UiA Faculty of Engineering and Science

PhD candidate report, midterm evaluation

Working title: Safe Human-Robot Collaboration in Assembly Line Using 3D Sensors, Wearables and Elastic Joint Robots

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Information

PhD programme:	*Doctor of Philosophy of Engineering and Science, Specialisation in Engineering Sciences, Scientific field of Mechatronics*
Project title:	*Working title: Safe Human-Robot Collaboration in Assembly Line Using 3D Sensors, Wearables and Elastic Joint Robots*
PhD student:	*Even Falkenberg Langås*
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Co-supervisor 1:	*Associate Professor Daniel Hagen*
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Co-supervisor 2:	*Dr. Halima Zahra Bukhari*
Institution:	*Twilligent AS*
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The following current regulations apply:

- Regulations for the Degree of Philosophiae Doctor (PhD) at the University of Agder
- Supplementary regulations for the PhD programme in Engineering and Science

Signatures

		Even Falkenberg Langås
Date	Signature, PhD Student	Printed Name

The PhD candidate must submit the mid-term report to the evaluators 3 weeks prior to the date of evaluation.
Date for mid-term evaluation: ______________

Recommended benchmarks

- Article-compilation: 3 Journal papers and 3 conference papers (approximately)

Oral presentation

- 30-45 minutes presentation by the PhD candidate of key elements from the report.
- Discussion of report and presentation, including discussion of the wider thematic framework.
- Discussion of plans for completion of project and studies.

Safe Human-Robot Collaboration in Assembly Line Using 3D Sensors, Wearables and Elastic Joint Robot

1 Introduction

Humans have throughout the evolution sought for ways to ease their tedious and hard work. This started with developing tools before animals became a central part of our lives. They were crucial for us to grow as species due to their contribution to agriculture. Horses were used for plowing land and for transportation. Later on, wind mills were used to utilise wind energy for heavy tasks such as grinding grain, pumping water and sawing wood. The steam engine initiated the first industrial revolution, before the electric motor and the combustion engine, enabled mass production and assembly lines, hence the transition to Industry 2.0 [1]. During the 20th century there was a rapid growth of factories around the globe with large and powerful machinery. Enabling technologies of Industry 3.0 (information technology and electronics) meant that these machines could be automated, thereby increasing efficiency [2]. In the 21st century, technological concepts such as the internet of things (IoT), big data, artificial intelligence (AI) and digital twin (DT) emerged, enabling the transition to Industry 4.0 [3]. However, common for all industrial revolutions until now is the separation between human and machines due to the power, determination and lack of cognitive awareness present in most machines today. But just like we tamed animals in early human evolution, Industry 5.0 aims at bringing humans and machines closer together by building safer robots and intelligent sensory systems. For this goal to succeed, it is crucial that we gradually transition from caged machines to the field of human-robot interaction (HRI), to human-robot collaboration (HRC) and finally to human-robot teaming (HRT) to enable safe and harmonic collaboration for the future industry.

This research project aims to develop a system for safe HRC in an assembly line environment by utilising 3D sensor technology to detect and track humans, predict their movements, and control the movements of machines and robots accordingly. The project will involve installing a 3D sensor system in the assembly line and using algorithms to predict the movements of humans based on their past actions and the surrounding environment. The perception system will also be used to detect other objects in the assembly line, such as tools and obstacles, to improve efficiency and prevent collisions. In addition to this perception system, the project will use augmented reality (AR) and tactile feedback devices to create a user interface for the human operator, allowing the user to receive visual cues and tactile feedback to improve their interactions with the robot. The integration of such wearable technology will enhance safety in HRC settings. The effectiveness of the system will be tested in both simulated and real-world environments, and a case study will be presented to demonstrate its application. The expected outcomes of the project include real-time tracking of the pose of humans and the predicted path of their movements for the next few seconds, as well as the development of a user interface using AR and tactile feedback devices. Finally, this will be used to perform HRC tasks related to demanufacturing of used goods.

The objective of this work is threefold:

O1. Utilise sensor technology to detect and track humans and predict their motion in both simulation and real-world environments, and compare the effectiveness of different algorithms through testing in real-world scenarios.

O2. Integrate tactile feedback and AR to facilitate intuitive and efficient HRC in demanufacturing tasks.

O3. Ensure efficient and safe HRC through the integration of safe robots, tactile interfaces, and AR technology, along with human detection and motion prediction capabilities.

1.1 Background and Motivation

The development of industrial infrastructure is supported by the United Nations' Sustainable Development Goals (UN-SDG). UN-SDG is a call for action by all countries to achieve peace and prosperity while protecting the planet. In their goal number 9, "Industry, innovation and infrastructure", they emphasise the importance to "build resilient infrastructure, promote sustainable industrialisation and foster innovation" [4]. Further on, in 9.4, they urge to "upgrade infrastructure, and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes". Industry 5.0's emphasis on resource efficiency, clean technologies, and sustainable production processes aligns with the UN-SDG's call for a greener and more sustainable industrial sector. By optimizing production, reducing waste, and minimizing environmental impact, Industry 5.0 paves the way for a more resilient and sustainable industrial future.

In the context of HRC, robots are not just replacing humans in tasks, but are designed to work alongside them, augmenting their capabilities and creating a synergistic relationship. This collaboration allows for a more flexible and adaptable workforce, enabling humans to leverage their creativity, problem-solving skills, and decision-making abilities, while robots handle tasks that require precision, repetition, or involve hazardous environments.

The growing global demand for consumer goods is driving an increased need for production and recycling. It is forcing manufacturers to streamline their production through innovation. The use of robotic systems is a growing trend that can automate repetitive tasks such as pick-and-place and assembly. Furthermore, these robots and machines perform these tasks more efficiently and with higher loads than humans. Recycling on the other hand, can often include complex dismantling that requires dexterity, flexibility and cognitive decision making, which is only feasible for human operators. Because of the big gap between human and machines, most of these complex dismantling processes are done by human operators, if done at all. To streamline these processes, humans and machines can be combined to complement each other through HRI at first, then to a gradually more and more harmonious HRC and finally to synergistically achieve HRT. This is a crucial step towards EU's goal of becoming climate neutral before 2050.

This PhD project is part of the industrial PhD scheme from The Research Council of Norway, with the executive company being Twilligent AS, a norwegian start-up located in Arendal. Twilligent AS is positioned in the market of developing DTs for industrial SMBs and intends to be a catalyst for DTs towards industry 4.0. The company was founded in February 2021, and has successfully delivered the first commercial DT to their pilot customer Slamrensing AS. This work was presented at HICSS in January 2023 [5]. Currently, the company is working on several projects regarding DTs, and have been selected as research and development (R&D) partner in applications for multiple innovation projects for the industrial sector (IPN).

The aim for the doctoral project is to expand the possibilities and strengthen Twilligent's DTs, which will add value for their customers within the manufacturing and logistics domain. It will strengthen the technical competences in the company, thereby benefitting the co-workers through the knowledge acquired from the project. Twilligent aims to develop products and services based on the research findings.

1.2 Reflections

In addition to providing time for research and technical development, the PhD project has given me time to reflect on philosophical and ethical implications of my work. I have learned about the importance of having a clear motivation to work towards a better future for society. My published paper on this topic [6] shows my dedication to ensure that my work leads to a human-centric industry focused on improving the worker satisfaction in industrial settings.

The paper sheds light on how DTs and AI within HRT can enhance collaboration, improve efficiency, and promote worker satisfaction. However, there are concerns that need to be carefully considered within this domain. Privacy and data security concerns, issues of autonomy and control, questions of intellectual property and ownership, as well as psychological and societal impacts, are among the key ethical considerations addressed in the paper.

2 Problem Statement

To the best of our knowledge, there is not much literature on designing complete HRT systems integrating perception systems, tactile feedback and AR for physical collaboration. Although there is a great deal of research on HRI and HRC, there is still a gap towards efficient, comprehensive HRT that needs to be closed.

HRT refers to a scenario where the human and robot work together as equals, with the robot possessing the ability to make decisions and take actions independently in support of the team's objectives. Both the human and robot depend on each other to achieve a shared goal, and neither can perform the task without the other. This project aims to take a gradual approach, moving from minimal interaction to full teaming.

Based on the literature review [7] and research from the first half of the PhD project, the following research gaps have been found:

- *Lack of robust algorithms for accurately predicting human behaviour in HRT scenarios.*
- *Lack of robust and reliable methods for integrating tactile feedback with AR interfaces.*
- *Limited research on the integration of tactile and AR interfaces with other sensing modalities, such as 3D sensors.*
- *Lack of comprehensive frameworks for user interfaces for HRT applications.*
- *Lack of holistic approaches that fully integrate HRT.*

Based on these research gaps, the following research questions have been derived:

RQ1: How can 3D sensory information be used to accurately detect and predict human motion in real-time inndustrial environments?

