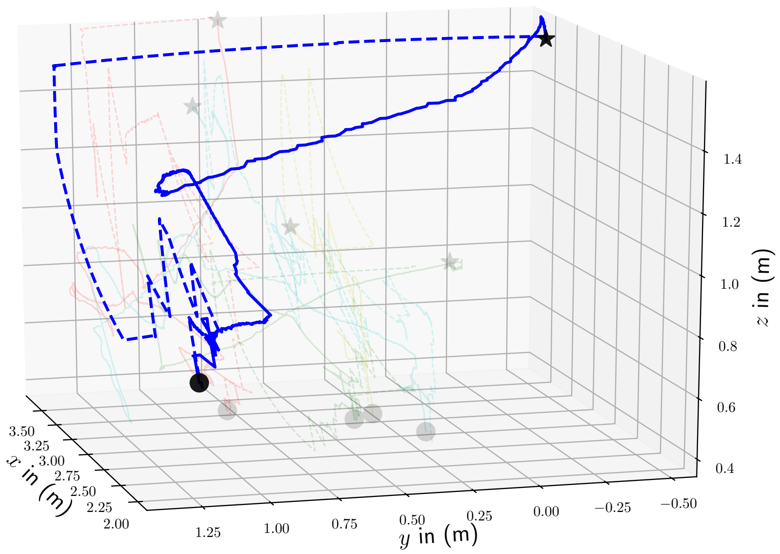


Figure 5.16: Recorded end-effector path during the user study. The starting and borehole positions are changed for each participant and visualized with stars and spheres, respectively. Solid: virtual fixtures. Dotted: without virtual fixtures.

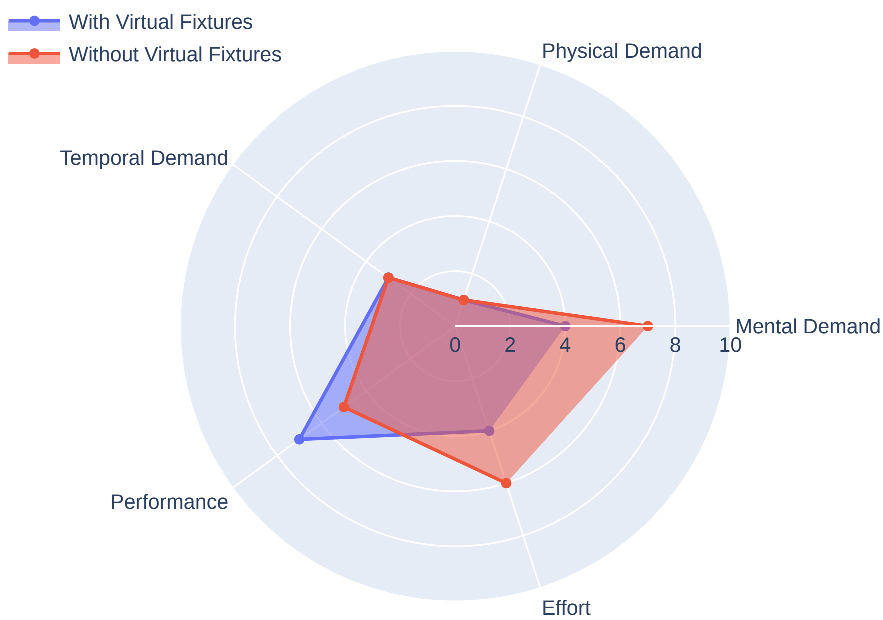


Figure 5.17: Results from the NASA-TLX questionnaires in radar graph.

during training that captures the machine-specific nonlinearities in the relationship between control inputs and system state changes. The learned control policy then guides human operators in optimal joint control for task performance. In teleoperation, the experience of human operators heavily influences task performance, as they can only verify the machine's resulting motion after execution. To address this issue, we propose an assistance system that provides guidelines for optimal joystick maneuvers and joint combinations through virtual fixtures. By doing so, safe teleoperation can be ensured, and errors during the task can also be minimized. We demonstrate our framework's effectiveness in inserting an 8cm diameter chisel into a 10cm diameter borehole. Our method is evaluated through a user study, which shows promising results in reducing the mental burden and effort required to perform the task. Furthermore, the resulting end-effector path shows that virtual fixtures allow the task to be performed with fewer motions, as operators tend to use multiple joints with the aid of virtual fixtures simultaneously.

In future work, we plan to enhance the visual feedback provided in our framework. In the current setup, occlusions frequently occur due to the fixed camera position. By incorporating a mobile platform capable of dynamically navigating around the workspace to obtain the best camera view based on the relative pose between the construction machine and the target object, we intend to improve further the visual feedback provided to the operator. Furthermore, our future plans include extending the proposed approach to encompass various tasks. In the current stage, the agent within the RL framework is focused on learning a specific task, namely the insertion of a hammer into a borehole. However, by instructing the agent in the general approach to maneuver the manipulator towards the desired goal pose, considering the underlying dynamics and the coordination of different joints, the proposed system can be utilized more effectively for multiple tasks.

Chapter 6

Communication Technologies in Construction

The content in this chapter, encompassing both text and figures, has been reproduced from the following peer-reviewed papers. In these papers, the first author conceptualized the ideas, conducted experiments, and carried out the scientific writing, while the second author contributed to the experiments and the last author reviewed the original draft and contributed as the scientific supervisor: • Lee, H.J., Krishnan, A. and Brell-Cokcan, S. 5G in construction: from deployment to evaluation for robotic applications. Constr Robot 8, 6 (2024). https://doi.org/10.1007/s41693-024-00121-1

A stable, low-latency, and high-bandwidth communication infrastructure is indispensable for effective teleoperation or automated control of construction machinery. Despite the vital importance of this aspect, limited exploration has been undertaken thus far. This chapter presents a comprehensive study that begins by detailing the strategic deployment of the new communication technology-namely, the 5G network, underscoring its tailored features and functionalities designed specifically to meet the demanding requirements of construction sites. Through a series of diverse experiments involving different types of full-scale construction machines, we vividly demonstrate the tangible benefits of 5G technology in this context. Leveraging comparative studies with WiFi technology and real-world tests, this methodology highlights the improvements in communication facilitated by 5G networks. This holistic exploration not only fills a critical gap in understanding the potential of 5G in construction machinery communication but also offers a roadmap for leveraging this technology to further develop the construction industry.

6.1 Introduction

Construction encompasses projects from residences, roads, tunnels, and bridges to energy infrastructure such as nuclear and wind power plants. This industry plays an essential role in our society, and the projects' efficiency has a significant impact on our lives. Despite this considerable importance, the current degree of automation within construction is still relatively low compared to other industries, with difficulty and demand largely carried out manually by human workers. Here, construction sites constantly undergo changes throughout different stages of development, each presenting distinct hazardous conditions for human workers, such as heavy machinery operation, exposure to harmful materials, and the risk of falls from elevated structures. To mitigate these risks, teleoperation, which removes the necessity for control of heavy construction machinery in direct proximity, has become a crucial component in the construction industry today [80].

Teleoperation commonly facilitates machinery control at the individual joint level, see Fig. 6.1. When a human operator remotely controls the machine, from a safety-controlled environment like a control container, their control relies heavily on visual feedback [81]. In this context, the quality of visual feedback assumes a crucial role, with the provision of 3D information, including depth data, proving to enhance the telepresence experience for human operators. This enhancement contributes significantly to the operator's sense of being physically present and engaged in the remote operation of the machinery, which is essential for ensuring effective and safe teleoperation [82]. Moreover, as most construction machines are mobile machines due to the dynamic nature of construction sites, the control signals from the control device are often wirelessly transferred to the machines. Here, robust wireless communication between the control device and the machine is mandatory to ensure safe control.

As previously emphasized, a fundamental prerequisite for effective control of machines is the establishment of stable, low-latency communication with the machine, coupled with data transmission capabilities that maximize bandwidth to enhance the quality of visual feedback. Over the past few years, wireless communication technologies like WiFi and Fourth-Generation (4G) mobile networks have been employed to facilitate robust communication with machines or sensors for purposes such as monitoring hazardous areas, alerting workers in risky situations, and collecting on-site data [83]. While these communication technologies can partially address certain industry requirements, they fall short in meeting all demands, particularly those related to bandwidth and time-critical communication. In response to these challenges, the Fifth-Generation (5G) technology has emerged as a technology poised to fulfill the specific needs of the construction industry [84].

6.2 Litearature review

6.2.1 Automated construction machine

Motivated by the achievements observed in various industries, notably the automotive sector, researchers have dedicated their efforts to integrating automated systems into construction sites since the 1970s. The primary goal has been to address the persistent productivity challenges that have plagued the construction industry [85]. One notable example of this research direction is found in [56], where researchers enhanced a teleoperated deconstruction machine to facilitate a more precise and semi-autonomous deconstruction process. Similarly, another study focused on augmenting an off-the-shelf excavator to enable partial automation of excavation tasks [86].

In recent years, there has been a notable development in the automation of construction machinery, driven by data-driven methodologies. This modern approach involves techniques such as approximating the nonlinear behavior of hydraulic machinery by analyzing the operation data from the real world [87, 88] and developing an efficient controller capable of successfully executing the task even in different scenarios [46]. These advancements mark a significant shift in the construction automation landscape, as they leverage data and computational methods to improve the efficiency and adaptability of construction equipment.

In this context, the importance of on-site communication technology is huge, as it serves as the backbone for orchestrating the synchronized efforts of various automated construction machinery and systems. Real-time data exchange and communication networks enable these machines to share vital information, coordinate their activities, and adapt swiftly to changing conditions on the construction site.

Moreover, this technology facilitates remote monitoring and control, allowing operators to oversee operations, identify issues, and make necessary adjustments in real-time, even from a distance. As construction automation continues to evolve, the role of robust and reliable on-site communication technology cannot be overstated, as it underpins the seamless integration and operation of the interconnected machinery that drives efficiency and productivity in the modern construction industry.

Figure 6.1: The human operator controls the machine solely based on intuition in direct proximity to the machine.

