SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics: Games Engineering

Development of an Augmented Reality Interface for Intuitive Robot Programming

Jan Gerrit Eberle

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Entwicklung eines Augmented Reality Interface für die intuitive Roboterprogrammierung

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I confirm that this master's thesis is my own work and I have documented all sources and material used.

Munich, 15. November 2023 Jan Gerrit Eberle

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Abstract

This thesis is dedicated to the research of a feedback mechanism in the context of learning from demonstration, which is intended to improve the interaction between humans and robots. In this context, an augmented reality interface for the HoloLens 2 in combination with the SARA robot was developed and subsequently evaluated in a user study with 20 participants. The aim was to investigate the influence of feedback during the learning from demonstration process on the intuitive interaction with the robot, the efficiency of the demonstrations, the reduction of the knowledge gap between man and machine and the quality of the demonstrations.

The results show that augmented reality interfaces have the potential to improve the intuitive handling of the robot. Furthermore, they have the potential to increase the user's understanding of the robot's learning process. However, no specific quality improvements were found in the results of algorithm learning from demonstrations. The discussion of the results emphasizes the importance of user preferences and requirements in the development of augmented reality interfaces for learning from demonstration systems.

Future research will focus on investigating more complex tasks, alternative output devices and different interaction methods for non-expert users. These findings will help to better understand how augmented reality technologies can improve the approach of learning by demonstration and make it more intuitive for non-experts.

Contents

1 Introduction

Could robots soon be our new everyday colleagues? This question is more relevant today than ever before, as small and medium-sized enterprises are struggling with a persistent shortage of staff, which is affecting efficiency and productivity. This lack of qualified staff not only poses financial risks, but also threatens the existence of many businesses [HK22; DIH23].

In this context, the use of robots offers a promising solution for many tasks in the manufacturing industry and other areas. However, the conventional programming of robots often requires special expertise and a certain technical affinity, which makes them inaccessible to non-experts. This poses a significant hurdle to digitising within the context of robotics, especially in smaller companies that produce only small batch sizes or have frequently changing tasks. However, especially in the case of monotonous work and in areas where skilled staff are limited, robotics could be a crucial factor in saving resources.

The solution to this problem lies in the development of an intuitive programming interface that allows employees without special robotics knowledge to quickly and easily adapt robots for different tasks. This would not only increase efficiency and free up skilled staff for complicated tasks, but also reduce costs and enable small businesses to use robotics technology in an effective way.

Intuitive programming and especially Learning from Demonstration, abbreviated LfD, is a promising approach that allows non-experts to teach robots by demonstrating a task. However, learning through demonstrations has some limitations that are particularly problematic for inexperienced users, that is, a user group that is not familiar with the field of robotics. One major limitation with the current state of the art is the quality of the demonstration, which significantly influences the result of the algorithm [SZH18]. Another problem is the discrepancy in the level of knowledge between humans and machines. During the execution of such systems, there is a knowledge gap between the user and the robot in terms of what the user thinks they have taught the robot and what the robot has actually learned [SH20]. This can cause uncertainty and distrust of the system and frustration among users.

In this regard, previous research has highlighted the need to understand how data can be displayed to the user and how the user can and should interact with the data in Learning from Demonstration [Azu+01; Bru+06]. In particular, the need for feedback to close this knowledge gap was pointed out [SZH18], as well as the need to establish a set of proven user interface elements for common tasks in industrial application environments [Pae14].

Past works presenting feedback solutions focus on the feedback mechanism, but are mainly directed towards expert users. In most cases, users are assumed to have advanced prior knowledge, which does not correspond to reality. Even experts cannot always guarantee error-free demonstrations in the LfD process [SGR22].

This thesis explores how Augmented Reality, abbreviated AR, can be used as a solution approach to enable intuitive programming of robots for non-experts. AR offers the possibility to merge the real and virtual worlds and provide users with an immersive and visual interface to interact with robots. We will explore the use of AR in this context in more detail and develop a solution that will enable even non-expert users to program robots in an intuitive way. AR technology has the potential to provide visual feedback to the user that can help them understand the robot's learned behaviour and improve their demonstrations. For this purpose, an AR concept is developed and implemented, which is then evaluated by a user study. The user study explores various aspects of the developed interface in terms of intuitiveness and effect on the user.

This thesis aims to contribute to the existing body of knowledge by investigating the potential of AR technology in relation to LfD and its impact on the knowledge space, as well as the user's ability to provide better demonstrations.

In doing so, the outline is divided as follows. First, an introduction to the topic of Augmented Reality and Learning from Demonstration. Afterwards, the problems are discussed in more detail before an interface concept is developed and implemented. The hypotheses are then confirmed or rejected through a user study. The results are then discussed. This thesis then ends with a conclusion and an future outlook.

2 Fundamentals

This section explains the basic terms and concepts that will be used in this thesis. The concepts of Augmented Reality, Learning from Demonstration and the Lerosh project are introduced, before introducing related work in this context in the next chapter.

2.1 Intuitive Programming of Robots

There are several approaches for the intuitive programming of robots. Some of these include Natural Language Processing, where the user can formulate tasks in natural language, Walk-Through Programming, where the user moves the end effector to perform and record the task, and Learning from Demonstration, where the robot learns a task from the user's demonstration [Vil+18]. In this paper we follow the principle of Learning from Demonstration in more detail, but the findings of this paper can be useful for other principles as well.

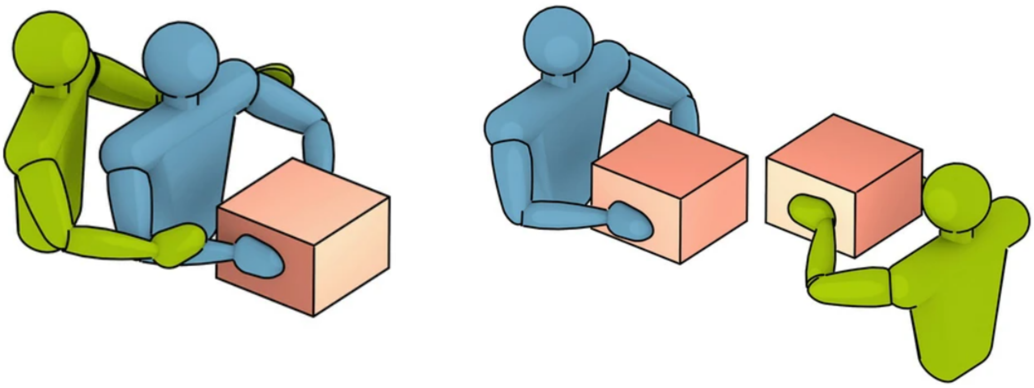
2.1.1 Definition

Learning from Demonstration (LfD) or Programming by Demonstration (PbD) is a method to simplify robot programming by allowing users to transfer their skills to the robot through more intuitive interactions. This allows non-experts to program robots through an intuitive interface [Bla+18; TSC12]. Non-experts are defined here by humans who have little or no technical expertise in the field [SZH18].

LfD algorithms rely on demonstrations provided by users to learn new skills [Cal18]. A human Demonstrator demonstrates a task which is then translated into a new skill for the machine. By deriving movement paradigms, demonstrated actions can then be applied to other or similar tasks.

Demonstration approaches

There are several types of demonstration approaches to train a robot. One of them is through kinaesthetic learning or observation learning [Rav+20], which are visualised by Calinon et al. [Cal18] in Figure 2.1. The blue person symbolizes the robot and the green person the human teacher.



(a) Kinesthetic Learning (b) Observational Learning

Figure 2.1: Illustration of demonstration approaches [Cal18]

- **Kinesthetic learning** In kinaesthetic learning, the user demonstrates the desired movements of the robot through physical movement. For example, a robot arm can be moved into the desired positions or trajectories.
- **Observational learning:** In observational learning, the robot learns by passively observing the user. The user performs the task with his own body while the robot acts as a passive observer. For example, by observing the manual grinding with a grinding block.