RQ2: How can tactile feedback and AR be integrated to facilitate intuitive and efficient HRT in demanufacturing tasks involving used goods?

RQ3: How can we efficiently and safely perform HRT by integrating safe robots, tactile and AR interfaces with human detection and motion prediction?

The completed work related to these research questions is presented in the next section.

3 Completed Work

This chapter presents an overview of the accomplishments achieved during the first half of the PhD project. It provides detailed insights into the progress made towards addressing RQ1 and RQ2 in section 3.4 and 3.5, respectively.

3.1 Coursework

Table 1: Coursework components

Course Code	**Course Name**	**Credits**	**Responsible Institution**	**Semester**	
ENE701	Applied Statistics Course for Engineering	5	UiA	Spring 2023	✓
EX603	Theory of Science and Ethics	5	UiA	Spring 2023	✓
MAS601	Design, Modelling, and Simulation of Mechatronic Systems	5	UiA	Spring 2023	✓
VB8005	Digital twin for sustainable manufacturing	7.5	NTNU	Spring 2024	✓
ENE607	Special Syllabus (Robotics design, implementation and programming in ROS2)	5	UiA	Spring 2025	
ENE705	Selected Topics in Engineering (Introduction to Machine Learning for Robotics)	5	UiA	Spring 2025	

Table 1 shows the approved coursework component table. While the majority of coursework has been successfully completed, there are two outstanding courses that require final reports for official completion:

- ENE607: Special Syllabus (Robotics design, implementation and programming in ROS2)
- ENE705: Selected Topics in Engineering (Introduction to Machine Learning for Robotics)

The lectures and tutorials for these courses is completed and only the term paper is left. The term papers for these courses will be strategically aligned with the future work plans for the PhD project:

- The term paper for ENE607 will focus on the implementation and evaluation of human motion prediction algorithms in a laboratory setting. The term paper will thereby align with the planned journal paper on this topic, which will be elaborated in Section 4.
- The term paper for ENE705 will explore the integration of tactile feedback and insights from RQ1 into an AR user interface for remote HRI. This paper will align with another planned journal paper as explained in Section 4.

This approach allows for a synergistic connection between coursework and research objectives, optimising time and resources while ensuring the completion of academic requirements.

3.2 Publications

The following details the scholarly output generated during this phase of the PhD project, including both published works and those in the review process. Table 2 lists papers written as the main author, while Table 3 lists additional papers where I have contributed as a co-author during the PhD project period.

Table 2: List of papers written as main author.

ID	Conference/Journal, title and authors	Status
C1	**Conference:** 2023 IEEE Symposium Series on Computational Intelligence (SSCI) **Title:** Harnessing digital twins for human-robot teaming in industry 5.0: Exploring the ethical and philosophical implications **Authors:** E. F. Langas, M. H. Zafar, and F. Sanfilippo	Published
C2	**Conference:** 2024 10th International Conference on Automation, Robotics and Applications (ICARA) **Title:** Human trajectory simulation in industrial settings using the ornstein-uhlenbeck process and deep learning based classification **Authors:** E. F. Langås, M. H. Zafar, S. O. Nyberg, and F. Sanfilippo	Published
C3	**Conference:** 2024 IEEE 12th International Conference on Control, Mechatronics and Automation (ICCMA) **Title:** Inclusive digital twins with edge computing, cloud communication and virtual reality for remote human-robot interaction **Authors:** E. F. Langas, H. Z. Bukhari, D. Hagen, M. H. Zafar, and F. Sanfilippo	Accepted for publication
J1	**Journal:** Journal of Intelligent Manufacturing **Title:** Exploring the synergy of human-robot teaming, digital twins, and machine learning in industry 5.0: A step towards sustainable manufacturing **Authors:** E. F. Langas, M. H. Zafar, and F. Sanfilippo	Under review

Table 3: List of publications as co-author.

Conference/Journal, title and authors	My contributions
Journal: Robotics and Computer-Integrated Manufacturing, 2024 **Title:** Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review **Authors:** M. H. Zafar, E. F. Langås, and F. Sanfilippo	Investigation, Original draft, Review and editing
Journal: Results in Engineering, 2023 **Title:** Empowering human-robot interaction using semg sensor: Hybrid deep learning model for accurate hand gesture recognition **Authors:** M. H. Zafar, E. F. Langås, and F. Sanfilippo	Software, Review and editing
Conference: 2023 IEEE Symposium Series on Computational Intelligence (SSCI) **Title:** From rigid to hybrid/soft robots: Exploration of ethical and philosophical aspects in shifting from caged robots to human-robot teaming **Authors:** M. T. Hua, E. F. Langås, M. H. Zafar, and F. Sanfilippo	Original draft, Review and editing
Conference: 2024 IEEE International Conference on Omni-layer Intelligent Systems (COINS) **Title:** Multimodal fusion of eeg and emg signals using self-attention multi-temporal convolutional neural networks for enhanced hand gesture recognition in rehabilitation **Authors:** M. H. Zafar, E. F. Langås, S. O. G. Nyberg, and F. Sanfilippo	Data collection, Review and editing
Conference: 2024 10th International Conference on Automation, Robotics and Applications (ICARA) **Title:** Real-time gesture-based control of a quadruped robot using a stacked convolutional bi-long short-term memory (bi-lstm) neural network **Authors:** M. H. Zafar, E. F. Langås, and F. Sanfilippo	Software, Review and editing

3.3 Literature Review

As part of the journey towards HRC, we wrote a review article to help map the vast amounts of literature on the topic. A paper titled "Exploring the Synergy of Human-Robot Teaming, Digital Twins, and Machine Learning in Industry 5.0: A Step Towards Sustainable Manufacturing" (J1) has been submitted to the Journal of Intelligent Manufacturing. This section presents excerpts from the submitted paper. In addition to the excerpts in this section, the paper covers: new insights into the human-centric nature of Industry 5.0, including DT of robots and humans and mixed reality (MR) human-machine interfaces (HMI); an in depth review of AI strategies in HRI/C/T systems, including robotic perception systems for predicting human behaviour as well as robotic decision making algorithms; elaboration of DT based HRI/C/T for disassembly tasks.

3.3.1 Abstract (Excerpt from J1)

Sustainable manufacturing remains a central objective of Industry 5.0. By successfully implementing harmonic human-robot teams in intelligent industrial systems, the efficiency and well-being of human workers can be increased. Achieving this requires a gradual approach from caged robots to advanced, seamless collaboration between humans and robots. Initially, that means transitioning to human-robot interaction (HRI) where there is an exchange of commands between the human and the robot. Further advancements within safety considerations, including collision avoidance through advanced machine vision, enable the exchange of workspace that defines human-robot collaboration (HRC). The next stage is physical HRC (pHRC) which requires safe and controlled exchange of forces through impedance and admittance control. Finally, this paper describes human-robot teaming (HRT), which is defined by the exchange of solutions as teammates. This is enabled by combining cutting-edge technologies such as digital twin (DT), advanced vision sensors, machine learning (ML) algorithms and mixed reality (MR) human-machine interfaces for human operators. By reviewing these technologies, the paper highlights current challenges, limitations and research gaps within the field of HRT and suggests potential future possibilities for HRT, such as advanced disassembly of used goods for a more sustainable manufacturing industry.

3.3.2 Methodology (Excerpt from J1)

A comprehensive search strategy was employed to identify relevant studies. Further on, primary studies published between 2020 and 2024 was identified. This relatively short timespan was chosen due to the rapid advancements in AI and robotics in recent years, requiring up-to-date literature for this review. The following electronic databases was used: Google Scholar and Web of Science.

Table 4 shows the search terms used to identify the primary studies within the different fields. Only review papers was considered as candidates for being primary studies for further investigations. After extracting the relevant review papers, the titles and abstracts of the remaining articles were screened based on the following inclusion criteria: (1) focus on Industry 5.0 concepts and technologies, (2) exploration of HRI/C/T in industrial settings, (3) utilisation of DT technology and (4) application of ML algorithms. For a paper to be included, it had to fulfill (1) or (2) and (3) or (4).

The full texts of the primary studies were retrieved and assessed. Further on, Connected Papers was used to find other relevant studies that might have been missed in the initial search through a visual graph. Additionally, reference lists of included articles were manually searched for other potential studies.

This review is limited by the scope of the databases searched and the specific keywords used. It's possible that relevant studies published in other sources or using different terminology might have been missed. Additionally, the quality of the included studies varied, with some lacking detailed methodological descriptions or reporting biases. However, efforts were made to mitigate these limitations through a comprehensive search strategy and a critical appraisal of the included studies.