6.2.2 5G technology for construction site

Despite the immense potential that 5G networks hold for revolutionizing monitoring, control, and automation within the construction industry, there has been limited exploration of this area so far. Particularly in the context of teleoperated or automated construction machinery, establishing a reliable wireless communication system is paramount. It plays a crucial role in ensuring the safety and robustness of operations. Despite its fundamental importance on-site communication receives comparatively little attention in the existing literature. In the few available studies, communication technology is already recognized as a significant challenge in the context of automated construction machinery [89]. Additionally, other works [90] introduce various concepts for integrating 5G technology into construction tasks. However, these efforts primarily provide theoretical frameworks and broad overviews, lacking empirical validation through real-world experiments conducted with on-site 5G networks. While the foundational concepts outlined in these studies are undeniably valuable, their applicability is limited due to the absence of practical implementation and testing.

In the study presented in [54], the researchers embarked on a series of real-world experiments featuring a mobile robot, which, in collaboration with a WiFi network, aimed to facilitate 3D sensing applications within teleoperation scenarios. This research not only explored the feasibility of such applications but also delved into the intricacies of leveraging 5G technology to meet the evolving demands of these systems. In [91], the authors undertake a comprehensive investigation into the advantages afforded by 5G technology. By comparing the performance of 4G and 5G networks within a simulated environment, they analyzed the potential enhancements that 5G could bring to the construction industry. Nevertheless, it is important to note that both of these studies, while providing valuable insights into the promise of 5G, predominantly relied on WiFi networks or simulations for their experiments. As a result, critical questions regarding the practical implications unanswered and underscores the need for more comprehensive research and experimentation in this important domain.

In recent years, notable companies such as Doosan Infracore have successfully showcased the 5G-based remote control technology for construction machinery. However, while these demonstrations have piqued interest, the intricate technical details that underpin this technology have remained unpublished, as observed in [92]. Similarly, the noteworthy research conducted by [93] has unveiled the advantages of harnessing on-site 5G networks within the context of unmanned bulldozers, operating in real-world scenarios. However, the study falls short in providing a comprehensive breakdown of the 5G network architecture and performance comparisons with WiFi or 4G alternatives. This deficiency in technical insights is particularly significant given the absence of information regarding the deployment strategy and the installation of an on-site 5G network. The construction site emerges as a dynamic environment characterized by the transitory nature of both its physical location and available resources. The construction sites, where projects typically last from one to several years, see a lot of shifting resources like containers and infrastructures. This makes it especially challenging to set up a stable wireless network, as the required network coverage changes. Also, the network signal is affected by the buildings being built and all the construction materials, such as concrete and metal. Thus, questions, such as how to deploy and install 5G networks, including their radio equipment and antennas, to work reliably in this ever-changing open field of construction sites, are of great importance and should not be neglected.

To bridge these knowledge gaps, this chapter proposes a complete framework of the on-site 5G technology in the construction sector from the deployment, usage in a use case, and the demonstration of its benefits. In this context, the strategy for the deployment of a 5G network to the construction site is first discussed. The main characteristics and functionalities of this 5G mobile network that are deployed based on the discussed strategy are then highlighted. Then, the use case with an automated construction machine is explained, where the usage of 5G technology shows its benefits. Furthermore, a hardware and software architecture for the integration of 5G in the defined scenario is presented.

6.3 On-site Deployment of 5G Network

Figure 6.2: Reference construction site at RWTH Campus Melaten

As mentioned in the previous section, the construction site is a dynamic environment where the location and resources are both temporary. Often, small and medium-scale projects last between one to five years. Moreover, the existing resources (containers, cranes, etc.) tend to be dynamic during this period. This, in turn, causes a hindrance in the scalability or maintenance of a stable wireless network. Additionally, signal coverage is affected by the presence of the buildings undergoing construction and large quantities of concrete and metal often found on construction sites. Thus, the natural question arises, how a 5G network, especially the radio units and antennas, can be deployed in this ever-changing working environment when the construction site consists of an open field.

6.3.1 Deployment Strategy

In this context, we utilize a tower crane as a transmission tower to which the radio units and antennas are attached. The use of heavy-payload machinery is common on construction sites. Especially the usage of cranes is predestined on construction sites to enable the lifting and movement of heavy materials and equipment. Leveraging the existing infrastructure of a tower crane provides several advantages for deploying a 5G network in such dynamic environments:

- Firstly, tower cranes are typically positioned at central locations on construction sites, offering an elevated and strategic vantage point. This positioning enhances the line-of-sight communication between the radio units and antennas, minimizing signal obstructions caused by nearby structures or construction materials.

- Secondly, tower cranes possess robust structural stability, capable of withstanding heavy loads and adverse weather conditions. This inherent stability ensures the durability and reliability of the

5G network components attached to the crane, even in challenging environmental circumstances.

- Furthermore, tower cranes often have a high payload capacity, allowing for the installation of multiple radio units and antennas simultaneously. This multi-node deployment approach enhances network coverage and capacity, effectively mitigating the signal attenuation caused by obstacles commonly encountered in construction sites.

- To ensure seamless connectivity and efficient network operation, a dedicated power supply is established to energize the radio units and antennas attached to the tower crane. This power supply is typically integrated with the crane's electrical system, enabling continuous and reliable operation without relying solely on temporary or auxiliary power sources.

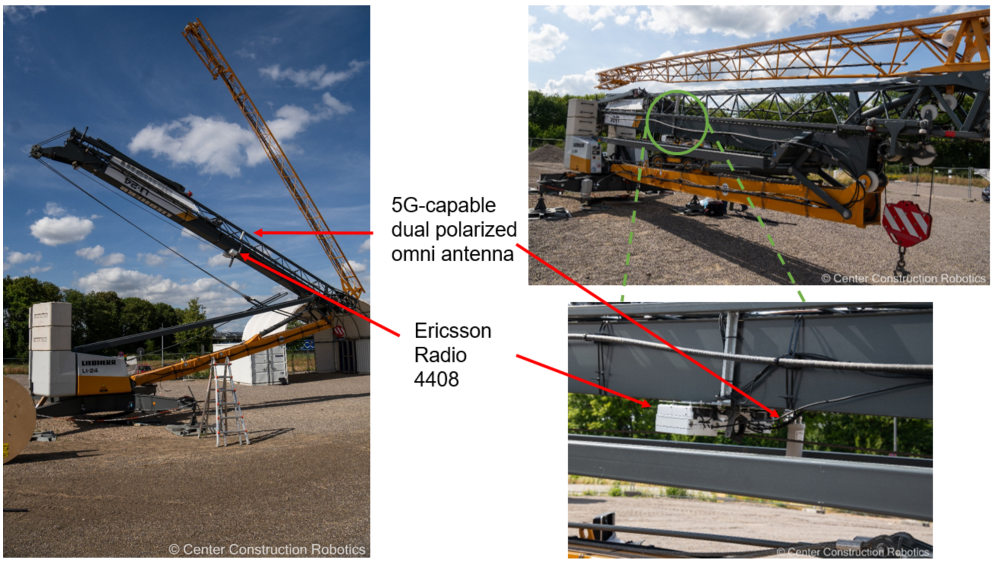


Figure 6.3: On-site network setup, utilizing the tower crane as a transmission tower.

6.3.2 Installation of the 5G network

The deployment and testing of the 5G network in this study were conducted at the Reference Construction Site located at RWTH Campus Melaten in Aachen, Germany, encompassing an area of approximately 4.000 m^2. Figure 6.3 illustrates a snapshot of the construction site.

Here, in this open field, the establishment of a robust communication infrastructure is paramount for the successful deployment of a 5G-enabled robotic system. To achieve this, we utilized Ericsson Micro Radio 4408 units, which were purposefully designed to support 5G technology, ensuring seamless connectivity and communication within the network. In conjunction with these radio units, we employed 5G-capable dual-polarized omni-antennas. These antennas were chosen for their unique ability to provide omnidirectional coverage, enabling signal transmission and reception in all directions. The dual-polarized functionality further bolsters the efficiency of data exchange, thereby enhancing the overall performance of our communication network.

The installation phase required meticulous consideration of several crucial factors. The stability, weight capacity, and height of the crane were meticulously evaluated to guarantee the secure placement and operation of the mounted network equipment, even in adverse weather conditions. To achieve this objective, we meticulously chose the Liebherr L1-24 tower crane, carefully considering these pivotal parameters to guarantee comprehensive coverage of the reference construction site. The crane's specifications, including a maximum hook height of 19 meters, a lifting capacity of up to 2.500 kilograms, and a maximum radius of 25 meters, were pivotal factors in ensuring the adequacy and efficiency of our operations at the site.

During installation, the Ericsson Micro Radio 4408 units were securely affixed to the crane's structure, with meticulous attention given to ensuring their stability and protection against any potential vibrations or movements induced by the crane's operations. Subsequently, the 5G-capable dual-polarized omni-antenna was strategically positioned alongside the radio units on the crane. The height at which it was mounted proved crucial in ensuring comprehensive coverage in all directions, free from interference caused by on-site structures and buildings. The choice of this specific antenna type was guided by its dual-polarized capabilities, which significantly enhance the efficiency of signal transmission and reception. This feature proves especially beneficial when the crane undergoes rotational maneuvers during its operational phases.

A critical aspect of our installation process was the management of cables. We placed significant emphasis on the delicate nature of fiber cables, necessitating their careful attachment to the crane's structural framework. This preemptive measure was taken to prevent any potential disruptions to the crane's maneuverability and to mitigate safety risks. Of particular note is the tower crane's ability to fold up or down in response to changing wind conditions. To accommodate this feature, we employed jumper cables in the crane's folding region, specifically concerning the fiber connections.

6.4 Construction machines

To demonstrate the benefits of utilizing the deployed 5G technology in the context of controlling construction machinery, we first provide a brief description of the necessary hardware modification of Brokk 170 that allows the 5G-based control. Next, the control method is introduced that takes the sensor readings as feedback via the 5G network and plans the next necessary motion to build a closed-loop mechanism.

Figure 6.4: Brokk 170 (left) and INNOK 444 (right) with their hardware employed in this project for automated tracking of trajectories and detecting humans

When utilizing an automated construction machine like the Brokk 170 on a site, the incorporation of a visual sensor, exemplified by a camera, stands as a critical safety provision aimed at averting collisions with human beings. In this context, the camera serves as a critical component of the machine's sensory apparatus, facilitating the detection of human beings within its operational vicinity. However, inherent to any camera system is the limitation of a confined perspective, resulting in blind spots or dead angles that could compromise safety. To mitigate these limitations and ensure comprehensive surveillance, the consideration of alternative monitoring methods becomes pivotal. One such strategic approach involves utilizing a secondary construction machine as a third-eye for monitoring, complementing the camera's perspective and significantly enhancing the overall situational awareness. This approach effectively addresses the limitations of a single-camera viewpoint and offers a robust solution for ensuring the safety and efficiency of autonomous construction operations in dynamic and crowded environments.