Functionality

The functioning of LfD can be described in several steps:

- **Data collection:** First, the system acquires data, for example, of the movement and action of the teacher, this can also include environmental information. Data can be collected by cameras, sensors on the robot, etc.
- **Data representation:** The captured data must then be converted into an understandable form for the system, which can then also be fed into the learning algorithm. In kinesthetic teaching, for example, the configuration of the robot over time could be used. In observational learning, for example, the user can use their hand to perform the demonstration and the contact points with the surface can be tracked.

- **Learning algorithm/modeling:** The captured data can then be fed into machine learning methods and algorithms and a model can be created that is able to mimic the demonstrated behaviour. This aspect in particular is an important point for LfD. Several methods have already been explored in research, including approaches such as symbolic reasoning methods, reinforcement-learning-based methods, dynamic system modelling methods, probabilistic methods, particle-based approaches, and geometric-based methods [SH20].
- **Imitation:** After the model has been created, the demonstration can be replicated.
- **Refinement and adaptation:** The system continues to learn and adapt its behaviour. This can be done by new input from the user.

Knowledgespace

The knowledgespace is the knowledge base of the robot. This can be a wide range of variables and data sets. For example, the robot can include a knowledgespace in which each object in the robot's workspace is stored with its position and orientation. We refer to this knowledgespace as ontology in this thesis.

2.1.2 Possibilities

LfD systems offer a number of advantages that make them a promising method in intuitive robotics programming. The three main advantages of LfD systems are:

- **Intuitive**. Allows non-experts to program robots and enables intuitive/easy knowledge transfer [Rav+20].
- **Performance:** More time-efficient, effective and resource-saving for systems that need to be frequently reprogrammed [Mol+15].
- **Data efficiency:** Needs less data compared to other machine learning approaches [Rav+20].

2.1.3 Limitations

Although LfD is a promising approach to robotics programming, there are also some limitations and challenges associated with this approach. These limitations can affect the performance and applicability of LfD systems and require careful consideration. Some of the main limitations and challenges are listed below:

- **Human-machine problem:** LfD must also address human-robot interaction problems such as the selection of an appropriate interface, variability in human performance and knowledge, and differences between different human subjects. The success of LfD depends not only on the person teaching the robot, but also on the platform used (robot and interface) [Rav+20]. One challenge is that robots cannot give feedback in the same way as humans, which can impact the trust in robots [Die+20].

- **Demonstration**. When a system relies on human input during its learning process, its performance depends significantly on the quality of the data provided by humans. Three main problems can result from inadequate demonstrations in the context of teaching applications: unconsidered states, ambiguous demonstrations and unsuccessful demonstrations. Especially with inexperienced users, such a lack of demonstration can occur, resulting from a lack of a mental model or an unclear understanding of how the robot learns during the learning process. In addition, different learning policies can change the requirements for the data to be provided. Especially for naive users, it can therefore be difficult to determine the optimal learning strategy [SH20; SZH18; Rav+20].

- **Machine Learning:** LfD-algorithms are impacted by challenges in machine learning, including the curse of dimensionality, incremental learning, learning from sparse datasets and noisy data [Rav+20]. LfD also suffers from lack of robustness to changes in initial conditions [Lue+19].

- **Variations:** LfD must account for various forms of variation that are more complex than simple recording and playback. Variations may occur due to requirements of the task to be performed or the kinematic structure of the robot [Cal18]. For example, it is easier to put a sugar cube into a cup than to put a golf ball into the same cup.

- **Control theory problematics:** When LfD is used to control a physical robotic system, challenges arise from control theory, such as predicting the response of the system in the presence of external disturbances, ensuring stability on contact, and guaranteeing convergence [Rav+20].

2.2 Augmented Reality

In the literature, the term Augmented Reality (AR) has been frequently discussed and defined for quite some time. AR generally refers to the integration of virtual information such as text or images into a real environment [Fur11; Pro23; Azu+01].

This is also known as mixed reality because there is a mixture of reality and virtuality. Milgram et al. [Mil+94] has illustrated the underlying concept clearly in a diagram, which can be seen in Figure 2.2. The left side of the spectrum represents reality and the right side represents a purely virtual world. Between these extremes, we define a mixed reality, which is a mixture of both. In addition, we can divide it again into two areas. In an Augmented Reality, which provides the real world with virtual objects and an Augmented Virtuality, which integrates aspects from reality into the virtual world.

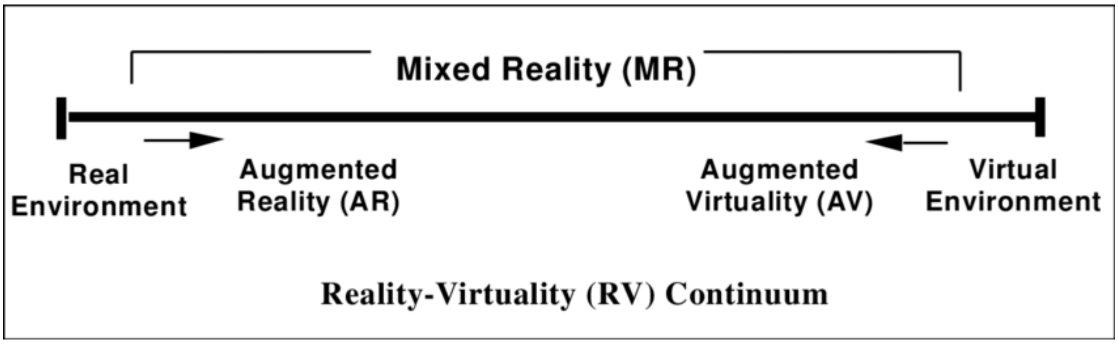


Figure 2.2: Visualization of the mixed reality continuum [Mil+94]

AR has the potential to change the way we interact with and program robots. Four relevant areas where AR is already being used in robotics today include: Intuitive Robot Programming, Advanced Robot Guidance, Robot Maintenance and Diagnostics, and Training and Education. In doing so, AR can help optimize processes, reduce errors and downtime, and increase efficiency and profitability.

2.2.1 Technology

Thanks to the continuous improvement of output devices, we have an increasingly wide range of options available to us today. In this context, it is important to emphasize that AR is not limited to specific output devices [Fur11]. The most common output devices for AR applications are Hand-held Device (HHD) such as tablets or smartphones, Head-Mounted Display (HMD) such as AR glasses, or projection devices such as overhead projectors [Azu+01]. With respect to HMD, an additional distinction is made between "see through" and "video based". Some applications also use stationary displays such as computer monitors. In terms of input devices for interaction, touchscreens, hand tracking systems, haptic gloves, or even mouse and keyboard are often used [Nag+22; NO23].

2.2.2 Possibilities

The integration of AR into robotics opens up a variety of possibilities and benefits that can significantly improve human-robot interaction and robotics programming. In the context of robotics, some of the key benefits of AR are:

- **Rapid teaching of content:**. Fast content delivery is an important benefit as search time for relevant information becomes increasingly important. By using AR technology, information can be quickly and more efficiently communicated. In doing so, the relevant data can be displayed in the user's field of view, as well as information can be projected directly onto the workpiece [MS17].
- **Sustained communication of content:** By combining different senses, content can be conveyed in a more sustainable way. By considering multisensory learning in the development of AR applications, communication processes and structures can be optimized [MS17].
- **Simplification of complex processes:** AR makes complex applications in the technical field tangible and understandable [MS17].
- **Multitasking capability:** AR can also contribute to the parallelization of different activities. Visualization of additional information can efficiently support complex activities, which increases multitasking capability [MS17].
- **Reduction of mental workload:** A study by Stadler et al. [Sta+16] shows that the mental workload can be reduced. This refers to expert users, as well as novice users, but for these the processing time increases.
- **Support:** Especially in manual workflows, for example in assembly or maintenance, AR proves to be an effective tool to support users. According to forecasts, AR is expected to reduce the downtime of production facilities by 50% and thus bring a significant advantage in cost and time savings [LU22].

2.2.3 Limitations

The integration of AR into robotics certainly offers many advantages, but there are also some challenges and limitations that need to be considered. These limitations can be divided into hardware-, user-, and interface-specific problems:

- **Hardware:** For example, head-mounted displays may have insufficient brightness, poor resolution, a field of view that is too small, or a lack of display contrast.