Table 4: Search terms used for finding literature.

	Search Terms	**Hits on Google Scholar**	**Primary Studies**
Term 1	"Industry 5.0" OR "Industry 5"	16,900	[3, 8]
Term 2	"Human-robot interaction" OR "HRI" OR "Human-robot collaboration" OR "HRC" OR "Human-robot teaming" OR "HRT" AND "Robot"	151,000	[9, 10]
Term 3	"Digital Twin" AND {Term 1}	3,800	[11]
Term 4	"Digital Twin" AND {Term 2}	5,110	[12]
Term 12	"Artificial intelligence" OR "Machine learning" OR "Deep Learning" AND {Term 1}	16,700	[13]
Term 13	"Artificial intelligence" OR "Machine learning" OR "Deep Learning" AND {Term 2}	18,500	[14, 15]

3.3.3 Human-Robot Interaction, Collaboration, and Teaming (Excerpt from J1)

In the literature, words like "interaction" and "collaboration" are used interchangeably. To be able to differentiate the research, this section will explain the different stages of collaboration. Table 5 shows the gradual difference between HRI to HRT and Table 6 explains it in more detail. Further on, Figure 1 visualises the content in the tables.

Human-Robot Interaction

HRI refers to the field of study that focuses on the design and use of robots, and how they interact with humans [20]. It involves understanding the ways in which humans perceive and respond to robots, as well as the ways in which robots can be designed to better fit into human environments and respond to human needs. The field of HRI draws on knowledge from a variety of disciplines, including computer science, psychology, sociology, and engineering.

Table 5: The difference between HRI, HRC, pHRC and HRT.

	Exchange commands	**Share workspace**	**Exchange forces**	**Exchange solutions**
Human-Robot Interraction (HRI)	X	-	-	-
Human-Robot Collaboration (HRC)	X	X	-	-
Physical Human-Robot Collaboration (pHRC)	X	X	X	-
Human-Robot Teaming (HRT)	X	X	X	X

Table 6: Explanation of the difference between HRI, HRC, pHRC and HRT.

	Description	**Case study**
HRI	Relies on exchanging commands. This can include traditional manual control of the robot, or more sophisticated commands like gestures or voice commands.	[16]
HRC	Also includes sharing workspace, which means that safety considerations is critical.	[17]
pHRC	In addition to sharing the workspace, pHRC includes the exchange of forces. In other words, it includes physical contact between the human and the robot	[18]
HRT	HRT is defined by the exchange of solutions as well. This means that both the human and the robot can suggest solutions and contribute physically and in planning, as equal teammates.	Lacking

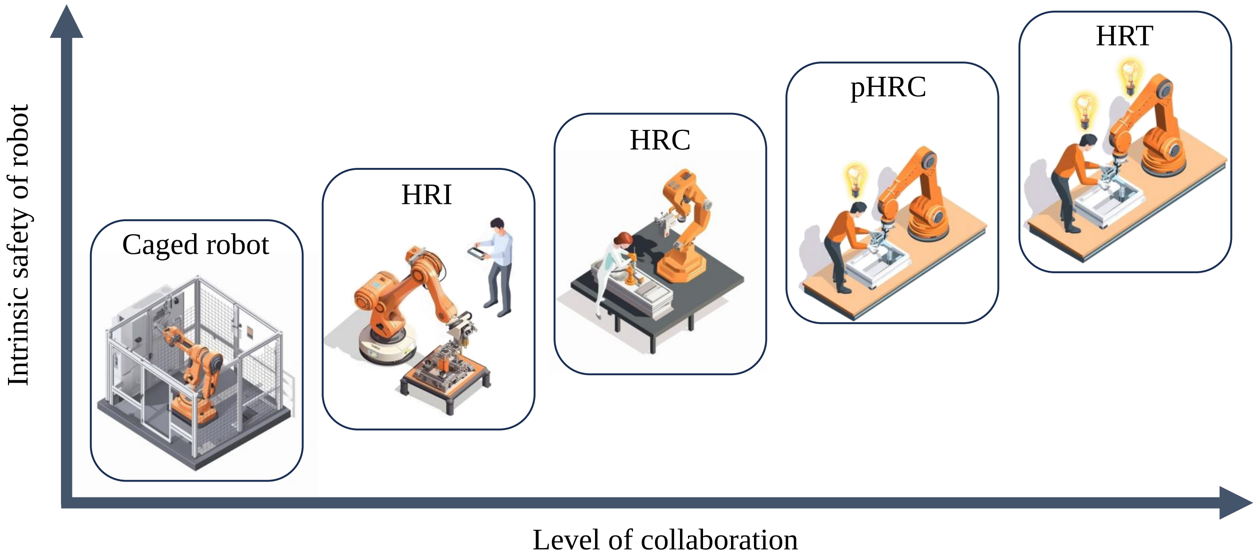


Figure 1: Human-robot collaboration stages [19].

Researchers study the ways in which humans perceive and respond to different robot features, such as their appearance, behaviour, and movement. They also investigate how humans and robots can interact in ways that are safe, efficient, and comfortable. In practice, HRI can involve the development of user interfaces and control systems that allow humans to interact with robots in a natural and intuitive way [21]. For example, a robot may be designed to respond to human gestures or speech, or it may be equipped with sensors that allow it to perceive and respond to human emotions and intentions.

In this paper, HRI is only defined by the exchange of commands between the human and robot. However, the workspace of the robot is separated from the human, which implies that the robot does not need to be intrinsically safe. Workers can interact with this robot in numerous ways. Most industrial robots come with a controller, typically with a touch panel and a joystick, as visualised in Figure 1 in the HRI box. Such a controller can be used to manually control the joints of the robot or the end-effector.

Other ways of interacting with the robot is through wearable sensors. By equipping the human with Inertial Measurement Units (IMU), one can detect different movements of made by the human, and use that as control inputs for the robot. Another method is to use surface electromyography (sEMG) sensors. sEMG sensors can detect electrical signals triggered by the activation of muscles. For example, different hand gestures can provide seperable sEMG signals that could trigger different commands for the robot [22].

Sometimes it can be inconvenient to use wearable sensors, as they require the worker to put on equipment that might be uncomfortable or not within the health, safety and environment (HSE) regulations of the company. In that case, external sensors might be the better option. Vision sensors such as traditional 2D cameras or state-of-the-art 3D sensors (i.e. 3D cameras or light detection and ranging (LiDAR) sensors) can be used to detect gestures made by the human. Further on, voice commands can be detected through the use of microphones. However, this might be disturbed by loud noises that are often present on factory floors in the manufacturing and process industry.

Contactless Human-Robot Collaboration

HRC refers to the concept of humans and robots working together towards a common goal in a shared environment [23]. This type of interaction is different from HRI, which is more focused on how humans and robots interact with one another, whereas HRC focuses on their joint performance and cooperation [24] in a shared workspace. One important aspect of HRC is ensuring that the robots are designed in a way that they can understand and respond to human cues and intentions. This requires the use of sensors and algorithms that can perceive human actions and emotions, as well as interfaces that allow humans to control the robots and receive feedback from them. Compared with HRI, HRC has a much higher safety demand due to the shared workspace. This requires an intrinsically safe robot to avoid dangerous contact between the robot and the human. Obstacle avoidance techniques are therefore implemented to tackle this challenge. This is enabled through the use of advanced vision sensors and path planning algorithms.

Physical Human-Robot Collaboration

Physical HRC (pHRC) differs from contactless HRC in that the human and robot exchange forces through physical contact. This implies that the robot needs to be safe, meaning that forces and torques need to be monitored and controlled. For example, by using a low-cost sensing approach, functions for torque sensing at the joint level, sensitive collision detection and joint compliant control need to be achieved [25, 26]. Even more intrinsically safe are soft/elastic robots [27, 28, 29]. Research on soft robotics is rapidly evolving to try and solve difficult tasks that require caution and precision, such as handling biological materials or fragile objects or collaborating with humans. Tuan et al. presented a soft robotic arm in [30] with elastic joints and rigid links. This makes the robot intrinsically safe, depending on the end effector. Simultaneously, it gains the strength benefits of the rigid links. However, the elastic joints limits the payload capacity, which is a challenge within soft robotics. Similarly to HRC, pHRC requires an intrinsically safe robot, but one should also consider the physical, cognitive, and emotional aspects of collaboration, and design safety mechanisms to prevent accidents and injuries in real-time.

pHRC introduces some challenges due to the variations in torque requirements caused by the unpredictable force contributions from the human. Traditional industrial robots are normally controlled by a position controller where a very high stiffness is applied to all joints to maximise the precision. For pHRC, these stiff joints are dangerous when the robot is moving as the robot will use all it's power to follow the desired path. But for pHRC, the robot needs to be intrinsically safe. It should give way when there is contact, just like a human colleague would. To achieve this, a special control technique is applied: impedance control. Impedance control is an approach to dynamic control relating force and position. It is based on the definition of mechanical impedance:

$$\frac{F(s)}{\dot{X}(s)} = Z_m(s), \tag{1}$$

where Z_m is the mechanical impedance, F is the applied force and $\dot{X}$ is the velocity [31]. With this control strategy, the end-effector can be controlled to resemble a spring damper system. Further on, the spring stiffness and the damper coefficient can be tuned to fit a specific application. The drawback of impedance control is the reduced lifting capacity as the stiffness is reduced.