The decision to opt for a secondary construction machine as a third-

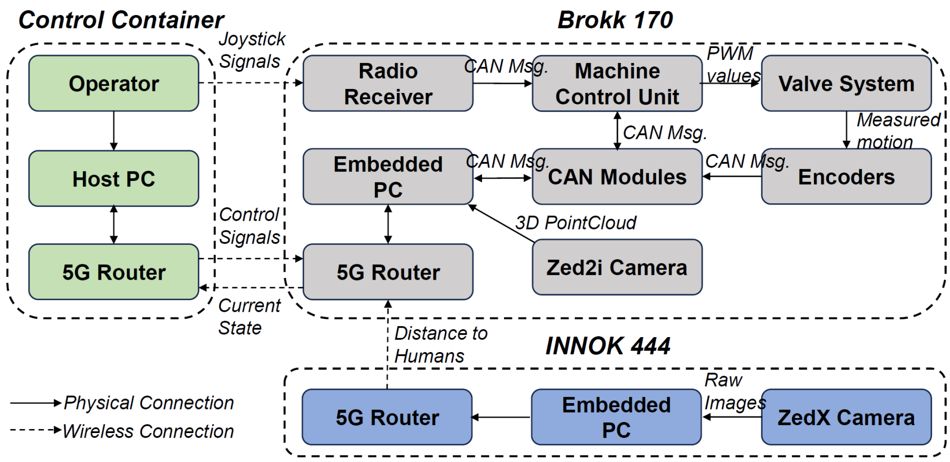


Figure 6.5: Schematic representation of the hardware setup

eye for monitoring, instead of integrating multiple cameras onto the automated construction machine, is driven by a holistic assessment considering various operational factors. While multiple cameras offer expanded visibility, their implementation introduces complexities in data processing, and system management, demanding sophisticated solutions and incurring higher costs. In contrast, employing an additional machine simplifies the setup and operational demands, ensuring a cost-effective approach. Although it necessitates an initial investment in acquiring another machine, its primary role in monitoring simplifies its technical requirements, maximizing its utility across multiple tasks when not actively engaged in surveillance. This strategic utilization of resources not only addresses blind spot concerns but also offers scalability, adaptability, and long-term cost-effectiveness over the project's lifecycle, making it an optimal choice for comprehensive site surveillance and safety in autonomous construction operations.

Thus, the system details and frameworks governing the INNOK444 mobile platform are outlined which informs Brokk 170 in the event of human presence nearby.

6.4.1 System description

This section presents an overview of the hardware configuration applied to the Brokk 170 construction machine, incorporating essential core adaptations tailored to allow the 5G-based control, see Fig. 6.4 and 6.5.

Brokk 170

Within the Brokk 170, the Controller Area Network (CAN) bus is facilitated to interconnect different sensors, actuators, and the Machine Control Unit (MCU). In the off-the-shelf setting without any modification, the operator exclusively controls the machine by sending the control signals through the control interface, i.e., control joysticks. The communication between the control joysticks and the MCU is realized using radio devices. The received joystick signals in the form of CAN messages are translated into the corresponding Pulse-Width Modulation (PWM) signals to actuate the valve systems and bring the manipulator in motion.

The fundamental additions to our system are depicted within the blue boxes in Figure 6.5, with the basic concept originating from prior research [56]. This concept revolves around the execution of resource-intensive tasks, such as motion planning and perception, on the Host PC, while relegating the onboard embedded PC to handle low-level control, specifically the actuation of valves and corresponding cylinders based on the provided control signals. By distributing tasks in this manner, we enable the possibility of substituting the Host PC with a cloud-based system in the future, capable of handling resource-intensive tasks for multiple interconnected construction machines. This approach eliminates the necessity of acquiring costly computing components for each individual machine, leading to a more scalable solution. However, it's essential to acknowledge that since functions like motion planning are executed on a separate Host PC rather than directly on the onboard PC, ensuring minimal latency and robust communication between the Host PC and onboard PC becomes a paramount concern. To address this challenge, we have incorporated 5G routers on both ends of the communication link.

To allow the programming option of the teleoperated construction, we first establish a bridged communication link with the MCU with the onboard embedded PC. This onboard embedded PC is equipped with a CAN bus controller, serving as a crucial intermediary that handles message filtration and forwarding tasks, seamlessly bridging the connection with the Brokk 170's MCU. With this setup in place, the machine can be teleoperated using the original joystick inputs while simultaneously remaining receptive to signals generated by algorithms residing on the Host PC in programming mode. These algorithmically-derived signals enable precise control over the machine's movements, resulting in optimized operational performance in terms of accuracy.

INNOK 444

In this project, we utilized the INNOK444 mobile platform for the mobile human detection process, as depicted in Fig. 6.4. The control box and chassis of the INNOK are rated IP65 and IP68 respectively, rendering them suitable for the challenging outdoor conditions commonly encountered on construction sites. Additionally, the platform's four-wheel differential drive enhances navigation on uneven and loose terrains.

To enable human detection as envisioned, we selected the ZedX stereo camera manufactured by Stereolabs, acclaimed for its expansive field of view spanning 110° x 80° and an effective depth range between 0.3 to 20 meters, ensuring a considerable detection scope for our experimental setup. Given the lack of a GPU in the initial compute module of the INNOK, we opted for a substitution, integrating the NVIDIA Jetson Xavier AGX 32GB model. This replacement facilitated seamless data and power transmission to the ZedX camera by employing a GMSL2 capture card connected directly to the Jetson module.

6.4.2 Control methods

The communication and processing of data and control signals among the INNOK, BROKK, and the control PC were established using the ROS framework. ROS, an open-source middleware framework, simplifies the development of robotic systems by offering features such as hardware abstraction, inter-process communication, and diagnostics.

Human Detection Pipeline

We developed a custom ROS package dedicated to identifying human poses in 3D Cartesian coordinates. The foundational component of our detection pipeline was the Zed SDK, an open-source resource [94]. This SDK facilitated image extraction and enabled human detection within the image stream. Operating at 1080p resolution and 30 fps, the camera initialization process set the stage for our analysis. Utilizing a pretrained model embedded within the Zed SDK, we detected humans within the RGB images, extracting the center of the respective bounding boxes to derive their 3D poses. These poses were converted into the Euler distances for each detection and published this information to Brokk 170 via the 5G network and WiFi5, respectively.

Throughout this work, the suggested human detection pipeline was utilized on a single spot while maintaining the INNOK robot stationary. This strategic approach aimed to emphasize and meticulously evaluate the performance of the network infrastructure supporting the communication between the INNOK and Brokk. By intentionally confining the testing to a fixed spot and halting the robot's movements, the focus centered on scrutinizing the network's reliability and latency factors. Within this controlled environment, a thorough evaluation can be conducted to appraise the network's resilience and effectiveness in enabling uninterrupted communication within this time-sensitive context. This aspect aligns closely with the pivotal focus of this research—examining the influence of 5G technology on automated machine control.

Trajectory Control

In the context of trajectory planning, our methodology involves pre-defining a path for the tool center point (TCP), specifically the hammer tip, and tracking along this designated path. This process initiates with the trajectory planner generating waypoints based on the current joint configuration. Subsequently, we convert the desired transitions between these waypoints into control inputs, notably PWM values, using the low-level controller, functioning here as the PID controller. To establish a closed-loop control system, we implement a control framework based on the Robot Operating System (ROS) [49].

The central control loop of this system operates at a fixed rate of 20 Hz. At each iteration of this loop, the system updates sensor data, such as the robot's joint states, and computes commands for individual joints to guide the manipulator along the operator-defined trajectory. In our study, employing pre-defined paths allows us to precisely track the same path under consistent conditions using both 5G and WiFi5 technologies. The pre-defined path is structured to involve the activation of multiple joints, moving across diverse directions.

6.5 Experimental Results

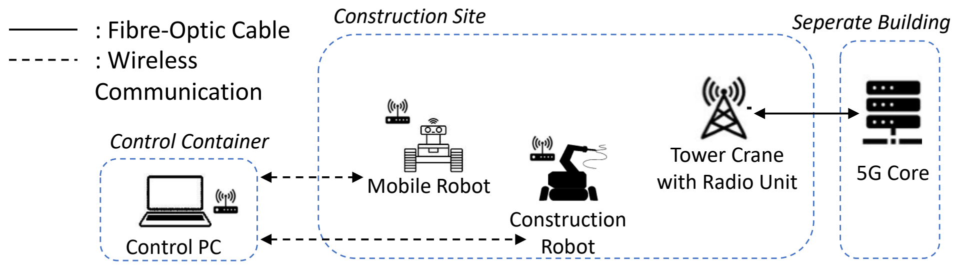


Figure 6.6: Schematic overview of the network setup.

6.5.1 Performance evaluation of the 5G network

In this section, we introduce the methodology used for evaluating network performance and detail the experimental setup implemented to measure these metrics at the construction site, see Fig. 6.6.

RRT test during crane operations

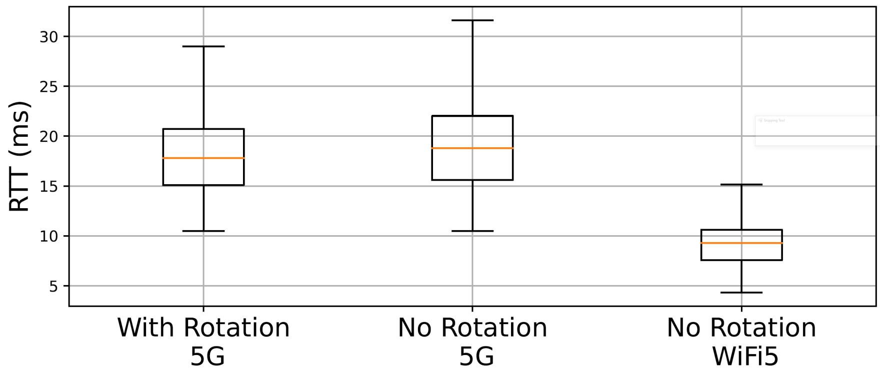
The primary focus of our testing revolves around assessing how the use of tower cranes impacts network performance. Specifically, we evaluate network performance by conducting round trip time (RRT) measurement tests during crane operations.