Other hardware-related problems, which also apply to handheld and projection-based approaches, can include size, weight, and cost [Azu+01]. Especially when it comes to applying such technologies in an industrial environment, a harsh environment can be damaging to the hardware [LKK18]. The hardware should be adapted to be used in parallel with safety measures. For example, it must be possible to use an HMD with a helmet [LKK18].

- **User concerns:** Cyber sickness can also be observed in some cases with HMD AR Applications, but not as pronounced as in virtual reality applications [Hug+20; Lut18]. Among other things, eye strain can also occur if the focus has to be changed frequently between the remote real world and the virtual object on the display [Blo14]. Also not to be underestimated are safety concerns for the user. Especially when objects in the real world are to be obscured by virtual objects. With see-through glasses such as the Hololens, it is not possible to completely cover the object, but attention can be significantly diverted from important information [Lut18].
- **Design Problems:** The interface of the AR Application can involve immense drawbacks. Contrary to the advantage that AR Applications can relieve the user mentally, the visualization of too much information or a too complex presentation can cognitively overload the user [Van07]. Not to be underestimated is also the wrong representation of objects, which are not optimized [LU22]. Also, the user should not be made dependent on the interface, so that important real-world information is obscured/hidden [Van07; LU22].
- **Expert Knowledge:** An obstacle to the use of AR solutions can be insufficient expert knowledge in companies, as well as a limitation to the correct use [LU22].
- **Social Aspects** Social aspects can also be limiting, for example many people rely on an unobtrusive fashionable appearance (for example helmet, gloves) [Van07] and also Mehler-Bicher et. al. [MS17] mentions a concern about the right to one's own image, which the use of cameras in public spaces entails, thus many people feel that their personal rights are violated.

2.3 Lerosh

The Lerosh project [wer23] is an innovative concept idea that aims to support small and medium-sized enterprises in digitization through the use of robotics. It was developed to enable in particular monotonous grinding work with the help of robots. The focus is on making programming and using robots accessible to non-experienced users without additional training.

The main goal of the Lerosh project is to save resources such as time and personnel. By implementing this concept, craftspeople could obtain a user-friendly and intuitive system with which they can teach robots on their own. This would enable them to implement specific tasks in batch size 1, which means that they can carry out individualized work efficiently.

One area where the Lerosh project is particularly useful is sanding, which is a widespread activity in many businesses. Nationwide, for example, some 40,000 carpentry stores, about 3,000 orthotics makers and about 1,200 musical instrument manufacturing businesses could benefit from the project's solutions. These industries could optimize their processes and increase their productivity by relying on the benefits of robot-based digitization [wer23].

In the course of this work, the concept will be developed in which a user programs a robot with the help of AR and LfD in such a way that this robot can then in return process a workpiece.

3 Related Work and State of the Art

This chapter presents research projects and scientific papers that have already addressed the use of AR in robotics. In particular, the use of AR in intuitive programming of robots is discussed, but areas such as robot maintenance and diagnostics as well as robot training and education are also explored to gain a broad insight.

3.1 AR in Intuitive Programming of Robots

In the category of intuitive programming of robots, several relevant works have been reviewed that use AR as a tool to improve user interaction and feedback in teaching and demonstration processes. Here are the most relevant works that relate to Learning from Demonstration systems:

- **Liu et al. [Liu+18]:** This work developed an AR interface specifically designed for HoloLens and a Rethink Baxter robot. The system uses LfD and allows the user to view the task graph during the teaching process. This graph provides high-level feedback to the user and indicates future states. In addition, the user can add new tasks to the graph.
- **Luebbers et al. [Lue+19]:** This work provides an AR interface that allows the user to set constraints that affect the execution of the robot. Before the actual execution begins, the trajectory of the end effector is virtually displayed to the user in the form of hologram waypoints. The interface allows the user to specify three different types of constraints: a height constraint, an orientation constraint, and a location constraint. These are visualized differently.
- **Mollard et al. [Mol+15]:** In this work, an interface was developed for a learning by demonstration system in which a robot performs an assembly task to build an object such as a chair. The AR system allows the system to request specific demonstrations or clarifications from the user. A user study with 14 participants validated the benefits of combining demonstration and feedback and emphasized the importance of informing the user of the knowledge acquired by the robot to improve programming time and accuracy. Despite the positive results of the user

study, it can be seen in Figure 3.1 that it is a more complex user interface, which requires prio knowledge of the field of robotics.

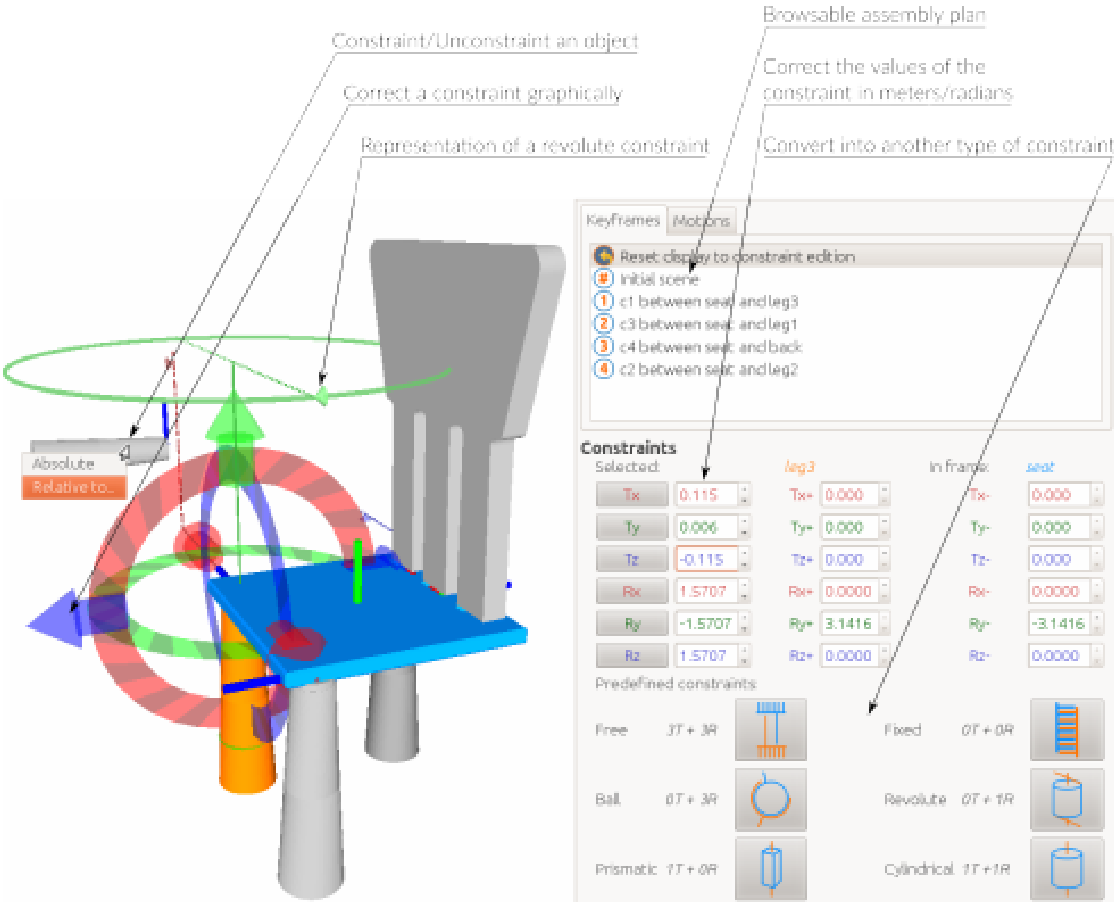


Figure 3.1: Interface of application to assembly a chair [Mol+15]

- **Soares et al. [SPM21]:** This work uses imitation learning to allow the user to draw a path in the air, which the robot then mimics. Design-specific considerations were made here, such as the color choice of the path to ensure a clear distinction from the industrial environment.