Admittance control is another technique that show promise in the context of pHRC. Mechanical admittance, A_m is defined as

$$A_m(s) = \frac{\dot{X}(s)}{F(s)}, \tag{2}$$

where A_m is equal to the inverse of mechanical impedance defined in equation 1 [31]. While impedance control can be used to react to the environments forces, admittance control can be used to manipulate the environment. For instance, in healthcare, admittance control can be used to guide blind patients through the hospital with a constant force.

Human-Robot Teaming

HRT is the concept of collaborating with a robot as a teammate rather than the traditional use, which is robot as a "tool" [32]. This implies that humans and robots work together towards a shared goal with both parties able to make decisions to achieve this goal. AI enables this stage of collaboration. By utilising a combination of multiple ML algorithms, the robot can achieve situational awareness making it capable of planning cognitively, thereby enhancing the efficiency and reducing the mental load on the human worker. One of the most compelling challenges when implementing ML algorithms in HRT, which was pointed out in [33], is the lack of relevant datasets for training algorithms. The difficulty lies mainly within simulating dynamic environments with humans involved due to the unpredictable nature of humans. HRT also raises ethical and philosophical issues, such as how much freedom the robot should have in executing these spontaneous plans without the approval of a human. This should be carefully considered for each application. Other enabling factors is represented by the increasingly ubiquity of sensors, which are placed in the working environment, on board of the robots and on humans by using wearables [34].

HRT systems are complex systems that involve the integration of multiple technologies and the coordination of human and robotic capabilities [35]. The following are some of the key complexities that need to be addressed in the design and implementation of HRT systems:

- Safety: Ensuring the safety of the human operator is a critical consideration in HRT systems. This requires careful design of the physical components of the robot, as well as the development of algorithms that can detect and respond to potential hazards [36].

- Human factors: Understanding and considering human capabilities, limitations, and preferences is crucial in HRT systems. This includes factors such as cognitive load, sensory and motor abilities, and emotional states [37].

- Interaction design: Designing the interaction between humans and robots is a complex task that requires understanding the ways in which humans perceive and respond to robotic systems, as well as the ways in which robots can be designed to better fit into human environments and respond to human needs [38].

- Task allocation: Determining the appropriate division of tasks and responsibilities between humans and robots is a complex problem, as it depends on the specific requirements of the task, the capabilities of the robots, and the limitations of the human operator [39].
- Adaptivity: HRT systems need to be able to adapt to changing conditions and respond to new information. This requires the development of algorithms that can modify the behaviour of the robots in real-time, based on the state of the environment and the human operator.

The research related to HRT is fragmented, and although there exists research on exchanging forces [18] and exchanging solutions [40], there is a lack of complete implementations of HRT systems adhering to its definition from Table 5. However, the convergence of AI advancements in large language models (LLMs) (e.g., ChatGPT-4 for sequence planning [40]) and robot learning strategies [14] points towards accelerated progress in HRT systems.

3.4 Progress on RQ1: Human detection and prediction

RQ1 focuses on developing robust algorithms for accurately detecting and predicting human motion in real-time environments using 3D sensor data. In alignment with this objective, significant progress has been made by leveraging insights from the research paper on human trajectory simulations and predictions [41].

The research paper introduces a novel method for simulating human trajectories using the Ornstein-Uhlenbeck (OU) process as well as deep learning-based classification. This approach has proven valuable in enhancing machine awareness of human behavior, a crucial aspect of HRC and HRT in industrial settings.

3.4.1 Key Achievements

- **Simulated Dataset Generation:** A simulated dataset was successfully generated, capturing the intricacies of human movement on a factory floor. This dataset serves as a foundation for training and evaluating classification models for human motion prediction. Figure 2 shows a visualisation of the generated dataset. It includes 10 unique reference paths and 1000 simulations for each path. Simulations used the Ornstein-Uhlenbeck (OU) process to generate the human trajectories.
- **Deep Learning Classification:** Stacked LSTM and stacked BiLSTM networks were employed to classify the generated dataset. These deep learning methods demonstrated promising results in predicting future human movements in 2D by classifying which reference path a person is on, thereby predicting the end goal.
- **Enhanced Machine Awareness:** The ability to predict human movements contributes significantly to increased machine awareness. This has direct implications for improving safety and efficiency in industrial environments where humans and robots collaborate.

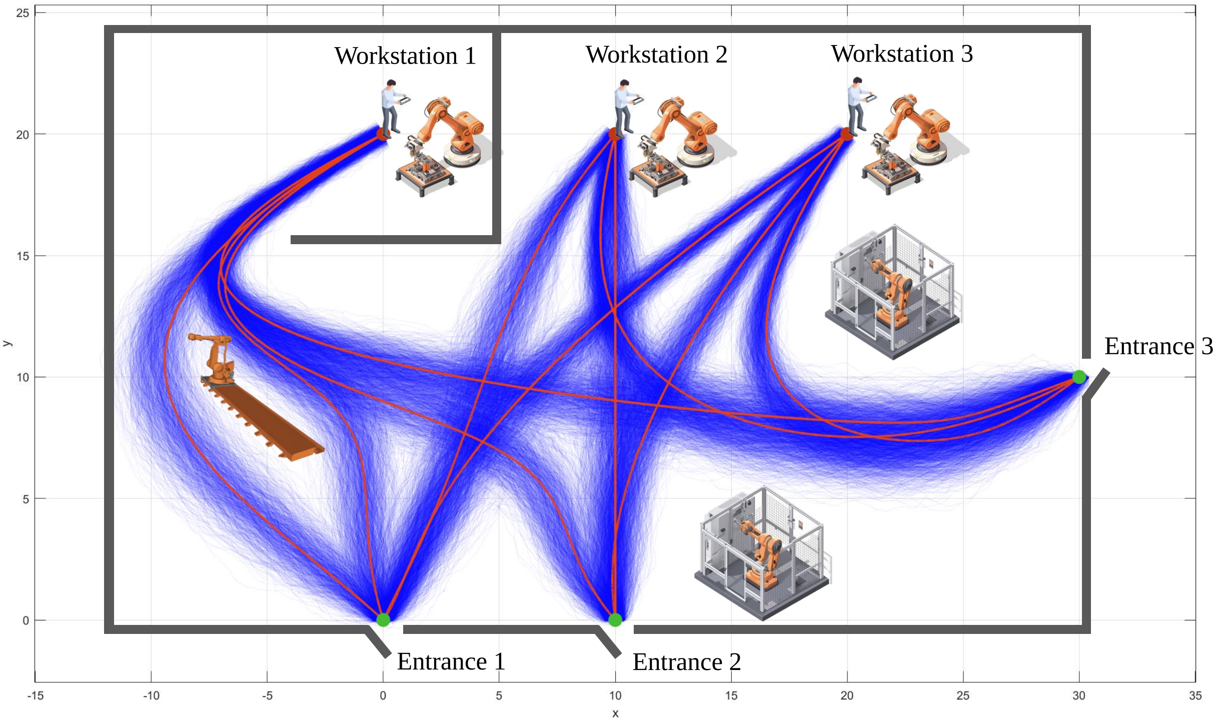


Figure 2: Results from 1000 simulations for each reference path [41].

3.4.2 Trajectory Simulations (Excerpt from C2)

A stochastic process called the OU process is used to simulate human trajectories for this project. The OU process is a famous stochastic process that was introduced in Uhlenbeck and Ornstein's 1930 paper [42], where they introduce a mathematically modified Brownian motion with drift towards a center.

The equations for a numerical OU process are given below:

$$dx_t = -\theta \left(x_t - x_{ref}\right) dt + \sigma dW_t, \tag{3}$$

where x_t is the simulated variable. The σdW_t is the pure Brownian motion term, whereas the rest is the drift, where θ is the strength of the mean reversion, meaning how strongly the simulated value is attracted to the reference path. In detail, x_{ref} is the reference point that x_t is attracted to, dt is the time step, σ is the volatility parameter that controls the amount of randomness in the simulation and dW_t is a Wiener process.