Although the RRT measurements depicted in Fig. 6.7 show slightly higher latency in 5G networks compared to WiFi5 in controlled environments, it's crucial to contextualize these findings within their respective experiment settings. WiFi5 is optimized for confined areas such as homes, offices, or specific public spaces, excelling in delivering rapid internet speeds within limited ranges, ensuring efficient data transmission. In contrast, 5G operates as a cellular network tailored for broad coverage, enabling connectivity across expansive geographical regions. The results obtained from the crane's utilization of the 5G network demonstrate commendable network quality even during the active operations of tower cranes. Significantly, in the WiFi5 test, the WiFi routers were positioned approximately 10 meters apart, spanning directly from the control PC housed in the control container to the Brokk 170 construction machine. With the 5G network, wireless communication encompasses additional interaction with the radio unit affixed to the crane. Nevertheless, the findings reveal that 5G demonstrates a performance on par with WiFi5, even in scenarios where WiFi typically excels.

Table 6.1: Uplink and Downlink Speeds for 5G and WiFi5 Networks

	5G	WiFi5
Uplink (Mbps)	∼80	∼180
Downlink (Mbps)	∼80	∼180

(a) Different antenna position during the crane rotation



(b) RTT to Brokk 170 with 5G and WiFi5

Figure 6.7: RTT Comparison in different scenarios, when the crane is rotating and when it's stationary

On-site heatmap analysis using RRT

As mentioned earlier, 5G is well known for its broad coverage. Here, we perform ping tests between the control PC and a mobile robot moving along a predefined straight-line path, originating from two different starting positions identified as 1 and 2, see Fig. 6.8. The objective is to comprehensively analyze network performance across the whole construction site in varying conditions, specifically under WiFi5 and 5G networks. These tests are conducted while the network experiences different occupancy levels, ranging from 0Mbps to approximately 40Mbps. Through this extensive experimental setup and assessment, the goal is to understand the potential impacts in situations where seamless real-time communication with mobile robots holds significant importance within construction sites.

The heatmap analysis in Fig. 6.8 illustrates a discernible performance contrast between the 5G and WiFi5 networks. Notably, the 5G network showcases a more consistent RRT throughout the mobile robot's trajectories. Conversely, the WiFi5 network displays more fluctuations in RRT values along the mobile robot's paths, indicating variability in performance at different points during its movement. This distinction in RRT stability highlights the superior reliability and steadiness of the 5G network compared to WiFi5, emphasizing its potential for consistent communication and data transfer in dynamic operational environments. The test was reiterated under identical conditions but with varying network occupancy at 40Mbps, representing 50% and 22% of the maximum bandwidth of 5G and WiFi5, respectively. The maximum bandwidth values from Table 6.1 was established through experimental iperf3 TCP measurements. This highlights the consistency of the test while exploring network performance under different utilization levels.

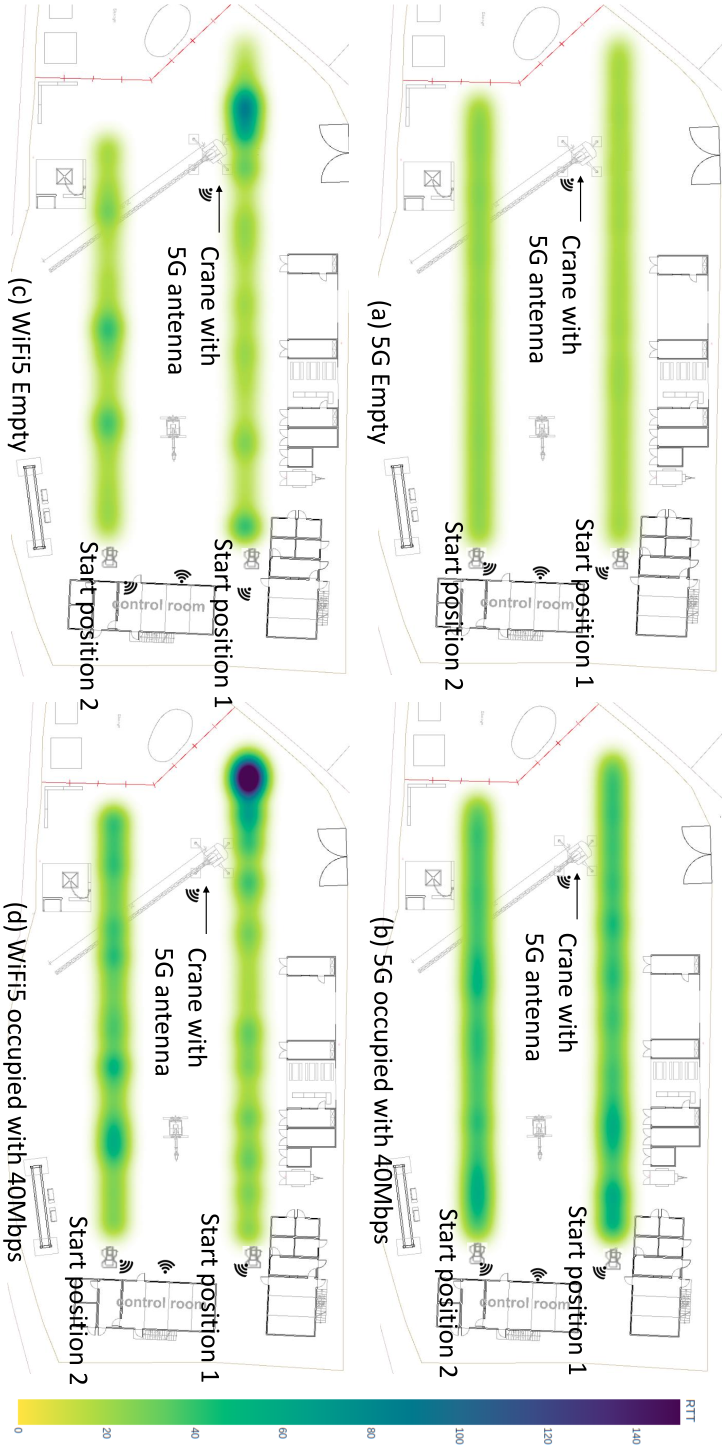


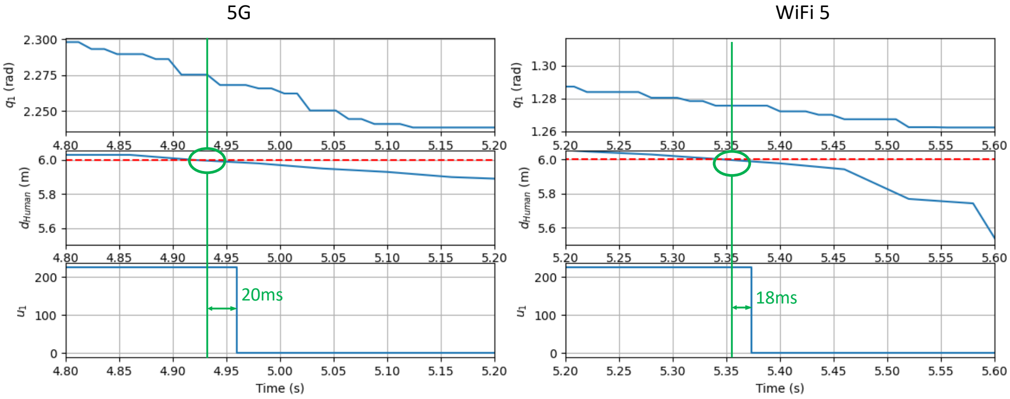
Figure 6.8: Assessing Round trip time between the control room and INNOK444, while it drives along a straight-line trajectory from start positions 1 and 2 under WiFi5 and 5G networks, respectively, with occupancies of 40Mbps

Time critical human detection test

To confirm the reliability of the 5G network in a time-sensitive situation, specifically when the control PC transmits wireless commands to the Brokk 170 construction machine and detects a human approaching the workspace, a validation was conducted. The mobile robot, acting as an additional surveillance measure alongside the Brokk 170 alerts the construction machine to halt its operations once the distance to the human falls below 6.0 meters, see Fig. 6.9 a.

The Brokk 170's base underwent rotation with a constant PWM value of 220 represented by u_1. Whenever the mobile robot detects a human within 6 meters of Brokk 170, Brokk 170 overrides the u_1 value, setting it to 0. The third plot within Fig. 6.9 displays the time interval between human detection and the alteration of the control command. In this time-sensitive experimental setup, the 5G network showcases performance akin to that of WiFi 5. This verification not only underscores the effectiveness of the 5G network but also establishes its practicality in enabling time-critical maneuvers within robotic systems.

(a) Stillshots from the human detection test



(b) Brokk 170's responses according to the estimated distance from humans with 5G (left) and WiFi5 (right) network, respectively, where the user-defined threshold of 6 meters is indicated by the red dashed line.

Figure 6.9: Results from the human detection test: the mobile robot signals the presence of humans to the construction machine

6.5.2 5G-based control of construction machine

This experiment evaluates the impact of the 5G network within the implemented tracking performance at the TCP path level. For this purpose, a TCP path is pre-defined where multiple joints need to change motion direction to complete the task, as depicted in Fig. 6.10. The impact of the 5G network is directly compared by preserving the gains of the low-level controller PID and simply replacing the utilized network, where the average and maximum position errors are reported. The used metrics and the corresponding formulas are listed in Table 6.2, where (x^D, y^D, z^D) and (x, y, z) are the target and actual positions, respectively, where N denotes the number of sample points.