This related work has shown how AR can be used to support intuitive programming of robots. They provide a high level of visualization, but have some limitations, especially in terms of suitability for inexperienced users and the impact of feedback. The question remains open in which context feedback can actually help or hinder.

In addition to AR applications for LfD systems, other studies have examined how the Microsoft HoloLens can be used as a feedback mechanism. For example, Blankemeyer et al. [Bla+18] and Guan et al. [Gua+19] used HoloLens in their work to enable intuitive programming of robots. Here, users can select or program motion paths. Gaschler et al. [Gas+14] present an approach using a handheld pointing device to program trajectories without using AR. This example illustrates that the nature of user input and interaction are also key aspects of intuitive programming.

3.2 AR in Robot System Maintenance and Diagnosis

Two promising applications of AR have been identified in the field of robot maintenance and fault diagnosis:

- **Diehl et al. [Die+20]:** The work of Diehl et al. focused on the use of AR in an industrial context. A verification tool was developed that allows users to detect errors in the execution. This was achieved through semantic descriptions and simulations of actual robot execution. Through a study, three different visualization technologies are also investigated, including through a Hololens 1 with AR simulation, a tablet with AR simulation, and a tablet with RViz-like simulation. It was found that users did not prefer the Hololens variant due to hardware-specific issues such as wearing comfort and limited field of view. In addition, some participants felt that it took more time and training to get used to interacting with the application on the Hololens compared to the tablet devices.
- **Avalle et al. [Ava+19]:** This project focused on the visualization of industrial robot errors using an adaptive AR system. This allowed to effectively display an error message according to the user in the room without being occluded or disturbing. The results showed that users were able to detect faults faster with the adaptive mode than with the non-adaptive solution. The ability to place error messages in the user's field of view helped overcome the limitations of the limited field of view of AR devices such as the Microsoft HoloLens.

These two papers highlight the potential of AR in fault diagnosis and maintenance of robotic systems. The work by Diehl et al. highlights the challenges that can arise when using HMDs such as the Hololens, while the work by Avalle et al. presents a promising solution for effectively visualizing faults, which could also be conceivable in the feedback domain.

3.3 AR in Robot Training and Education

In the area of training and education on the robot, two interesting works have been studied:

- **Cruz et al. [De +22]:** In the work of Cruz et al. a mixed reality application was developed for mobile devices that allowed users to select different desired trajectories, visualize the behavior of the robotic arm, and understand its operation through animations. The usability evaluation showed a high usability of the AR tool, indicating that the application is well suited in the training and support of industrial manipulators.

- **Herrera et al. [Her+20]:** This work focused on the application of AR technology as a tool for simulating a mobile manipulator robot training system to provide a better understanding of the robot's movements and to develop and evaluate autonomous control algorithms. For this purpose, they developed an application for training mobile manipulator robots using augmented reality. This application allowed users to interact with the robot, learn about its parts through animations, and visualize its movements in 2D or 3D markers. They conducted a survey with 15 participating engineering students, the results of which showed that the application is very useful for training mobile manipulator robots.

This work provides valuable insight into the use of augmented reality for robotic training, particularly in terms of feedback mechanisms that have been used effectively.

3.4 Summary

In this chapter, we have presented a variety of related works that address different aspects of our topic. These works have been analyzed in depth to provide important insights. In doing so, we have identified successful approaches as well as challenges and difficulties that researchers have encountered in this area.

The papers presented, provide a reference point and inspiration for our own work. They allow us to adopt best practices and methods to develop effective solutions. At the same time, the challenges discussed help us identify potential problems early and develop appropriate strategies to address them.

The summary of this related work provides valuable context for our own research and highlights the relevance and added value of our contribution to the field. In the next chapter, we will then revisit the exact issues at stake and elaborate on the concept we have developed.

4 Methodology

The focus of this chapter is the overall consideration and solving of the central challenges. For this purpose, they will be revisited in more detail before proposing a solution approach in the form of an AR interface.

4.1 The Challenge

In this section, we take a detailed look at the challenges that arise in robotic applications. These challenges are fundamental and require focused solution approaches to fully harness the potential of robotics technology and enable its application for non-expert in small businesses.

4.1.1 User-Related Problems

Missing intuitive solutions for non-expert users

One of the outstanding challenges is to create intuitive solutions that are accessible to non-expert users. In many cases, existing AR applications for robots are complex and require some previous knowledge in the field of robotics. This significantly limits the target user group to experts [Fu+23; SGR22]. A good example of a interface can be seen in 3.1. This would need a specific training for non-experts.

Immersion in the Task and Transparency

To address a broader audience it needs immersive and transparent solutions. The current user experience can be negatively affected by non-ergonomic interactions during human-robot interaction (HRI) and human-robot collaboration (HRC). This not only affects task performance, but also imposes an unnecessarily high cognitive load on users and may result in a rejection of the technology during user operation [Fu+23; AB17].

4.1.2 Learning by Demonstration

Dependence on the Demonstration

The effectiveness of LfD systems depends heavily on the demonstrations performed. The quality of the demonstrated actions determines how well the robot can learn the desired tasks. However, during the demonstration, interfering factors can also influence the data. The user performing the demonstration is a crucial factor in this regard.

Multiple Demonstrations Required In many cases, multiple demonstrations of the same task may be required to ensure that the robot successfully learns the desired capabilities. This may require additional investment of time and demonstrations [Fu+23]. Inexperienced users also face the problem that without instructions from the robot, there is no sense of when the demonstrations are enough or when to give a new demonstration. Maeda et al. [Mae+17], for example, develops a system based on this problem that uses an audio signal to request further demonstrations when the system is very uncertain.

Discrepancy Between User Expectations and Robot Learning

One of the most important problems in LfD is the rather a mismatch between the models (that the user has, the user believes the robot has and the actual model the robot has).

user and machine. A discrepancy may exist between the user's expectations and the robot's actual learning progress. The user might believe that the robot has learned certain skills, while in reality this is not the case [SZH18; SH20]. For this reason, many previous papers have also emphasized the need for feedback to the user. Thereby, especially for non-experienced users, this discrepancy can be a major obstacle that prevents the establishment of robots with LfD in small companies.

4.2 Feedback as Solution

In this thesis we present a feedback-mechanism as the central element of our approach to overcome the challenges in the field of robotics programming. Feedback plays a crucial role in increasing the efficiency, accuracy, and usability of the robotics programming process.

Our solution integrates various approaches, including learning by demonstration, learning by feedback, and knowledge transfer using AR, with the goal of optimizing the whole workflow of robotics programming. The use of AR-based feedback enables continuous improvement and adaptation of a human teacher's behavior, ultimately leading to improved demonstrations and better results [Mol+15].

Our feedback approach is specifically designed to suit novice users and serve as a guide to improve their interactions with the robot. It enables users to gain a deeper understanding of the system and perform tasks more effectively. Our main goal is to narrow the gap between human and robot capabilities, giving the human teacher insights into what the robot has already learned. This allows for more focused and efficient demonstrations without requiring a deep understanding of the learning processes.

The need to use directed feedback in AR interfaces is also emphasized by Paelke at al. [Pae14]. In this context, extensive research is needed to conduct extensive studies on visualization, interaction, and technological components to shape the future of user interfaces in work support systems.

Therefore, this study is devoted to explore how feedback, especially in the context of AR, can be used to improve learning by demonstration and, more importantly, to optimize robotics programming. We have carefully analyzed existing approaches and challenges in this area and identified the urgent need for a user-centric solution, especially tailored to non-expert users.

Our proposed solution involves the design of a user-centric AR feedback system that integrates various mechanisms to improve user understanding and optimize the robotics programming process. Through extensive testing and evaluation, we aim to ensure the efficiency and effectiveness of our solution and ultimately provide a validated user interface element for future LfD systems.

4.3 Hypotheses

In order to be able to evaluate our implemented solution, we have set up the following hypotheses, which we would like to investigate in the context of our feedback system. We mainly refer to our system in comparison to a system without feedback.