Modelling the position as an OU process leads to noisy and sporadic signal behaviour, which does not make sense for a walking person. Even when tuning θ and σ, it proves to be hard to get realistic results. However, the integral of the signal is relatively smooth. Therefore, modelling the velocity rather than the position as an OU process gives a smoother path much more resembling that of a real walking person. The reference velocity can be found by taking the discrete derivative of the reference paths (red lines) in Fig. 2. On the other hand, this approach enters drift, because the integrated error to the reference velocity is not compensated. This mandates a third solution, a hybrid, where the velocity is modelled as OU, but with an extra correction term from the position error. This leads to the final implemented equation for discrete OU simulations of velocity in equation 4, modified with a position term:

$$\begin{aligned} \vec{v}(t) = \vec{v}(t-dt) - \theta_v \cdot (\vec{v}(t-dt) - \vec{v}_{ref}(t)) \cdot dt \\ +\sigma \cdot dW_t - \theta_p \cdot (\vec{p}(t-dt) - \vec{p}_{ref}(t)) \cdot dt, \end{aligned} \tag{4}$$

Here, $\vec{v}$ is the simulated velocity as a 2D vector, t is time, $\vec{v}_{ref}$ is the reference velocity, $\vec{p}$ is the 2D position vector, and $\vec{p}_{ref}$ is the reference position. This equation utilises the smooth position caused by modelling the velocity as an OU process while compensating for the drift using the position term. In addition, for the simulated trajectories to reach the workstation's close proximity, θ is defined as a variable that increases as the person comes closer to the workstation. That leads to a higher reversion strength to the reference path. The equations below shows how the mean reversion strength for velocity and position is defined:

$$\theta_v(n) = 1.5 + 0.8\frac{n}{N} \tag{5}$$

$$\theta_p(n) = 0.1 + 2.9\left(\frac{n}{N}\right)^5, \tag{6}$$

where $\frac{n}{N}$ gives a number between 0 and 1 representing how far a person has travelled along the reference path. N is the total number of points on the discretised reference path, while n is the index of the reference point at the current time, t. For this model, $\sigma = 0.3$.

Finding n means finding the reference point on the reference path. A simple search algorithm is developed that searches a limited amount of points on the reference paths, in this case 1000. Fig. 3 shows how the initial search area marked with blue is used from the start. The reference point is defined as the point with the smallest Euclidean distance from the current position of the simulated trajectory. From that point, the reference position and velocity is extracted and used in the OU equations. As n increases, so does the starting point of the search area. This means that the search area will move proportionally to n.

To make the data more realistic, noise and sampling frequency are added to the data by considering a random number within ± 0.01 [m] and only storing the data when a certain sampling time is reached. Fig. 4 shows the results from introducing noise and sampling frequency into the simulation data.

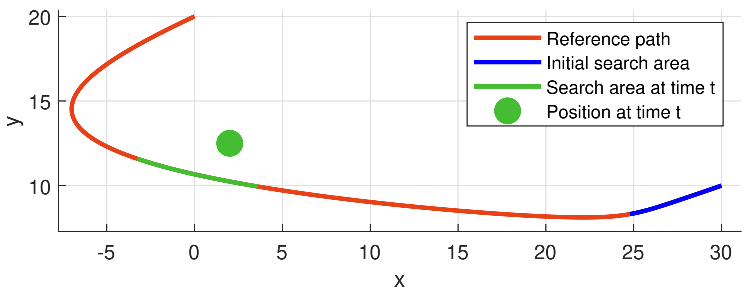


Figure 3: The search algorithm to find nearest point on the reference path

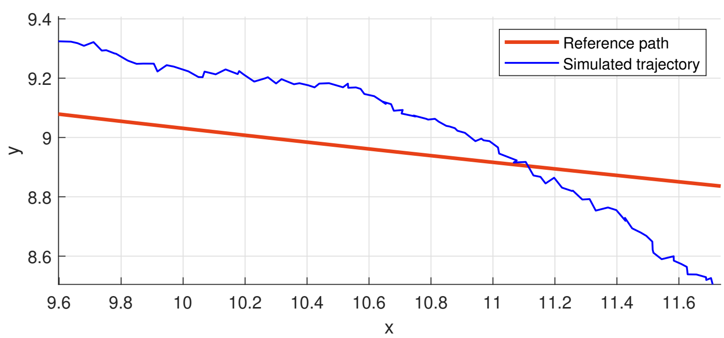


Figure 4: Noise and sampling frequency

3.4.3 Classification (Excerpt from C2)

This section presents the methods used for the automatic classification of human trajectories. Furthermore, this classification has the potential to predict the trajectory a person is following, thereby providing the target position. Based on that, collaborative machines can boot up and hazardous machines can slow down to increase efficiency and safety.

Long Short-Term Memory (LSTM)

LSTM is a type of RNN that handles longer sequential data and is designed to overcome the vanishing gradient problem. It has proven to be effective in various sequential and time-series tasks. The LSTM model consists of various gating mechanisms that control the flow of information, as shown in Fig. 5.

In this study, a stacked LSTM model is built consisting of 4 LSTM networks followed by two layers of plain artificial neural networks (ANN). Between every layer, the data is normalised using the batch normalisation method.

Bidirectional Long Short-Term Memory (BiLSTM)

Bidirectional LSTM (BiLSTM) is an extension of the LSTM architecture that processes input data in both forward and backward directions. It combines information from past and future context, making it well-suited for tasks that require capturing dependencies in both directions.

The general structure of a BiLSTM network is shown in Fig. 6. It consists of two LSTM layers: one processing data in the forward direction and the other in the backward direction. The hidden states are concatenated to create the final output.

The BiLSTM model used in this study uses the same stacked structure as for LSTM. The only difference is that the 4 LSTM layers are changed to BiLSTM.

3.4.4 Results and Discussions (Excerpt from C2)

Table 7 shows the evaluation metrics for both stacked LSTM and stacked BiLSTM. Both algorithms work reasonably well in classifying the test data. However, stacked LSTM seems to be the favourable algorithm with the best result for all metrics.

Fig. 7 shows the confusion matrix. It shows how many true and false predictions the algorithm made on the test data. Finally, Fig. 8 shows the accuracy and loss curves for both

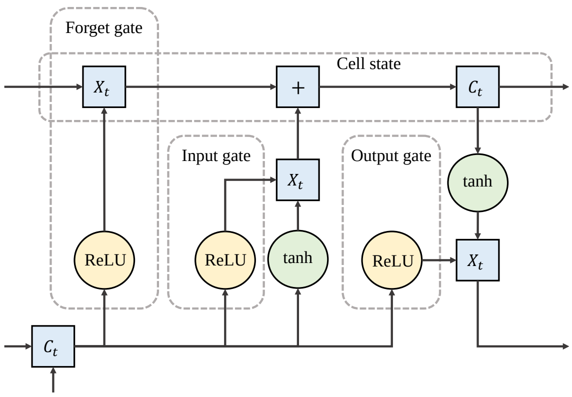


Figure 5: The structure of the LSTM model used in this study

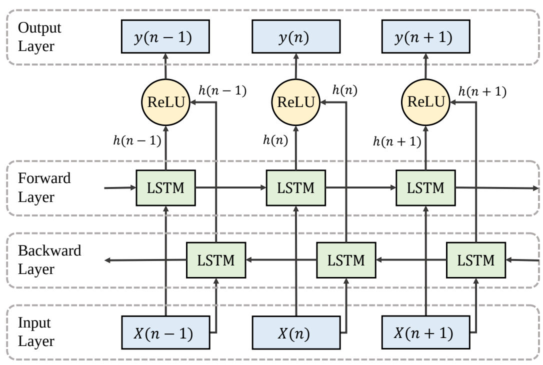
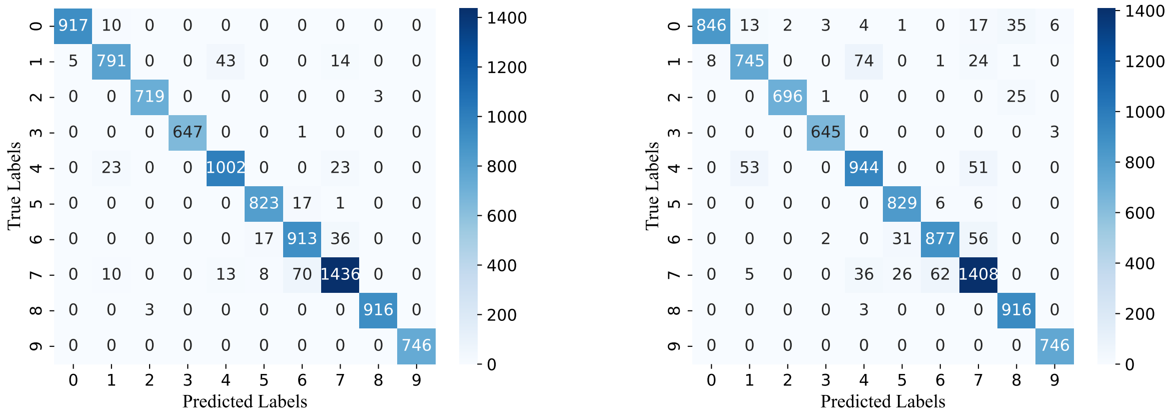