Metric	Formula
e_{p_avg}	$\frac{1}{N}\sum\sqrt{(x_t^D - x_t)^2 + (y_t^D - y_t)^2 + (z_t^D - z_t)^2}$
e_{p_max}	$\max\sqrt{(x_t^D - x_t)^2 + (y_t^D - y_t)^2 + (z_t^D - z_t)^2}$

Table 6.2: Metrics and corresponding formulas used for the evaluation of TCP path tracking

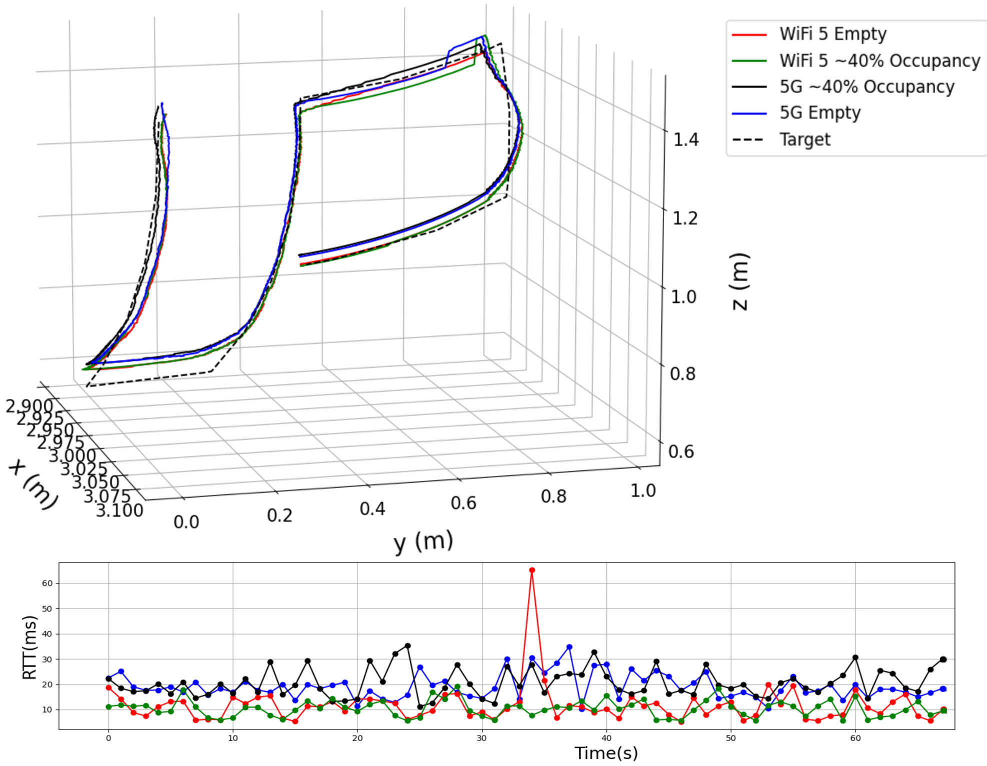
The results are visualized in Fig. 6.10 and summarized in Table 6.3. For the pre-defined TCP path, the results clearly demonstrate the capability of the proposed control framework. The most significant error occurs when multiple joints simultaneously change direction. Also, the reported error is partially caused by the limitation of the low-level controller. Due to the nonlinearity of the hydraulic system, the fine-tuned gains of the PID controller yields varying results depending on the direction of movement and the velocity amplitude [87].

Although both 5G and WiFi5 facilitate communication within control systems, the constraints of WiFi5 become increasingly evident within this particular application. Despite the measured RRT showing better latency outcomes for WiFi5, 5G distinguishes itself through its robustness, notably reducing unpredictable outcomes linked to reliable communication with the control PC, as illustrated by the peak in Fig. 6.10 b. Even though the resulting trajectory plot doesn't visually reflect this peak's impact, its presence underscores the significance of stable and consistent communication. The limitations of WiFi5 in this context become more pronounced when considering the intricacies of control frameworks requiring real-time, precise data communication. While the latency measurements might suggest an advantage for WiFi5, the robustness and reliability demonstrated by 5G, especially during critical control operations, position it as the more suitable choice for ensuring dependable communication and minimizing unforeseen fluctuations in performance.

Used Network	e_{p_avg} [cm]	e_{p_max} [cm]
5G Empty	5.3	10.3
WiFi5 Empty	5.1	9.1
5G ~40% Occupancy	4.6	9.7
WiFi5 ~40% Occupancy	5.8	10.2

Table 6.3: Trajectory tracking performance

(a) Stillshots from the trajectory tracking tests



(b) TCP path tracking results (Top) and the corresponding RRT measurement between the control PC and Brokk 170, where only the network configuration varies

Figure 6.10: Results from the TCP path tracking tests

6.6 Conclusions

This paper presents a comprehensive framework for implementing on-site 5G technology within the construction sector. It starts by detailing the strategic deployment of a 5G network, emphasizing its key features and functionalities tailored to construction site requirements. The exploration of a specific use case involving an automated construction machine vividly illustrates the tangible benefits of 5G technology in this context. Furthermore, this study compares the performance of the 5G technology with another type of communication technology, WiFi and highlights the imperative for further research. Overall, this presented work offers a holistic perspective, showcasing the potential and practicality of 5G in the context of automated construction machines.

Future research pathways involve delving deeper into the core attributes of 5G technology, particularly the exploration of Massive Machine-Type Communication (mMTC). In the existing network configuration, three end-devices—control PC, Brokk 170, and INNOK444—were employed. However, forthcoming investigations could encompass a broader array of end-devices commonly used at construction sites, aiming to scrutinize their performance variance compared to WiFi technology.

Chapter 7

Conclusion and Outlook

This chapter summarizes the main results and outlines future research directions.

7.1 Robotics in Construction

7.1.1 Conclusion

The integration of robotics within the construction industry represents a profound inflection point, offering benefits for elevating conventional construction practices. This fusion of technology and construction holds the promise of effecting transformative changes by substantially enhancing efficiency, bolstering safety standards, and ultimately amplifying productivity. Currently, construction robotics can be categorized into three different domains encompassing:

- the automation of construction machinery

- the adaptation of industrial robotic systems and
- the development of new construction-centric robotic solutions

emphasizing the multifaceted nature of this emerging field.

In light of the advancements in robotic technology, a key concern is how to effectively use robots on construction sites and integrate them into the construction industry. This involves adapting construction processes to make the most of this technology. Throughout history, the integration of new technologies like elevators, cranes, and advanced testing methods has played a crucial role in constructing taller skyscrapers. The main goal of construction robotics is to usher in a new era of technology that makes construction faster, safer, and more efficient. However, there are significant challenges, one of which is the need for robust sensor systems to enable robots to work autonomously and understand complex construction environments.

While there has been progress in artificial intelligence related to recognizing objects and analyzing scenes, understanding complex construction scenes with various objects and changing conditions (like weather, debris, and contaminants) in real-time remains a significant challenge. A central question is how construction processes can be adapted to improve how robots perceive their surroundings. Additionally, human workers are still essential on construction sites during this phase of development. So, it's crucial to consider human factors, including operator conditions and safety. This requires a careful evaluation of how construction procedures can be adjusted to reduce potential risks when humans and robots work together in the same space. In many cases, the importance of network infrastructure tends to be overlooked during the development of robotic systems. Nevertheless, to maximize the utility of construction robots, it is imperative to establish a robust on-site network infrastructure that facilitates seamless data communication among interconnected robotic systems. This foundational infrastructure plays a pivotal role in unlocking the complete capabilities of these technologies within the construction sector, fostering enhanced collaboration and coordination among diverse robotic entities engaged in a range of construction tasks.

7.1.2 Future Work

The construction industry's relatively low level of automation, when compared to sectors like manufacturing and aerospace, has become a focal point for potential innovation. There is a growing interest in incorporating existing robotic solutions or developing specialized robotic technologies tailored to the unique challenges of construction. However, several obstacles must be overcome. One significant challenge lies in closing the gap between design and engineering information and the practical application of automated production technology. The current limitations in transferring digital data from architects and engineers to construction sites hinder the seamless exchange of crucial information. Additionally, most traditional construction machinery is manually operated and does not effectively leverage the wealth of digital information generated by computer-aided design and engineering processes.

Looking ahead, the vision for construction sites involves a more dynamic collaboration between human operators and robots, with varying degrees of autonomy. This adaptability will be crucial because construction conditions and parameters differ widely from one project to another. Robotic systems will need to flexibly adjust their level of autonomy and operational mode based on task and environmental requirements. For instance, in tasks involving refurbishing or complex environments, robotic autonomy may need to be constrained to accommodate the presence of human workers or to navigate hazardous conditions effectively. In this dynamic construction environment, achieving the spatiotemporal requirements of on-site tasks will be essential for the success of robotic systems.

Furthermore, to truly enhance overall productivity on construction sites, there must be seamless coordination among multiple robotic systems and sensors, which may come from various vendors and exhibit different levels of autonomy. This includes not only integrating robotics but also finding synergy with conventional construction machines and human workers. This comprehensive approach, which takes into account various types of machines, on-site conditions, field workers, and the overarching construction project, presents a compelling and essential avenue for future research in the construction robotics domain.

7.2 Semi-autonomous approach for controlling the construction robot

7.2.1 Conclusion

By augmenting a commercially available construction machine with motion sensors and an embedded computer, the machine is transformed into an intuitive programmable robot. This robot can receive control commands from a host PC securely placed in a control container alongside the human operator. This configuration enables remote monitoring and allows the human operator to interactively define high-level task objectives, reducing the cognitive load on the robot. Additionally, the inclusion of a trajectory-tracking controller adds a layer of precision control at both joint and task levels. Moreover, visualizing planned motions before execution empowers operators to pre-plan and optimize deconstruction tasks, enhancing the controllability of the construction process.

The significance of this approach becomes particularly evident when considering worker safety and hazard mitigation on construction sites. By minimizing the need for direct proximity between human operators and machinery or workspaces, potential risks and hazards are significantly reduced. The ability to verify and fine-tune planned motions before execution plays a pivotal role in enhancing the overall controllability of dynamic processes such as the deconstruction process. Traditional teleoperation techniques often struggle with maintaining precise control over construction machines due to their complex degrees of freedom, which typically necessitate extensive training and experience. In contrast, this semi-autonomous approach places emphasis on integrating high-level objectives from human operators into the process and translating these objectives into optimized motions. Consequently, it holds the promise of increased process safety and efficiency, especially in scenarios where task precision is important.