H1: The use of the AR interface leads to an increased intuitive handling of the LfD robot compared to the use without interface

Users benefit from the visual interface in the sense, that the programming process of the robot is perceived to be more intuitive.

H2: Visualization of the process helps increase the efficiency of the demonstrations in terms of accuracy, compared to situations without visualization

The feedback provided about the LfD process allows the user to achieve more accurate results in the segmentation.

H3: The use of visual feedback allows to reduce the existing knowledge gap between humans and machines

The knowledge gap described by Sena et al. [SZH18] between humans and robots can be reduced by using AR Feedback.

H4: Compared to discrete feedback, continuous feedback while the demonstration is still in progress can increase effectiveness in terms of quality

Compared to discrete feedback provided after a demonstration is complete, we hypothesize that real-time feedback during the demonstration is more beneficial to the user. This is based on research by Sena et al. [SZH18; SH20].

H5: Targeted use of AR technologies can further improve the learning by demonstration approach and make it more intuitive

Our hypothesis is that using AR interaction methods such as hand tracking to enable imitation learning in our process can make user interaction more intuitive and user-friendly.

4.4 AR Interface

For the AR interface, we developed a concept combining the HoloLens 2 and DLR's Safe, Autonomous Robotic Assistant (SARA) robot. This interface was purposefully designed to address the previously described challenges in human-robot interaction in an efficient manner.

To begin, we would like to explain the basic workflow for robot programming that we have established as a starting point. Then, we will formulate the requirements that our system must meet in order to address the challenges mentioned above.

4.4.1 Process for Programming Robots with AR

The concept for the interaction between human and robotic system is described in this section, where the user in this case is an employee in a manufacturing facility. This was developed specifically for the interaction with an AR Device. In Figure 4.1 this process is visually represented as a flowchart diagram. The steps of this concept are described below:

- **Workpiece scanning:** The user places the workpiece on the table and performs a complete scan, looking at the workpiece from all sides. This scan generates

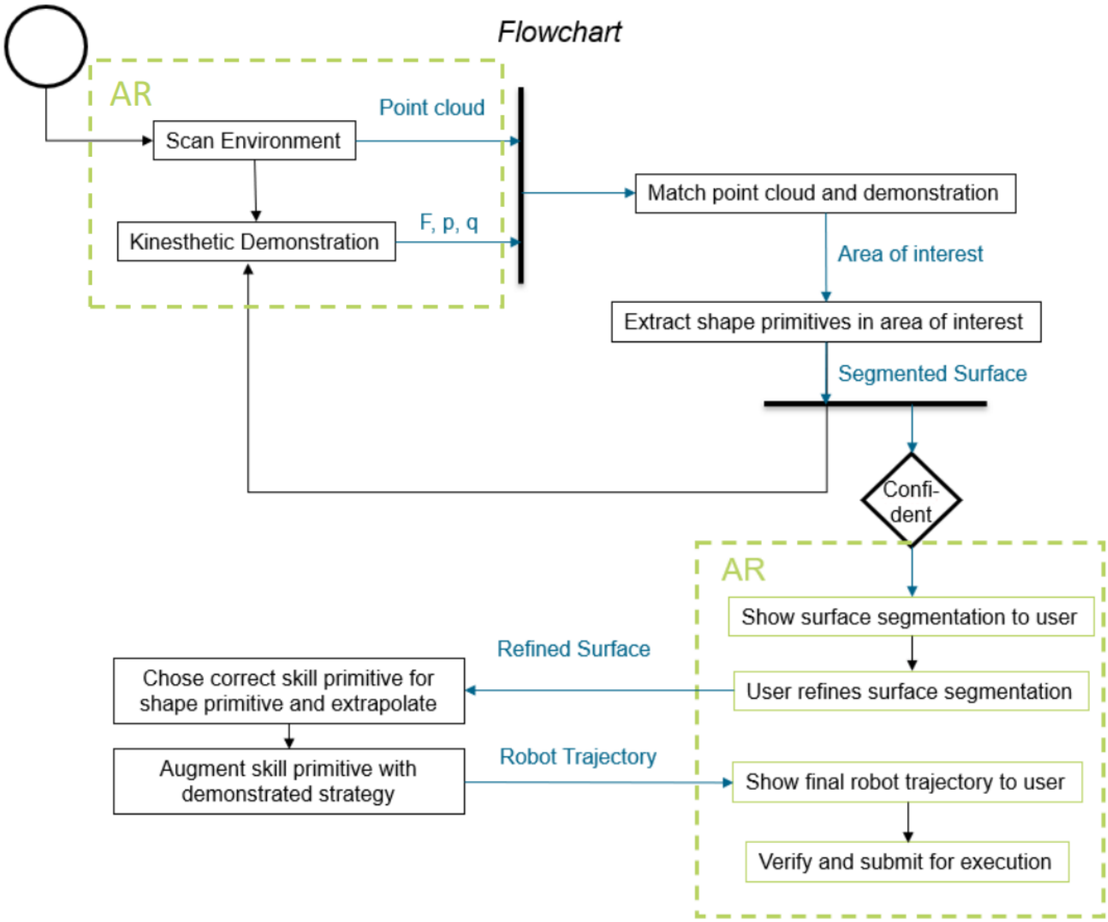


Figure 4.1: Flowchart diagram of the process flow for programming the robot using the AR interface

a detailed 3D point cloud of the workpiece, which is passed to the algorithm. Before the scanned object is passed on to the robot, it is displayed to the user for verification to identify any errors before continuing to the next step.

- **Demonstration on the workpiece:** the user performs a demonstration on the workpiece by using the robot's end effector to demonstrate the desired grinding surface. The contact points recorded during the demonstration are converted by the robot into an appropriate geometric shape that best matches the recorded points of the demonstration and the scanned workpiece. This matched geometric shape can be presented to the user for evaluation. If the fit is insufficient, the user can perform further demonstrations to improve the result.

- **Setting up no-go zones:** Once the appropriate shape is found, it is presented to the user for final review. Here, the user has the option to mark no-go zones on this shape that the robot should avoid during processing. The robot can then calculate a trajectory for processing. If needed, the no-go zones can be adjusted iteratively, recalculating the trajectory each time until the user agrees.

- **Review and execution:** the calculated trajectory for processing the workpiece is presented to the user. In this final step, the user has the opportunity to review the trajectory before it is executed by the robot.

4.4.2 Concept Approach

Implementing our concept and hypotheses requires various settings and design decisions, which are explored in this paper. In doing so, we follow design guidelines from related research areas. The goal is also to establish user interface elements that can be used in future LfD applications.

In H1 we evaluate the effectiveness of our interface in general. Our goal is to investigate whether the interface provides an intuitive and user-friendly solution for the users.

Regarding H2, we investigate whether the quality of the demonstration can be affected by the presence of feedback. We compare whether the method without feedback is different from the methods with feedback to check the validation of the developed interface in terms of added value for the user in terms of quality. We measure the quality by the accuracy of the results, which are segmented by the robot.

As part of H3, we provide several visual elements to convey information to the user. We visualize the contact points that the user enters during the demonstration, as well as the intersection of the point cloud that matches the segmented surface. We also explore whether the additional display of the segmented surface adds value for the user. In doing so, we implement the information directly on the workpiece as suggested by Bruno et al. [Bru+06].

In the context of H4, different update rates are enabled during the demonstration process, either in the form of real-time continuous feedback or discrete feedback provided after the demonstration is complete. This approach is based on research by Sena et al. [SZH18], who use discrete feedback in their solution. Our goal ist to find an update rate which is better than the one original proposed.

As part of H5, research is being conducted to determine whether the use of AR solutions can further support users. According to the findings of Gavish et al. [Gav+11], observational learning is properly integrated into the training protocol to increase the efficiency of training. As an example, we test whether interaction with the robot can be eliminated by a virtual input tool and imitation learning can be used to simplify the interaction for the user.