Figure 6: The structure of the BiLSTM model used in this study

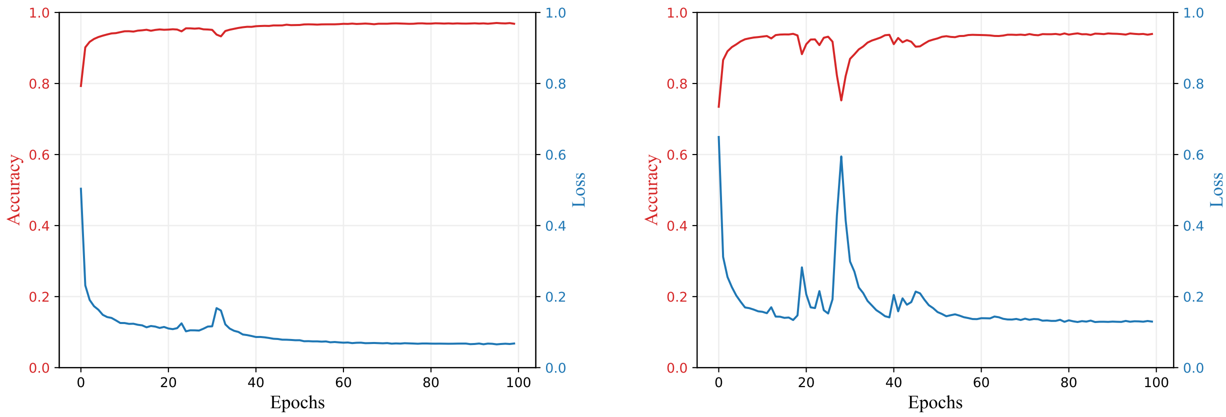
Table 7: Path prediction comparative analysis

Technique	Accuracy	Precision	Sensitivity	F1-Score
Stacked LSTM	0.9677	0.9679	0.9677	0.9678
Stacked BiLSTM	0.9397	0.9403	0.9397	0.9396



(a) Confusion matrix for the stacked LSTM model (b) Confusion matrix for the stacked BiLSTM model

Figure 7: Confusion matrices



(a) Accuracy and loss for the stacked LSTM model (b) Accuracy and loss for the stacked BiLSTM model

Figure 8: Accuracy and loss curves

algorithms through 100 epochs. The stacked LSTM algorithm shows a much more stable improvement as the number of epochs increase.

From the confusion matrix, it is clear that paths 6 and 7 are sometimes hard to distinguish. The same can be seen for paths 1 and 4, although less significantly. These confusions are not surprising, as these paths have overlapping segments that makes it hard to predict on smaller segments of those paths.

The dataset used for this study holds no faulty data, which makes it easier for the algorithms to both train and make predictions. In real world applications, there would be more unpredictable behaviour, e.g., people changing paths midways or taking a u-turn because they forgot a tool. However, in industrial environments where production procedures follow fixed patterns, it is safe to assume that most movements also follow patterns. The results from this study suggest that for such applications, it should be possible to predict future movements, thereby increasing machines' awareness of humans.

3.4.5 Conclusions (Excerpt from C2)

This paper presented a novel method of simulating human motion using the Ornstein-Uhlenbeck (OU) process. Furthermore, those simulation data of paths followed by a human being were classified using a stacked long short-term memory (LSTM) network. This approach was then compared with a stacked bidirectional LSTM (BiLSTM) network. Using these approaches, the target workstation can be well predicted, thereby increasing efficiency and safety by booting up collaborative systems or slowing down hazardous machinery before a human arrives at the target workstation. Such predictions improve machines' awareness of humans in industrial settings, which is a crucial aspect of the transition to Industry 5.0.

The classification methods can be applied to other use cases. An extension to 3D Cartesian coordinates can also be considered. With such an extension, one can, for instance, predict arm movements in 3D for human-robot collaboration (HRC) and teaming (HRT). In essence, this approach could aid in enhancing machines' awareness of humans, thereby facilitating the smoother execution of HRC/HRT tasks while ensuring heightened safety measures.

3.5 Progress on RQ2: User interface

The work towards addressing RQ2 is dedicated to developing an intuitive and effective user interface for HRC, with a focus on remote interaction and control. The research paper on VR and remote control (C3) has directly contributed to advancements in this area by presenting a framework that enables real-time interaction with a DT of a complex mechatronic system through a VR application.

Figure 9 shows how the framework is divided into four parts: Production Facility, Edge Device, Cloud Communication Broker and Remote User Node. Firstly, the production facility is where all the equipment required to execute the industrial process can be found. This can include, but is not limited to, programmable logic controllers (PLCs), sensors and actuators. Secondly, the edge device controls the flow of communication between devices on the production facility and performs pre-processing of data before sending it to the cloud, thus ensuring proper structure and context of the data. Data sent to the cloud is accessed by the remote client in its original format via the cloud communication broker. The remote user node can publish and subscribe to this broker to enable remote monitoring and control in an immersive VR application.

A case study is presented to validate the proposed framework in a real-world scenario. Figure 9 shows the outline of the case study. This section will explain the physical environment for the case study, followed by detailing the bi-directional communication to the remote user node through the edge device and the cloud communication broker. Further on, the user interface of the developed VR application will be presented. Lastly, relevant edge computing based calculations are explained.

3.5.1 Key Achievements

- **Framework Development:** A robust framework was established, integrating ROS 2, Node-RED, an MQTT broker, and a VR application to facilitate seamless communication and control between the remote user and the physical environment.

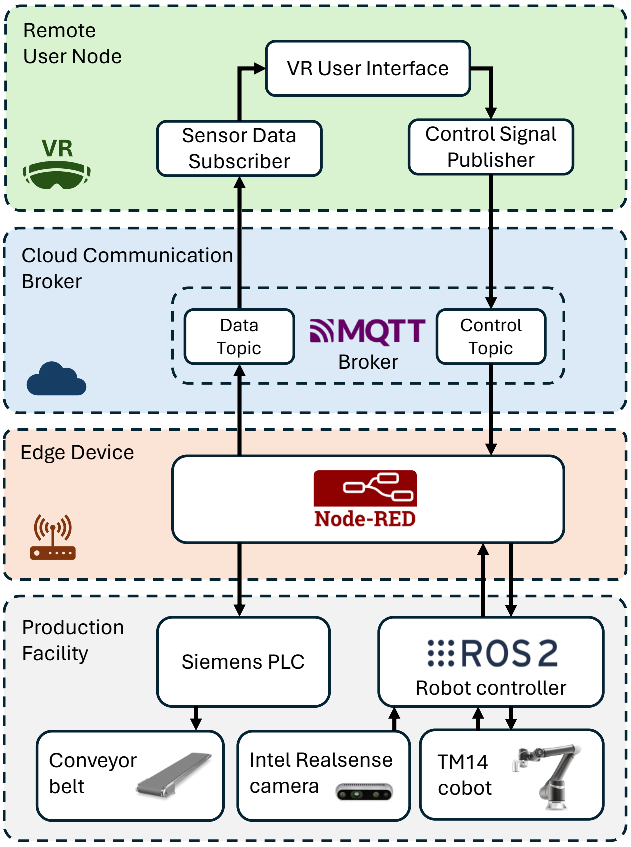


Figure 9: Overview of the case study setup featuring a cobot, camera, PLC, and conveyor belt within the digital twin framework for real-time remote control and monitoring [43].

- **Real-time Remote Control:** The framework successfully demonstrated real-time remote monitoring and control capabilities, allowing users to manipulate a collaborative robot and monitor sensor data in a virtual environment.
- **Enhanced User Experience:** The VR application provided an immersive and intuitive interface for interacting with the DT, enhancing the user experience and facilitating efficient HRI.

3.5.2 Results

Experiments were performed to validate the performance of the framework. The code for the case study and a video showing the execution of the experiments can be seen online at: https://github.com/evenlangas/robot-control-virtual-reality-mqtt. The control proxy, see Figure 10 is manipulated to send control signals from the virtual environment while monitoring the returned sensor data from the robot. In this way, the successful communication and correct implementation of kinematics is validated. Figure 12 shows a sequence of setting numerous setpoints for the robot as well as the robot's response.