7.2.2 Future Work

As the research points towards future directions, the concept of adaptiveness during hammering attempts is highlighted. Given the continuously changing nature of the structure's surface throughout the deconstruction process, finding ways to dynamically adjust and adapt the hammering strategy is crucial for efficient and effective operation. Additionally, the exploration of 5G technology's potential in this context opens up exciting possibilities for further enhancing communication and data exchange between the operator and the machine. Furthermore, while the current work primarily revolves around the use of a hammer as the primary tool, the aspect of material reuse remains relatively unexplored. Future investigations promise to dive deeper into the controlled dismantling of structures using alternative tools, such as a wall saw, with a focus on preserving elements and materials for potential reuse, thus aligning with sustainability objectives in the construction industry.

7.3 Assistance methods for teleoperated construction robot

7.3.1 Conclusion

The application of teleoperation constitutes a critical component of the construction industry, facilitating the remote control of machines by operators from a safe distance. Nevertheless, remote operation of these machines at the joint level, using individual joysticks, mandates extensive training for operators to achieve proficiency due to the machines' multiple degrees of freedom. Furthermore, the verification of the resulting machine motion can only occur after execution, making optimal control a challenging endeavor. Even experienced operators may require months of training to coordinate multiple joints to achieve the desired end-effector or tool motion, resulting in reduced productivity and diminished local precision and work efficiency. To tackle this issue, two assistive methods for teleoperation are proposed.

The first method, referred to as task space control, empowers the human operator to directly manipulate the end-effector in the task space. This approach provides a more intuitive means of interacting with the environment, without the need to consider the complex multi-degree-of-freedom nature of the construction machine. Although task space control is a well-established technique, it typically relies on the availability of an accurate dynamic model. However, constructing such a dynamic model for a construction machine is challenging due to various factors, including hydraulic actuators, linkages, and nonlinearities. To address these challenges and enable effective task space control, a data-driven actuator model is developed from the real operation data. This model establishes a relationship between changes in system states and corresponding control signals, replacing the dynamic model and obviating the necessity for a low-level controller. It directly generates control signals based on the desired system states. Utilizing this actuator model, a RL framework is introduced that learns an effective policy for task space control within a simulation environment. To bridge the gap between simulation and reality, the data-driven actuator model is incorporated during training to capture machine-specific nonlinearities in the relationship between control inputs and system state changes. The learned control policy takes desired velocities in the x-, y-, and z-directions in task space as input and directly produces the corresponding control signals. In contrast to conventional methods, the RL-based approach offers the advantage of not relying on a dynamical model, rendering it suitable for hydraulic machines where such models are typically unavailable. Moreover, the proposed method outperforms the Jacobian-based approach in terms of accuracy and robustness when striving to achieve changed task space goals.

In the second method, the control policy derived from the RL framework is transformed into virtual fixtures, which serve as guidance for human operators in optimizing joint control for task execution. In many instances, human operators do not directly benefit from the knowledge generated regarding the automated control of construction robots. While construction robots possess the capability to execute precise end-effector motions by managing and coordinating each joint, this knowledge often remains confined to the robots and is not effectively transferred to human operators. However, given the unstructured and dynamic nature of construction sites, implementing autonomous approaches across all construction sites can be challenging. Consequently, the transfer of knowledge from autonomous control policies to operators can be advantageous. This knowledge transfer would enable operators to harness the optimized movements acquired through autonomous approaches and apply this knowledge to subsequent teleoperation tasks. Consequently, the second method introduces an assistance system that furnishes guidelines for optimal joystick maneuvers and joint combinations through the use of virtual fixtures. This approach ensures safe teleoperation and minimizes errors during task execution. In this context, the RL framework is employed to enable robots to acquire efficient skills through interactions with the environment. To assess the effectiveness of the proposed framework, a user study is conducted using a Brokk 170 construction machine, evaluating its performance in a typical construction task involving the insertion of a chisel into a borehole. The effectiveness of the proposed framework is evaluated by comparing the performance of participants in the presence and absence of virtual fixtures. The results of this study illustrate the potential of the proposed framework in enhancing the teleoperation process.

7.3.2 Future Work

In the context of teleoperation, a pivotal consideration is the quality of visual feedback provided to human operators. As the direct proximity between human operators and workspaces is avoided for safety reasons, the enhancement of visual information assumes a critical role in teleoperation systems. In the research presented above, the visual information is transmitted at a rate of 3 Hz, imposing substantial strain on the local WLAN network, particularly due to the streaming of 3D point clouds and 2D RGB images. Addressing this challenge, one potential alternative for improvement is to leverage the high bandwidth capabilities of 5G technology, which can facilitate the provision of more detailed and real-time visual feedback during teleoperation. This advancement has the potential to significantly enhance operator situational awareness during the teleoperation. Another promising avenue for enhancing visual feedback involves the integration of a mobile platform into the teleoperation setup. In the current configuration, occlusions are a recurring issue due to the fixed camera position. To mitigate this limitation, the incorporation of a mobile platform equipped with the capability to dynamically navigate around the workspace, optimizing the camera's view based on the relative pose between the construction machine and the target object, offers a viable solution. Such a mobile platform can autonomously adjust its position to provide the most advantageous visual perspective, further improving the quality and effectiveness of visual feedback in teleoperation scenarios.

Moreover, for an even more effective utilization of the data-driven actuator model, it becomes intriguing to explore the prospect of implementing on-the-fly training using real-time data. In this approach, as the construction machine actively operates in the field, the actuator model continuously adapts and refines itself by drawing insights from the real-time operational data it encounters. This eliminates the necessity for the traditional offline process of collecting operation data and conducting model training, thus making the system more agile and responsive to the dynamic and unpredictable challenges inherent in construction tasks. As it continually refines its understanding of the operating environment, the actuator model can achieve a higher level of precision and efficiency. This adaptive learning capability holds the promise of significantly enhancing the overall framework of the data-driven approaches presented in this study, paving the way for improved performance and versatility in teleoperated construction machinery.

7.4 Communication Technologies in Construction

7.4.1 Conclusion

The inherent mobility of construction machines, stemming from the dynamic nature of construction sites, underscores the necessity for effective communication channels. While tethered mobile machines offer advantages like high bandwidth and low latency, their reliance without computationally intensive path planning algorithms severely limits maneuverability in unstructured environments, like construction sites. This limitation heightens the risk of damage and compromises system robustness. Hence, there's a pressing need for deeper exploration of wireless networks, particularly in the context of construction sites. The increasing integration of mobile robotic applications within these sites has propelled recent advancements towards wireless networks, emphasizing the criticality of investigating and optimizing these communication frameworks. This shift highlights the evolving landscape and the pivotal role of wireless networks in enhancing the functionality and efficiency of automated construction machines.

In order to study the advantages presented by the emerging 5G technology within this context, an on-site 5G network is being examined. This evaluation encompasses the comprehensive framework, starting from deployment and extending to validation through real-world experiments involving full-scale construction machines. This comprehensive approach aims to thoroughly investigate and understand the practical implications and potential benefits that the implementation of 5G technology could offer within the realm of construction machinery. Furthermore, a comparison between the 5G and WiFi technology is conducted to highlight the imperative for further research.

The results of the first test of the 5G network on the crane show the characteristics of each hardware component. The stable signal quality of the omni-antenna setup even during the rotation of the crane exhibits good signal quality. This forms the basis for further research into harmonising the network configuration with the use cases in the construction industry. The analysis comparing 5G and WiFi5 networks via heatmap revealed clear performance distinctions. Throughout the robot's movements, 5G consistently maintained lower Round Trip Time (RRT), indicating superior stability. In contrast, WiFi5 displayed fluctuations in RRT, suggesting less consistent performance during the robot's operation. This difference underscores 5G's reliability and steadiness in dynamic operational settings. Despite WiFi5 showing better latency, 5G's strength lay in its robustness, reducing unforeseen communication issues with the control PC. While this impact might not be visually apparent in the trajectory plot, the presence of such peaks emphasizes the importance of reliable communication. Though WiFi5 may offer lower latency and high bandwidth, 5G's demonstrated robustness, especially during crucial control operations, positions it as the preferable choice for ensuring dependable communication and minimizing unexpected performance fluctuations in real-time, precision-demanding control frameworks.

7.4.2 Future Work

This holistic exploration not only fills a critical gap in understanding the potential of 5G in construction machinery communication but also offers a roadmap for leveraging this technology to further develop the construction industry. The initial findings mark a significant leap forward in showcasing the enhanced robustness and coverage capabilities of 5G over WiFi. However, they also reveal the need for continued investigation and development. Further analysis into the direction of

Massive Machine-Type Communication (mMTC) is required to fully explore the benefit of 5G. Moreover, forthcoming investigations may delve into pioneering methods that fuse the strengths of both 5G and WiFi technologies. This fusion could provide another communication paradigm within construction environments, fostering a synergy that maximizes reliability, bandwidth, and adaptability. These strategic avenues of inquiry promise to propel the construction industry into a new era of connectivity, efficiency, and technological advancement.

Bibliography

[1] Bock, T., and Linner, T. (2017). Construction Robots: Elementary Technologies and Single-Task Construction Robots. doi:10.1017/CBO9781139872041

[2] L. B. Rosenberg (1993) "Virtual fixtures: Perceptual tools for telerobotic manipulation," Proceedings of IEEE Virtual Reality Annual International Symposium, Seattle, WA, USA, 1993, pp. 76-82, doi: 10.1109/VRAIS.1993.380795.

[3] Stentz A, Bares J, Singh S, Rowe P (1998) A robotic excavator for autonomous truck loading. In: Proceedings IEEE/RSJ international conference on intelligent robots and systems. Innovations in theory, practice and applications (Cat. No.98CH36190), Victoria, 1998, vol 3, pp 1885–1893

[4] Lublasser, E., Hildebrand, L., Vollpracht, A, and Brell-Cokcan, S. (2017). Robot-assisted deconstruction of multi-layered facade constructions on the example of external thermal insulation composite systems. Construction Robotics, 1(1/4), 39-47. hdoi:10.1007/s41693-017-0001-7

[5] Merckaert, K., De Beir, A., Adriaens, N., El Makrini, I., Van Ham, R., Vanderborght, B. (2018). Independent load carrying and measurement manipulator robot arm for improved payload to mass ratio. Robot Comput-Integr Manuf, 53, 135–140. doi:10.1016/j.rcim.2018.04.001

[6] Lee, H. J., and Brell-Cokcan, S. (2021). Cartesian coordinate control for teleoperated construction machines. Constr Robot, 5(1), 1-11. doi:10.1007/s41693-021-00055-y

[7] Hutter, Marco and Leemann, Philipp and Stevsic, Stefan and Michel, Andreas and Jud, Dominic and Hoepflinger, Mark and Siegwart, Roland and Figi, Ruedi and Caduff, Christian and Loher, Markus and Tagmann, Stefan, "Towards optimal force distribution for walking excavators," 2015 International Conference on Advanced Robotics (ICAR), Istanbul, Turkey, 2015, pp. 295-301, doi: 10.1109/ICAR.2015.7251471.