4.4.3 Requirements

In order to implement this programming concept in a high-quality manner, specific requirements have been formulated that the AR application must meet. These requirements are based on previous work and the current state of the art. The requirements are as follows:

- **Feedback:** The interface should provide feedback to the users to help them understand the system and adjust their demonstrations accordingly. This includes contextual information, visualizations, and adaptation to the environment.
- **User-friendliness:** The interface should be user-friendly and intuitive without overwhelming the user or relying too heavily on the interface.
- **Real-time:** The interface should be as responsive as possible, and avoid delays as well as being equipped with a discrete update rate.
- **User Interaction:** The interface should allow user interaction to fix bugs and improve or customize demonstrations.

These requirements form the basis for the development of the application, which is described in detail in the next chapter.

5 Implementation

In the following chapter, the developed application is presented and discussed in more detail, focusing on the main components.

5.1 Hardware and Software

For the implementation of the application, the HMD: Microsoft HoloLens 2 was chosen as the display device. This decision was made especially because of its advantages, which we discussed previously, in terms of intuitiveness and the possibility of user-free interaction, which could be especially beneficial for non-expert users.

Unity version 2021.3.6f1 on Windows was used to implement the application. The SARA lightweight robot from German Aerospace Center (DLR) is used to demonstrate and execute the developed application.

In addition, a hand tracking system was used by Unity and the Mixed Reality Toolkit (MRTK) to enable interaction between the user and the AR application. This system allows the user to interact with the application without physical controllers.

5.2 Interface Components

This section describes the implementation highlights and the various components.

5.2.1 Robot Logic

The logic of the robot is not covered in detail in this paper, but is mentioned for completeness. The robot logic has a relatively simple structure. The algorithm expects as input a representation of the workpiece, as a point cloud, and a demonstration on the robot. During the demonstration, contact points are recorded that lie on the surface of the workpiece. The algorithm then fits a primitive shape to these contact points that best match the points on the workpiece. The result of the algorithm provides the intersection of the point cloud of the workpiece with the fitted primitive shape, as well as the primitive shape itself. The implementation of this algorithm is beyond the scope of this work and is taken as given. We reference the primitive shape found by the algorithm as a segmentation or segmented shape.

5.2.2 User Interface Design

The User Interface (UI) consists of several graphical components, including the hand menu, which serves as the main menu for the user and from which pop-up menus can be accessed. In addition, design decisions have been made that affect the rendering of the UI objects, particularly in terms of shaders and materials.

Menu

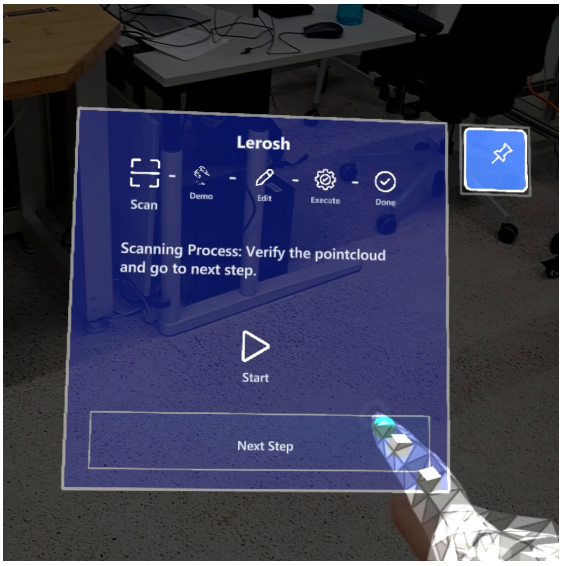
There are a total of three popup menus: ontology, lerosh, and settings, which are accessed through a central hand menu. The MRTK plugin assets were used as a template, as they have been optimized through numerous user tests and provide an optimized user experience. In

- The **Ontology menu** allows the user to view the knowledge space of the robot in relation to the elements in the ontology.
- The **Lerosh menu** allows the user to start and step through the process for grinding the workpiece. In Figure 5.1 you can see the three main steps of the application menu. Warnings are also displayed to the user as in Figure 5.1 b). Above the menu, the process and status are visualized for the user to follow. Depending on the step, individual settings can be made as shown in Figure 5.1 c).
- The **Settings menu** was designed mainly as a tool for development. Here the user can set the IP address of the server, view the log, and access the calibration of the coordinate systems.

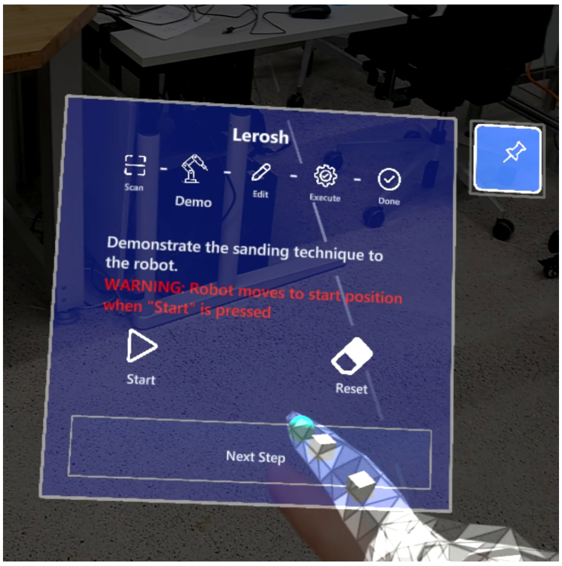
Shaders and Materials

Shaders and materials were purposefully chosen to be used in industrial environments while being easy for users to understand. Different features have been colored differently to provide clear visual distinction. For example, the point cloud is displayed in white by default. When selected, it changes color to either blue to represent segmentation or red to highlight no-go zones. The segmented primitive shape is displayed in green, and contact points are highlighted in pink. Care was taken to create a strong contrast between the colors and with the environment.

To visualize the workbench, a full 3D model was first used to overlay with the real workbench. However, an accurate 3D model affected the performance of the HoloLens and occluded the objects on the table, preventing them from being seen by the user. The solution was to take a more discreet approach, using a grid shader. This was designed to show only the tabletop as a grid, which improved performance. Nevertheless, this



(a) Scanning process



(b) Demonstration process

(c) Editing process

Figure 5.1: Lerosh-Menu Steps

also resulted in the objects on the workbench disappearing visually. Therefore, the visualization of the workbench was replaced by four corner points.

Virtual Hands

To more closely link the virtual world with the real world, the user's hands are tracked and a virtual model is superimposed on them. This is a feature of MRTK that greatly improves the visibility of hands and facilitates interaction with virtual objects. This overlay also allows the virtual objects to not overlap the real hands, providing a better view of the environment. This is an effective alternative to occlusion, where virtual objects can block the view of real objects. The virtual hands provide the user with a more user-friendly way to interact with the virtual objects.

5.2.3 Communication

Communication between the HoloLens 2 and the robot represents one of the central components. A server is used for this, which acts as an intermediary between the different parts of the system.

Server

The server acts as the central interface and connection point between the components: HoloLens, Robot and Ontology. It is based on a simple Flask server that can be accessed by the HoloLens via REST requests. In addition, the server accesses the ontology and the robot's knowledge space via DLR's Links and Nodes middleware.

An important task of the server is to process requests and forward them to the appropriate components. For example, requests to generate point clouds are sent to the server and forwarded from there to the robot.

In addition, the server acts as a data storage device. Important information and data are stored on the hard disk, including created point clouds and calibration data.

Data

The processing of information and data plays a crucial role in the implementation. This data processing is mainly done on the server side. An example of this is the conversion of functions into mesh structures or the conversion of point clouds into appropriate data types.

The server is responsible for managing various types of data exchanged between the HoloLens and the robot. To make the transfer and storage of data efficient, the JSON format is used as one of the main formats. In addition, captured point clouds are stored as .PLY files on the hard disk.

Throughout the process, there is continuous communication between the HoloLens and the server. This allows the server to forward requests to the robot and perform calculations. This continuous data transfer plays a crucial role in the coordination of the process and interaction between the different components of the system.

5.2.4 Coordinate Systems

Coordinate systems play a critical role in this application because the HoloLens, Unity, and the robot each use different coordinate systems. There is no automatic alignment of these coordinate systems, so explicit calibration is required. The coordinate systems of HoloLens and Unity have differences, even when Unity is running on HoloLens. In addition, the robot's coordinate system differs significantly from those of HoloLens and Unity. Therefore, careful calibration and alignment of all three coordinate systems is essential.