A key performance indicator for a remote control system is latency. The mean of the latency between the edge device and the cobot was measured to 0.8ms. This suggests that the significance of the latency is found in the cloud communication broker because of the transfer of data over the internet. Figure 11 shows the data flow of which the latency is measured. It goes from the VR application built with Unity, to the MQTT broker, to the edge device through Node-RED, back to the MQTT broker and back to the VR application. A JSON message with 6 parameters (x, y, z, roll, pitch and yaw) is sent for the test. All

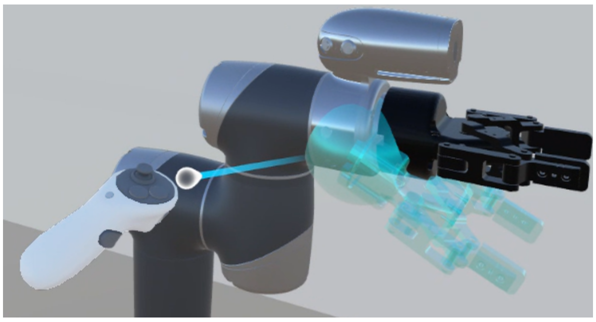


Figure 10: A control proxy (cyan colour) manipulates the reference point of the end-effector. The VR controller (white object on the left) intuitively moves the control proxy.

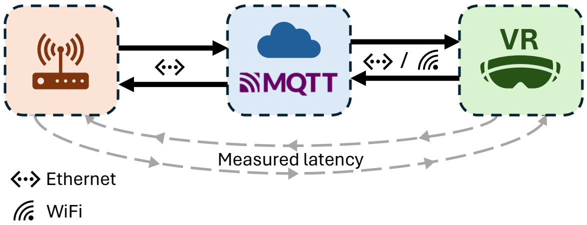


Figure 11: Diagram showing the data flow for the latency test.

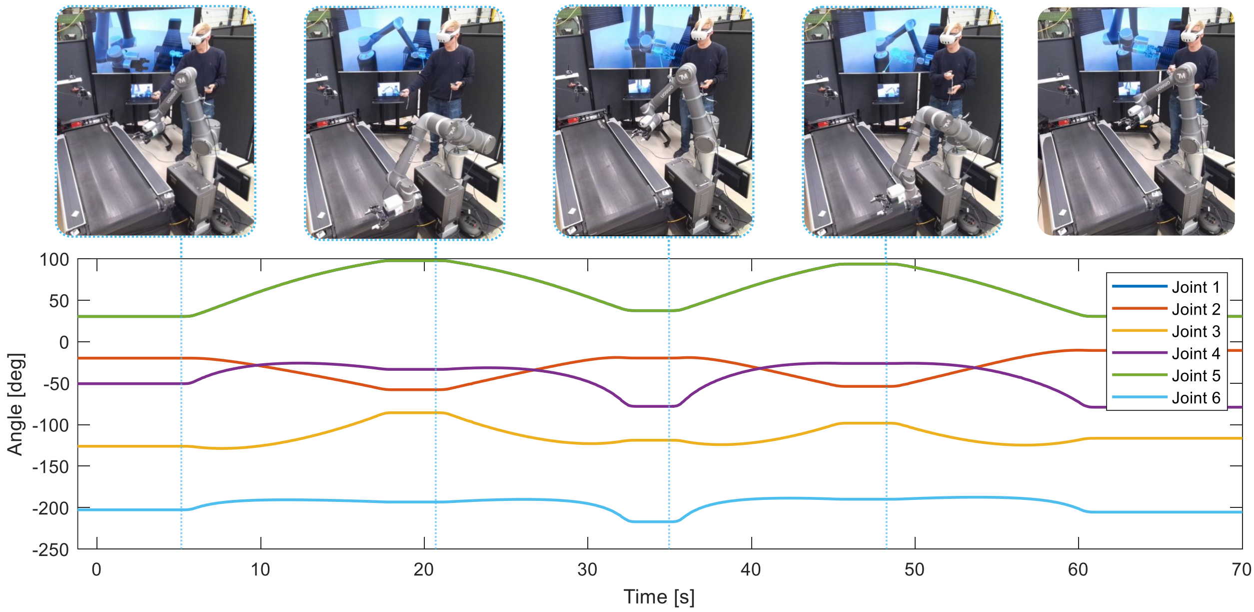


Figure 12: Results from setting waypoints in the VR environment. The vertical blue dotted lines represents a control signal given from the operator. Both the sensor data of the joint angles and the control signal is logged in the VR application, hence the small delay from sending a control signal to the change in joint angles.

parameters includes a float with 4 decimals places.

The results of the latency test is shown in Figure 13. The experiment is performed with two connection configuration. First, the remote user node is connected through a WiFi connection. In the second configuration, the user is connected through Ethernet. The latency with Ethernet connection is further investigated by plotting it in a histogram, see Figure 14. These plots supports the hypothesis that most of the latency is within the cloud communication, and the latency on the edge device can be neglected in this context.

The few spikes in Figure 13 suggests that a few signals can be unreliable for real-time connectivity. There are several potential reasons for hickups in the latency. For example, when measuring the latency from the Unity application, there might be a lag in framerate if the computational power capacity is exceeded. To address the computational bottleneck in some VR headsets, it is possible to connect the device to a more capable computer through USB-C. The application can then be run on the computer enabling increased computational power. Another reason could be overloading the cloud MQTT broker. However, this seems

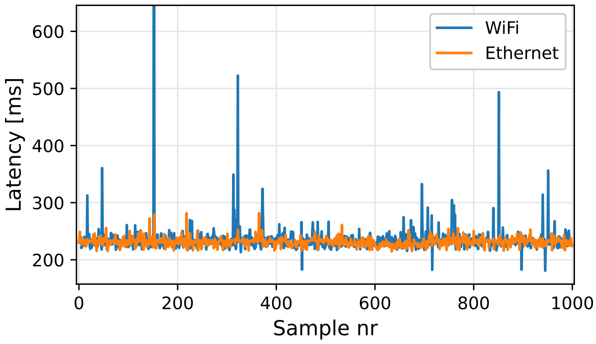


Figure 13: Measured latency from sending data in the following way: Unity –> MQTT broker –> Node-RED on edge device –> MQTT broker –> Unity [43].

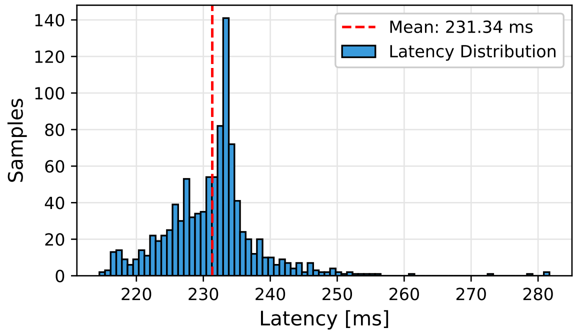


Figure 14: Histogram of the measured latency from sending data in the following way: Unity –> MQTT broker –> Node-RED on edge device –> MQTT broker –> Unity [43].

unlikely due to the relatively low amount of data passing through. On the other hand, it is worth noting that there are no outliers when the remote user node is connected to internet through Ethernet. This means that the spikes is likely caused by unstability in the WiFi connectivity.

In contrast to building a VR application, the use of Unity allows building the application to WebGL, which means it can run as a web application. Thus, it can be made accessible for a wide range of users without the need for VR headsets or installed software. Another reason to consider other alternatives is the fact that today's VR devices are bulky and heavy, and can cause discomfort when used for longer durations. Furthermore, the problem of motion sickness still pertains for some users.

3.5.3 Conclusions (Excert from C3)

In this study, a novel framework for digital twins of complex mechatronic systems, was introduced leveraging edge intelligence and real-time remote monitoring and control. Through the seamless integration of critical technologies such as Node-RED, Message Queuing Telemetry Transport (MQTT), virtual reality (VR), and Robot Operating System 2 (ROS 2), we have developed an architecture that unifies the virtual and physical realms. A case study was taken into consideration to illustrate the proposed framework in a real-world scenario, enabling users to communicate with, control, and monitor the physical environment remotely and in real-time via the VR application. This realistic scenario demonstrated how effective the proposed approach can be in bridging the gap between physical systems and their digital counterparts. The developed architecture and a video showing the execution of the experiments can be retrieved online at: `https://github.com/evenlangas/robot-control-virtual-reality-mqtt`.

A notable highlight of this framework is its potential to enhance inclusivity in industrial settings. The proposed methodology facilitates the integration of disabled individuals into production environments through remote manual human-robot interaction/collaboration/teaming, hence fostering a more inclusive and diverse workforce.