[8] Jud, D., Leemann, P., Kerscher, S., & Hutter, M. (2019). Autonomous Free-Form Trenching Using a Walking Excavator. IEEE Robotics and Automation Letters, 4(4), 3208-3215. doi:10.1109/LRA.2019.2925758

[9] Giftthaler, M., Sandy, T., Dörfler, K., et al. (2017). Mobile robotic fabrication at 1:1 scale: the In situ Fabricator. Constr Robot, 1, 3–14. doi:10.1007/s41693-017-0003-5

[10] Ryden, F., & Chizeck, H. J. (2012). Forbidden-region virtual fixtures from streaming point clouds: Remotely touching and protecting a beating heart. IEEE/RSJ International Conference on Intelligent Robots and Systems.

[11] Davies B. et al., (2006). Active-constraint robotics for surgery. Proceedings of the IEEE, 94(9), 1696–1704.

[12] Motzko, C., Fenner, J., Wöltjen, J., & Löw, D. (2016). Bewertungsmatrix für die Kostenplanung beim Abbruch und Bauen im Bestand. Datenbanksystem zur Analyse und Bewertung in Bezug auf Kosten, Technologien und Dauern. Forschungsinitiative ZukunftBau, 2975. Fraunhofer IRB Verlag.

[13] McKinsey Global Institute. (2017). Reinventing Construction Through a Productivity Revolution. Retrieved from `https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Operations/Our%20Insights/Reinventing%20construction%20through%20a%20productivity%20revolution/MGI-Reinventing-Construction\-Executive-summary.pdf` Accessed: 26 September 2023.

[14] Bock, T. (1988). Robot-Oriented Design. doi:10.22260/ISARC1988/0019

[15] Melenbrink, N., Werfel, J., & Menges, A. (2020). On-site autonomous construction robots: towards unsupervised building. Autom Constr, 119, 103312. doi:10.1016/j.autcon.2020.103312

[16] Jud, D., Leemann, P., Kerscher, S., & Hutter, M. (2019). Autonomous free-form trenching using a walking excavator. IEEE Robotics and Automation Letters, 4(4), 3208–3215. doi:10.1109/LRA.2019.2925758

[17] Johns, R. L., Wermelinger, M., Mascaro, R., et al. (2020). Autonomous dry stone. Constr Robot, 4, 127–140.

[18] Kim, J., Jin, M., Choi, W., & Lee, J. (2019). Discrete time delay control for hydraulic excavator motion control with terminal sliding mode control. Mechatronics, 64, 102265. doi:10.1016/j.mechatronics.2019.102265

[19] Haslam, R. A., Hide, S. A., Gibb, A. G., Gyi, D. E., Pavitt, T., Atkinson, S., & Duff, A. R. (2005). Contributing factors in construction accidents. Applied Ergonomics, 36(4), 401–415.

[20] Rubio, F., Valero, F., & Llopis-Albert, C. (2019). A review of mobile robots: Concepts, methods, theoretical framework, and ap-

plications. International Journal of Advanced Robotic Systems. https://doi.org/10.1177/1729881419839596

[21] Detert, T., Charaf Eddine, S., Fauroux, J. C., et al. (2017). Bots2ReC: introducing mobile robotic units on construction sites for asbestos rehabilitation. Constr Robot, 1, 29–37. https://doi.org/10.1007/s41693-017-0007-1.

[22] Dömel, A., Kriegel, S., Kassecker, M., Brucker, M., Bodenmüller, T., & Suppa, M. (2017). Toward fully autonomous mobile manipulation for industrial environments. International Journal of Advanced Robotic Systems, 14.

[23] Giftthaler, M., Sandy, T., Dörfler, K., et al. (2017). Mobile robotic fabrication at 1:1 scale: the In situ Fabricator. Constr Robot, 1, 3–14. https://doi.org/10.1007/s41693-017-0003-5

[24] Keating, S. J., Leland, J. C., Cai, L., & Oxman, N. (2017). Toward site-specific and self-sufficient robotic fabrication on architectural scales. Science Robotics, 2(5).

[25] Haarhoff, D., Brell-Cokcan, S. (2020). Apparatus for controlling a load suspended on a cord. Patent No. EP2020060477W. Available at: `https://patentimages.storage.googleapis.com/83/ca/52/53e80aa0303d1f/US20220185635A1.pdf`. Accessed: 26 September 2023.

[26] Podkaminer, N., & Peters, L. S. (2015). Construction robotics. Retrieved from https://construction-robotics.com/

[27] FBR. (2020). Hadrian X Out-door Construction and Brick-laying Robot from FBR. Available at: `https://www.fbr.com.au/view/hadrian-x`. Accessed: 26 September 2023.

[28] Montazeri, A., & Udo, E. J. (2016). Development of Dynamic Model of a 7DOF Hydraulically Actuated Tele-Operated Robot

for Decommissioning Applications. American Control Conference (ACC), pp. 1209-1214.

[29] Taylor, C. J., Chotai, A., & Robertson, D. (2010). State Dependent Control of a Robotic Manipulator used for Nuclear Decommissioning Activities. Intelligent Robots and Systems, pp. 2413–2418.

[30] Elkmann, N., Felsch, T., Sack, M., Saenz, J., Hortig, J. (2002). Innovative service robot systems for facade cleaning of difficult-to-access areas. 1. 756 - 762 vol.1.

[31] Iturralde, K., Feucht, M., Hu, R., Pan, W., Schlandt, M., Linner, T., Bock, T., Izard, J., Eskudero, I., Rodriguez, M., Gorrotxategi, J., Astudillo, J., Santos, J., Gouttefarde, M., Fabritius, M., Martin, C., Henninge, T., Nornes, S., Jacobsen, Y., & Elia, L. (2020). A Cable Driven Parallel Robot with a Modular End Effector for the Installation of Curtain Wall Modules.

[32] Lee, S., & Moon, J. I. (2015). Case Studies on Glazing Robot Technology on Construction Sites. https://doi.org/10.22260/ISARC2015/0077.

[33] Kim, P., Park, J. S., Cho, Y., & Kang, J. (2019). UAV-assisted autonomous mobile robot navigation for as-is 3D data collection and registration in cluttered environments. Automation in Construction. doi.org/10.1016/j.autcon.2019.102918

[34] Parietti, Federico, & Asada, Harry. (2014). Supernumerary Robotic Limbs for aircraft fuselage assembly: Body stabilization and guidance by bracing. Proceedings - IEEE International Conference on Robotics and Automation, 1176-1183. 10.1109/ICRA.2014.6907002.

[35] Wang, X., & Dunston, P. (2007). Design, strategies, and issues towards an augmented reality-based construction training platform. J. Inf. Technol. Constr., 12, 363-380.

[36] Kaneko, Kenji, Kaminaga, Hiroshi, Sakaguchi, Takeshi, Kajita, Shuuji, Morisawa, Mitsuharu, Kumagai, Iori, Kanehiro, Fumio. (2019). Humanoid Robot HRP-5P: an Electrically Actuated Humanoid Robot with High Power and Wide Range Joints. IEEE Robotics and Automation Letters, PP. 1431-1438. 10.1109/LRA.2019.2896465.

[37] Nuricumbo, Jorge Rene´, Ali, Haider, Marton, Zoltan Csaba, & Grzegorzek, Marcin (2015). Improving object classification robustness in RGB-D using adaptive SVMs. Multimedia Tools and Applications: An International Journal, pp. 1-19. Springer US. DOI: 10.1007/s11042-015-2612-7. ISSN 1380-7501.

[38] Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. J Field Robotics, 37, 362–386. https://doi.org/10.1002/rob.21918

[39] Horschel, D. S., Gibbons, P. W., & Draper, J. V. (1995). Performance benefits of telerobotics and teleoperation - enhancements for an arm-based tank waste retrieval system, report, Albuquerque, New Mexico.

[40] 5G.NAMICO: Networked, Adaptive Mining and Construction, North Rhine-Westphalia Ministry of Economic Affairs, Innovation, Digitalisation and Energy. (n.d.). Available at: `https://5g.nrw/best-practice/5g-namico/`. Accessed: 26 September 2023.

[41] Brell-Cokcan, S., & Lublasser, E. (2016). Novel technologies in the construction process for quality management in sustainable building production. Bauingenieur, 91(07/08), Germany.

[42] Directive 2008/98/EC on waste (Waste Framework Directive), 2008/98, Official Journal of the European Union (2013).

[43] U.S. Bureau of Labor Statistics. (2020). Number and rate of fatal work injuries, by industry sector. Retrieved April 24, 2023, from `https://www.bls.gov/charts/census-of-fatal-occupationalinjuries/number-and-rate-of-fatal-work-injuries-by/-industry.htm`

[44] Lee, H. J., Heuer, C., & Brell-Cokcan, S. (2022). Concept of a Robot Assisted On-Site Deconstruction Approach for Reusing Concrete Walls. Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC), 422-429. doi: 10.22260/ISARC2022/0058

[45] Brell-Cokcan, S., & Lee, H. J. (2022). Robotics in Construction. In: Ang, M.H., Khatib, O., Siciliano, B. (eds) Encyclopedia of Robotics. Springer, Berlin, Heidelberg. doi:10.1007/978-3-642-41610-1_218-1

[46] Lee, H. J., & Brell-Cokcan, S. "Reinforcement Learning-based Virtual Fixtures for Teleoperation of Hydraulic Construction Machine*," 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), Busan, Korea, Republic of, 2023, pp. 1360-1367, doi: 10.1109/RO-MAN57019.2023.10309417.

[47] Lampinen, S., Niu, L., Hulttinen, L., Niemi, J., & Mattila, J. (2021). Autonomous robotic rock breaking using a real-time 3D visual perception system. J Field Robotics, 38, 980-1006.