A visualization of the coordinate systems and how they relate to each other in the application can be seen in Figure 5.2. It should be noted that Unity uses a left-handed coordinate system, while HoloLens uses a right-handed system. The robot's coordinate system is also right-handed, but is also rotated. This requires a conversion of the coordinates when data is exchanged between the systems. Currently, this conversion is done on HoloLens because both HoloLens and the robot use the same coordinate system. In the future, however, it is planned to have this conversion done entirely by the backend.

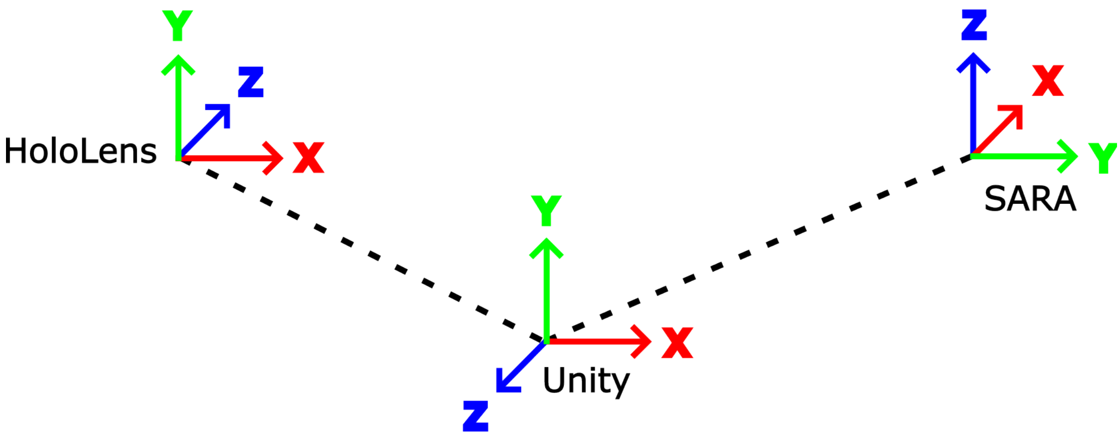


Figure 5.2: Visualisation of the three different coordinate systems and their linking in the application

Calibration

Alignment of all coordinate systems is done using calibration, which aligns all systems to the origin of Unity. The calibration of the robot was originally performed using the Vuforia Plugin, but proved to be insufficient due to its unreliability. Therefore, a switch was made to manual calibration, where the user positions the virtual workbench to match the real world. The calibration of the table can be seen in Figure 5.3. The 3D model of the workbench is placed accordingly in space.

Calibration of the HoloLens coordinate system was initially to be performed by an automatic process in which Unity accessed native pointers of the HoloLens. However, due to lack of experience and time constraints, it was also switched to a simpler manual calibration. This involves scanning a point cloud that is moved by the user to match the real world. Note that it is also possible to adjust the calibration through a control panel.

It is worth noting that the calibration of the coordinate systems was performed as accurately as possible, with the freezing of the axes for the table in particular providing greater accuracy than using Vuforia. This can be seen in Figure 5.3, where an options menu allows the user to freeze a specific axis or rotation around the Y-axis. This was sufficient for the purposes of this work, although automatic calibration will be done for future applications.

5.2.5 Ontology

An important component for displaying the robot's knowledge is the ontology. This component is decoupled from the Lerosh process, but may still be useful to the user in the future. A robot's ontology contains all the elements that are currently in the robot's workcell. These elements can be displayed through the user interface. This means, for example, that the robot's tools on the workbench can be made visible to the user. This can be seen in 5.4. In the future, the positioning of the workpiece to be processed could also be checked first through the ontology before starting the Lerosh process. This could avoid the possibility of positioning errors, such as placing a workpiece outside the robot's workspace. It could also be possible to display the penetration of the workpiece through the grinding process directly on the workpiece using a heat map. An example of how this could look is shown in 5.4.

The ontology is accessed through the server, which receives the data from the robot through a service call from the HoloLens. The data received is in JSON format and contains information such as the name, type, and position of the objects. These objects are already known to Unity and can be spawned into the scene as prefabs, taking into account their position with respect to the robot's coordinate system. In the future, the models can also be dynamically loaded from the server when the application is started.

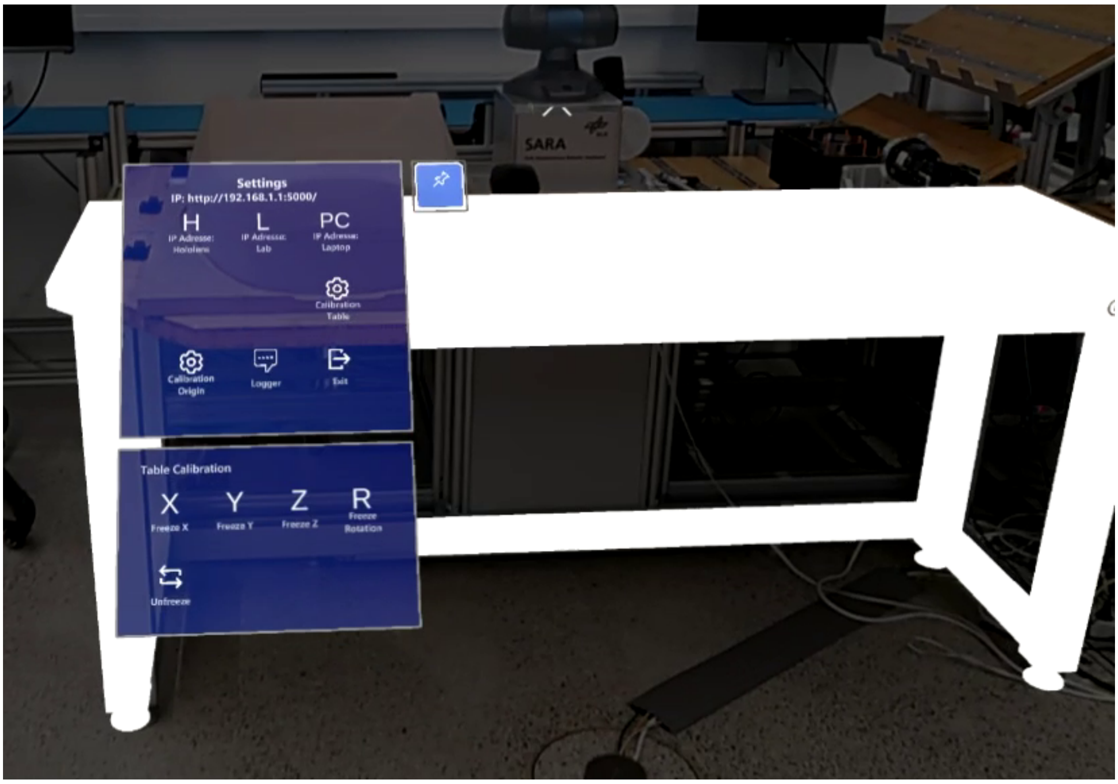


Figure 5.3: Calibration of the workbench which is in relation to the robot base

By moving the objects by the user and then confirming them, the objects can be updated in the ontology. This allows the user to interactively design the virtual environment and make changes in the ontology.

5.2.6 Scanning

The scanning process of the workpiece is the first step in the programming process. This process is performed by the HoloLens accessing its sensors, specifically the depth images from the Long Throw Sensor. The captured depth images are tagged with a transformation matrix to the origin of the HoloLens coordinate system and then transmitted to the server. This data transfer is done via sockets, as REST requests would be too slow. On the server, the backend accesses this data and generates a point cloud from the images and the transformations.