Our findings indicate that the suggested architecture provides a scalable approach to real-time remote monitoring and control in addition to increasing operational efficiency.

In the future, we plan to further improve the framework, explore additional use cases, and expand the VR application's capabilities, i.e, integration of haptic feedback, to handle more complex interactions and a wider range of industrial applications. This study lays the groundwork for innovative advances in edge intelligence and digital twins, which could have beneficial impact on a wide range of industrial domains.

4 Research Plan

This section presents a comprehensive breakdown of the research plan for the remaining period. Section 4.1, 4.2 and 4.3 explains the plan for completing the work related to RQ1, RQ2 and RQ3 respectively. Further on, Table 8 boils the work down into a list of planned publications. Lastly, the remaining work has been broken down into multiple subtasks, which can be seen in the Gantt chart in Section 4.4.

Table 8: Planned papers.

ID	Conference/Journal and title
J2	**Journal:** Robotics and Computer-Integrated Manufacturing **Title:** Enhancing Industrial Safety with Real-Time Human Motion Prediction Using Deep Learning and 3D Sensors **Summary:** This research will leverage algorithms from C2 to predict human motion within a controlled lab environment using 3D sensors such as the Qualisys Motion capture system or LiDAR systems. The project involves setting up the sensors in the mechatronics lab at UiA and will be incorporated into the DT framework presented in C3.
J3	**Journal:** IEEE Robotics & Automation Magazine **Title:** Augmented Reality Interface for On-Site Human-Robot Collaboration **Summary:** This paper will introduce an innovative augmented reality AR interface as a continuation of C3. The interface will leverage both visual and tactile feedback mechanisms. Through an AR headset, users receive real-time visual cues about the robot's status and actions, while a wearable device provides tactile feedback for enhanced situational awareness. Furthermore, the interface visualises the predictions of the human motion prediction model from the first planned paper, enabling users to anticipate and adapt to their robotic counterpart's movements. This integrated system aims to improve communication, coordination, and safety during human-robot collaborative tasks in various industrial and real-world settings.
J4	**Journal:** IEEE/ASME Transactions on Mechatronics **Title:** Physical Human-Robot Collaboration Integrating Mixed Rigid/Flexible Joint Robot With Augmented Reality Interface **Summary:** This paper will investigate physical HRC using a novel robot design incorporating both rigid and flexible joints. This will build on the work from Tuan et. al. [44]. The robot's unique construction enables it to execute precise tasks while ensuring safe interaction with humans. Impedance/admittance control strategies will be implemented to achieve physical collaboration with a human operator, allowing the robot to adapt its behaviour based on human input. Additionally, the AR interface from the previous paper will provide real-time visual guidance and enhance communication between the human operator and the robot.

4.1 Plan for RQ1

A key focus in the upcoming phase will be to validate and refine the human motion prediction algorithms developed thus far within a controlled laboratory setting. The Qualisys motion capture system and lidar sensors will be considered for data collection of high-fidelity data of human movement in the motion lab at UiA. This controlled environment will allow for precise ground truth comparisons and facilitate iterative algorithm optimization. The insights gained from C2 will be directly applied to predict human motion in this real-world scenario, with an emphasis on improving accuracy and robustness. This work will result in a journal paper (J2 in Table 8) that completes the work package related to RQ1.

4.2 Plan for RQ2

The next phase of development will involve expanding the user interface from C3 beyond VR to incorporate AR capabilities. This will enable on-site HRC, where users can visualise and interact with the robot and its environment in real-time using AR headsets or devices.

The AR interface will be further enriched with tactile feedback, providing users with tactile sensations that correspond to the robot's actions and interactions. Additionally, sEMG sensors will be utilized for gesture recognition and user feedback, allowing for more intuitive and natural control of the robot. This multimodal approach aims to create a seamless and immersive experience for on-site HRC. This work will be presented in J3.

4.3 Plan for RQ3

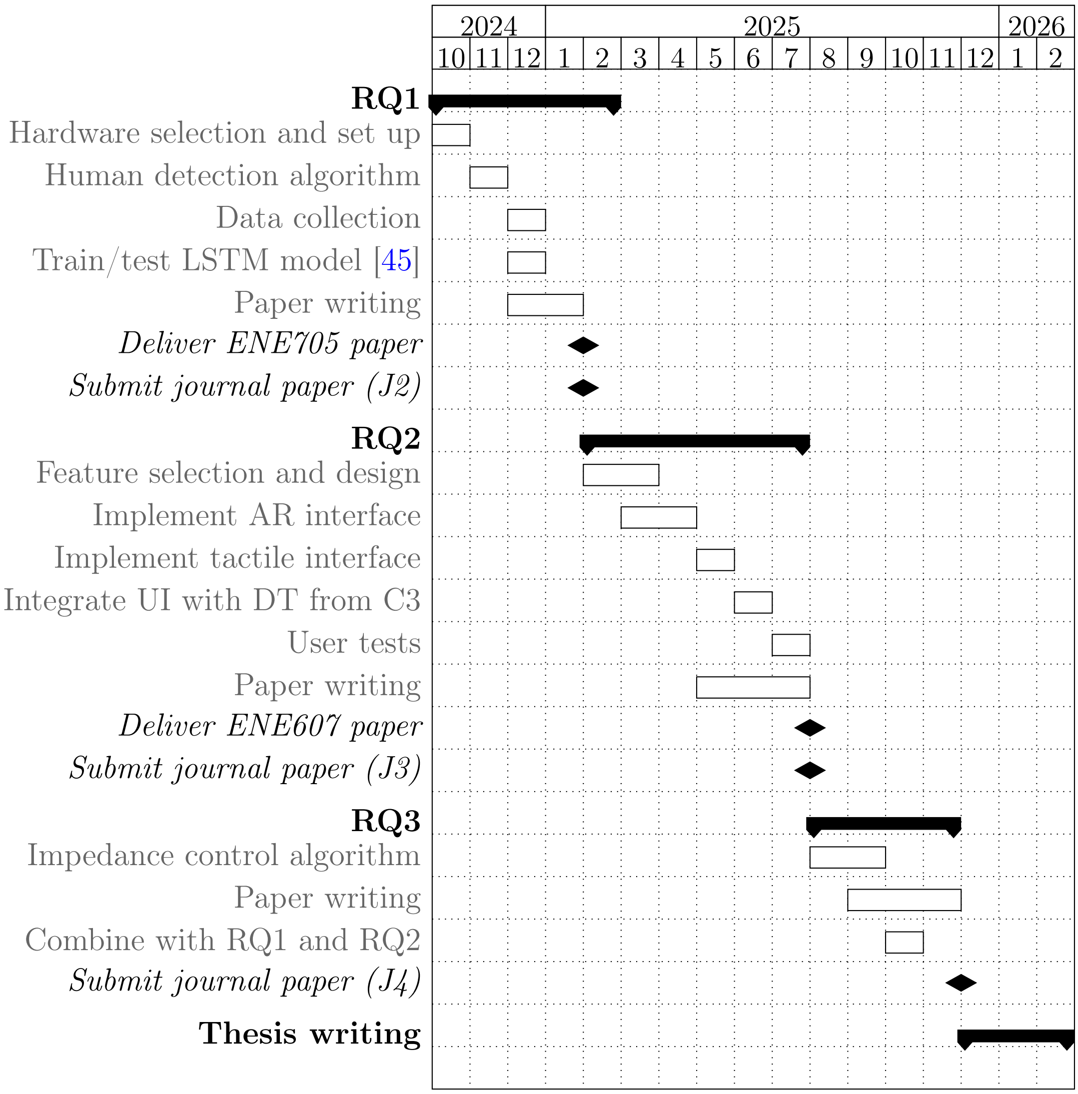
For addressing RQ3, we will combine the techniques developed when addressing RQ1 and RQ2 to implement a holistic approach to HRC. This system will incorporate 3D sensors, AR, and tactile feedback to enable human collaboration with their robotic teammate in a more natural and intuitive way.

Overall, the integration of these technologies in a single system will greatly improve the ability of the robot to collaborate effectively with humans in a variety of tasks. The use of 3D sensors and an AR-tactile interface will enable the robot to better understand and respond to the actions and needs of its human collaborator, leading to improved performance and greater efficiency in collaborative tasks. A use case will be presented where the robot will lift objects with a human operator using impedance and admittance control.

The robot will preferably be the one PhD candidate Minh Tuan Hua is developing, but for risk management, another robotic manipulator at UiA will be considered as a backup option, e.g. the Omron TM14 cobot, which was used in C3.

The work and results from adressing RQ3 will be presented in J4 as the final paper for the PhD project.

4.4 Projected Timeline



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