[48] Jud, D., Leemann, P., Kerscher, S., & Hutter, M. (2019). Autonomous Free-Form Trenching Using a Walking Excavator. IEEE Robotics and Automation Letters, 4(4), 3208-3215. doi: 10.1109/LRA.2019.2925758

[49] Coleman, D., Sucan, I. A., Chitta, S., & Correll, N. (2014). Reducing the Barrier to Entry of Complex Robotic Software: a MoveIt!

Case Study. Journal of Software Engineering for Robotics, 5(1), 3-16.

[50] Sucan, I. A., Moll, M., & Kavraki, L. E. (2012). The Open Motion Planning Library. IEEE Robotics & Automation Magazine, 19(4), 72-82.

[51] Jin, M., Lee, J., Chang, P. H., & Choi, C. (2009). Practical Nonsingular Terminal Sliding-Mode Control of Robot Manipulators for High-Accuracy Tracking Control. IEEE Trans. Ind. Electron., 56(9), 3593-3601.

[52] Ahn, K. K., Nam, D. N. C., & Jin, M. (2014). Adaptive Backstepping Control of an Electrohydraulic Actuator. IEEE/ASME Trans. Mechatron., 19(3), 987-995.

[53] Rusu, R. B., & Cousins, S. (2011). 3D is here: Point Cloud Library (PCL). 2011 IEEE International Conference on Robotics and Automation, 1-4.

[54] Lee, H. J., Krishnan, A., Brell-Çokcan, S., Knußmann, J., Brochhaus, M., Schmitt, R. H., Emontsbotz, J. J., & Sieger, J. (2022). Importance of a 5G Network for Construction Sites: Limitation of WLAN in 3D Sensing Applications. Proceedings of the International Symposium on Automation and Robotics in Construction (IAARC), doi: 10.22260/ISARC2022/0054.

[55] Chen, J. Y. C., Haas, E. C., & Barnes, M. J. (2007). Human Performance Issues and User Interface Design for Teleoperated Robots. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 37(6), 1231-1245. doi: 10.1109/TSMCC.2007.904974

[56] Lee, H. J., & Brell-Cokcan, S. (2023). Towards controlled semi-autonomous deconstruction. Constr Robot. https://doi.org/10.1007/s41693-023-00111-9

[57] Khatib, O. (1987). A unified approach for motion and force control of robot manipulators: the operational space formulation. IEEE Journal of Robotics and Automation, 3(1), 43–53.

[58] Nakanishi, J., Cory, R., Mistry, M., Peters, J., & Schaal, S. (2005). Comparative experiments on task space control with redundancy resolution. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Edmonton, AB.

[59] Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction. The MIT Press.

[60] Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. The International Journal of Robotics Research, 37(4-5), 421-436.

[61] Hwangbo, J., Lee, J., Dosovitskiy, A., Bellicoso, D., Tsounis, V., Koltun, V., & Hutter, M. (2019). Learning agile and dynamic motor skills for legged robots. Science Robotics, 4(26), eaau5872.

[62] Makoviychuk, V., Wawrzyniak, L., Guo, Y., Lu, M., Storey, K., Macklin, M., Hoeller, D., Rudin, N., Allshire, A., Handa, A., & State, G. (2021). Isaac Gym: High Performance GPU-Based Physics Simulation For Robot Learning.

[63] Schulman, J., Wolski, F., Dhariwal, P., Radford, A., & Klimov, O. (2017). Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.

[64] Makoviichuk, D., && Makoviychuk, V. (2021). rl-games: A High-performance Framework for Reinforcement Learning, `https://github.com/Denys88/rl_games`, Accessed: 26 September 2023.

[65] Buss, S. R. (2004). Introduction to inverse kinematics with Jacobian transpose, pseudoinverse and damped least squares methods. IEEE J Robot Autom, 17(1–19), 16.

[66] Chan, T. F., & Dubey, R. V. (1995). A weighted least-norm solution based scheme for avoiding joint limits for redundant joint manipulators. IEEE Trans Robot Autom, 11(2), 286–292.

[67] Nakamura, Y., & Hansafusa, H. (1986). Inverse kinematic solutions with singularity robustness for robot manipulator control. J Dyn Syst Meas Control, 108(3), 163–171.

[68] Ahn, K. K., Nam, D. N. C., & Jin, M. (2014). Adaptive Backstepping Control of an Electrohydraulic Actuator. IEEE/ASME Trans. Mechatron., 19(3), 987-995.

[69] Bettini, A., Marayong, P., Lang, S., Okamura, A. M., & Hager, G. D. (2004). Vision-assisted control for manipulation using virtual fixtures. IEEE Transactions on Robotics, 20(6), 953-966. doi: 10.1109/TRO.2004.829483.

[70] Rosenberg, L. B., & Stanford University. (1994). ”Virtual fixtures” : perceptual overlays enhance operator performance in telepresence tasks (dissertation).

[71] Feng, H., Yin, C., Li, R., Ma, W., Yu, H., Cao, D., & Zhou, J. (2019). Flexible virtual fixtures for human-excavator cooperative system. Automation in Construction, 106, 102897. doi: 10.1016/j.autcon.2019.102897.

[72] Rydén, F., & Chizeck, H. J. (2012). Forbidden-region virtual fixtures from streaming point clouds: Remotely touching and protecting a beating heart. 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, 3308-3313. doi: 10.1109/IROS.2012.6386012.

[73] Davies B. et al., (2006). Active-constraint robotics for surgery. Proceedings of the IEEE, 94(9), 1696–1704.

[74] Lee, M., Choi, H., Kim, C., Moon, J., Kim, D., & Lee, D. (2022). Precision Motion Control of Robotized Industrial Hydraulic Excavators via Data-Driven Model Inversion. IEEE Robotics and Automation Letters, 7(2), 1912-1919. doi: 10.1109/LRA.2022.3150785.

[75] Egli, P., & Hutter, M. (2022). A General Approach for the Automation of Hydraulic Excavator Arms Using Reinforcement Learning. IEEE Robotics and Automation Letters, 7(2), 5679-5686. doi: 10.1109/LRA.2022.3152865.

[76] Marion, P., Florence, P. R., Manuelli, L., & Tedrake, R. (2018). Label Fusion: A Pipeline for Generating Ground Truth Labels for Real RGBD Data of Cluttered Scenes. 2018 IEEE International Conference on Robotics and Automation (ICRA), 3235-3242. doi: 10.1109/ICRA.2018.8460950.

[77] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III.

[78] Bradski, G., & Kaehler, A. (2008). Learning OpenCV: Computer vision with the OpenCV library.

[79] Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139–183.

[80] Brell-Cokcan, S., & Lee, H. J. (2022). Robotics in Construction. In: Ang, M.H., Khatib, O., Siciliano, B. (eds) Encyclopedia

of Robotics. Springer, Berlin, Heidelberg. doi:10.1007/978-3-642-41610-1_218-1

[81] Chen, J.Y., Haas, E.C. and Barnes, M.J., ”Human performance issues and user interface design for teleoperated robots.” 2007 IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 37(6), pp.1231-1245

[82] Mast et al., (2013). Teleoperation of Domestic Service Robots: Effects of Global 3D Environment Maps in the User Interface on Operators. Cognitive and Performance Metrics. 8239. 392-401.

[83] I. Johansson, S. Dadhich, U. Bodin, and T. Jönsson, “Adaptive Video with SCReAM over LTE for Remote-Operated Working Machines,” Wireless Communications and Mobile Computing, Vol. 2018, S. 1–10, 2018, doi: 10.1155/2018/3142496.

[84] 3GPP. TR 38.913: Study on Scenarios and Requirements for Next Generation Access Technologies (Release 16); v:16.0.0; 3GPP: Route des Lucioles, France, July 2020.

[85] McKinsey Global Institute. (2017). Reinventing Construction Through a Productivity Revolution. Retrieved from `https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Operations/Our%20Insights/Reinventing%20construction%20through%20a%20productivity%20revolution/MGI-Reinventing-Construction-Executive-summary.pdf`, Accessed: 26 September 2023.

[86] D. Jud et al., ”HEAP - The autonomous walking excavator”, Automation in Construction, Jg. 129, S. 103783, 2021, doi: 10.1016/j.autcon.2021.103783.

[87] Lee, H. J., & Brell-Cokcan, S. (2023). Task Space Control of Hy-

draulic Construction Machines using Reinforcement Learning. doi:10.48550/arXiv.2307.09246

[88] Lee, H. J., & Brell-Cokcan, S. (2023). Data-Driven Actuator Model-Based Teleoperation Assistance System. 20th International Conference on Ubiquitous Robots (UR), Honolulu, HI, USA, 2023, pp. 552-558, doi: 10.1109/UR57808.2023.10202488.

[89] Dadhich, S., Bodin, U., & Andersson, U. (2016). Key challenges in automation of earth-moving machines. Automation in Construction, 68, 212–222. doi:10.1016/j.autcon.2016.05.009

[90] Mendoza, J.; de-la-Bandera, I.; Álvarez-Merino, C.S.; Khatib, E.J.; Alonso, J.; Casalderrey-Díaz, S.; Barco, R. 5G for Construction: Use Cases and Solutions. Electronics 2021, 10, 1713. https://doi.org/10.3390/electronics10141713

[91] Xiang, Y., Xu, B., Su, T., Brach, C., Mao, S. S., & Geimer, M. (2021). 5G meets construction machines: Towards a smart working site. 2021 International Conference on Computing and Communications Applications and Technologies (I3CAT), Ipswich, United Kingdom. doi:10.1109/i3cat53310.2021.9629426

[92] Doosan Group (2019). Doosan Debuts Germany-Korea 5G Remote Control Solution in Europe. Retrieved from `https://www.doosan.com/en/media-center/press-release_view?id=20171901&page=1&` Accessed: 26 September 2023.

[93] You, K., Ding, L., Zhou, C., Dou, Q., Wang, X., & Hu, B. (2021). 5G-based earthwork monitoring system for an unmanned bulldozer. Automation in Construction, 131(103891), 103891. doi:10.1016/j.autcon.2021.103891

[94] Stereolabs. (2023). Zed SDK [Software Development Kit]. Retrieved from https://github.com/stereolabs/zed-sdk/tree/master/body%20tracking