An alternative option was to access MRTK's spatial mesh. However, this spatial mesh is very coarse and a more accurate representation would require too much computing

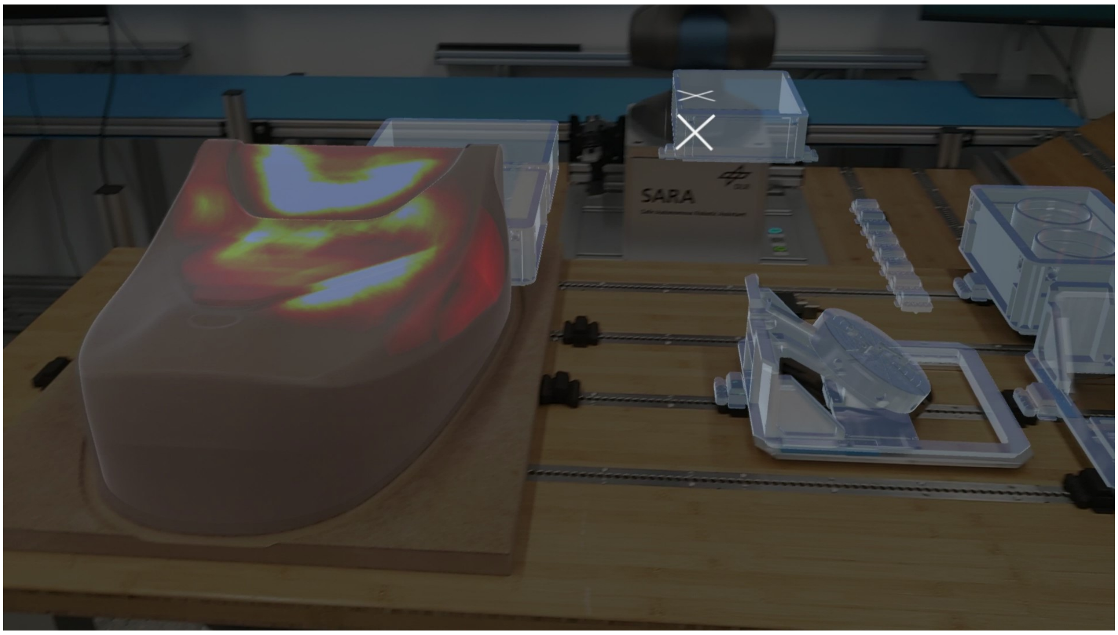


Figure 5.4: Ontology displayed onto the workbench

power, which is not feasible with HoloLens 2.

The generated point cloud is requested by Unity during scanning and displayed as a particle system. However, this is a trimmed-down version of the point cloud in order not to impair performance by too many particles.

Sensor Streaming

The sensors are accessed indirectly through Unity, as they access the HoloLens data due to a DLL plugin written in C++. The repository for this plugin comes from GitHub [Gsa23]. After some adjustments, it was possible to access the LongThrow sensor instead of the AHAT sensor. Accessing the HoloLens data through the C++ plugin creates an additional coordinate system that we reference as the HoloLens coordinate system. In order to access the sensor data, developer mode must be enabled on HoloLens.

An alternative method was to access the sensor directly through Unity using the MRTK plugin. Then the conversion of the coordinate systems could be done in a later step. However, due to lack of experience and insufficient documentation, this approach was not pursued.

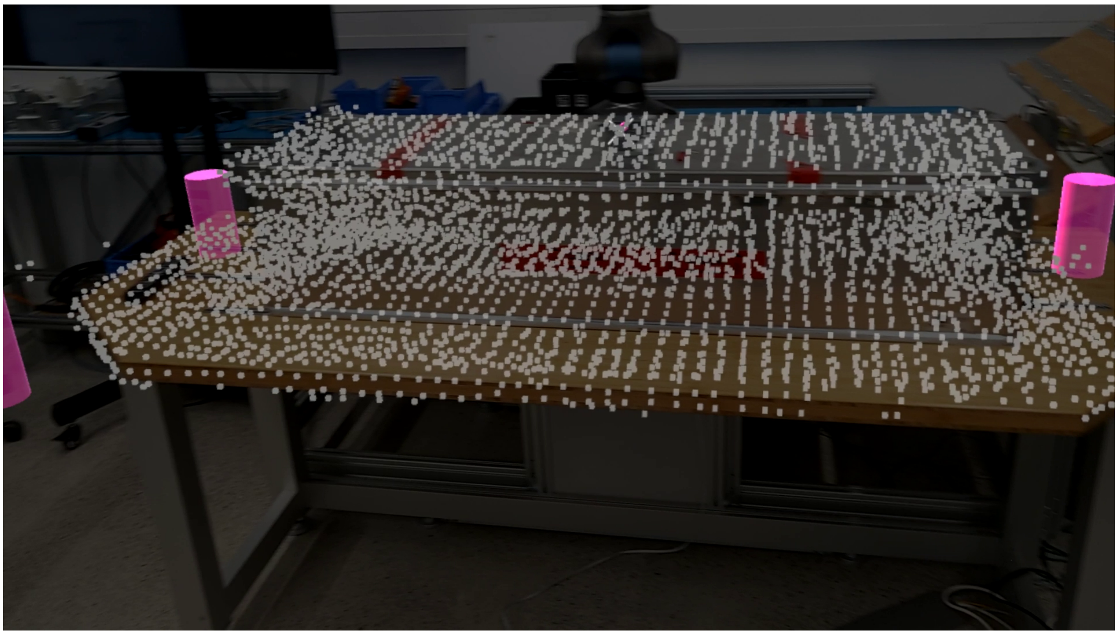


Figure 5.5: Pointcloud visualised on top of the workbench

Point Cloud Generation

Point cloud generation is one of the most important components of this work, as it serves as input to the LfD algorithm. In our application, point clouds play a central role as they provide a deep understanding of the environment and provide valuable context for our robot. These point clouds not only serve as input to our algorithm, but are also used as output to the user.

The basis for generating these point clouds is the depth image. Here we use a matrix leading from the HoloLens object to the origin of the HoloLens coordinate system, and a matrix leading from the HoloLens object to the depth sensor object. Internally, we use a look-up table to convert the depth points of the frame to the correct position in space.

Our software uses the Open3D library to process the above data and generate high-quality point clouds. These are then exported to a .PLY file. To ensure the quality of our point clouds, we overlay different point clouds and perform downsampling to simplify overlapping points.

We also tried to apply different algorithms like global registration with ICP or RANSAC to optimize the point clouds. Unfortunately, these approaches did not provide the desired results and required too much computational time.

It is worth mentioning that the coordinate systems and matrices provided by the

HoloLens are stable enough, so no further algorithms are needed for stabilization. This allows precise and efficient processing of point clouds in our application.

Visualization of the Point Cloud

The point cloud is visualized as a particle system in Unity as seen in Figure 5.5. Computing the position is non-trivial, since particle objects cannot be easily rotated like GameObjects. To display the point cloud correctly, we put the particle system into a GameObject that represents the origin point of the HoloLens. This GameObject is related to the Unity coordinate system, so calibration as described is necessary. When calculating particle positions, a transformation matrix of the origin point of the HoloLens is used to calculate the transformation and rotation of each particle in the Unity world coordinate system. This ensures that the point cloud is displayed correctly in space.

5.2.7 Demonstration

The demonstration is next to the pointcloud one of the crucial components in the LfD algorithm. It involves recording contact points that are subsequently used in the segmentation algorithm. This demonstration can be done in a number of ways, playing a critical role in the interaction and training of the robot.

On the Robot

A common method of demonstration is carried out directly on the robot. This involves a physical demonstration in which the end effector is equipped with a special grinding tool with a sensor. This end effector is used by the user to sand a workpiece. During the interaction, the sensor measures the applied force. When the measured force exceeds a predefined threshold, a contact point is recorded. These contact points are published by the robot via DLR's Links and Nodes middleware. The backend server can then access these published contact points and stream them to the HoloLens. The contact points are then visualized as pink spheres to the user, like suggested by Fang et al. [FON14]. The visualized feedback can be seen in 5.6.

With the Interface

An alternative way to demonstrate is to use the HoloLens glasses, which eliminates the need for the robot itself. We developed this approach in the context of H5. In this method, the contact points are recorded through the interface. In this case, a drawing tool is provided to the user, which can then be used to mark contact points on the

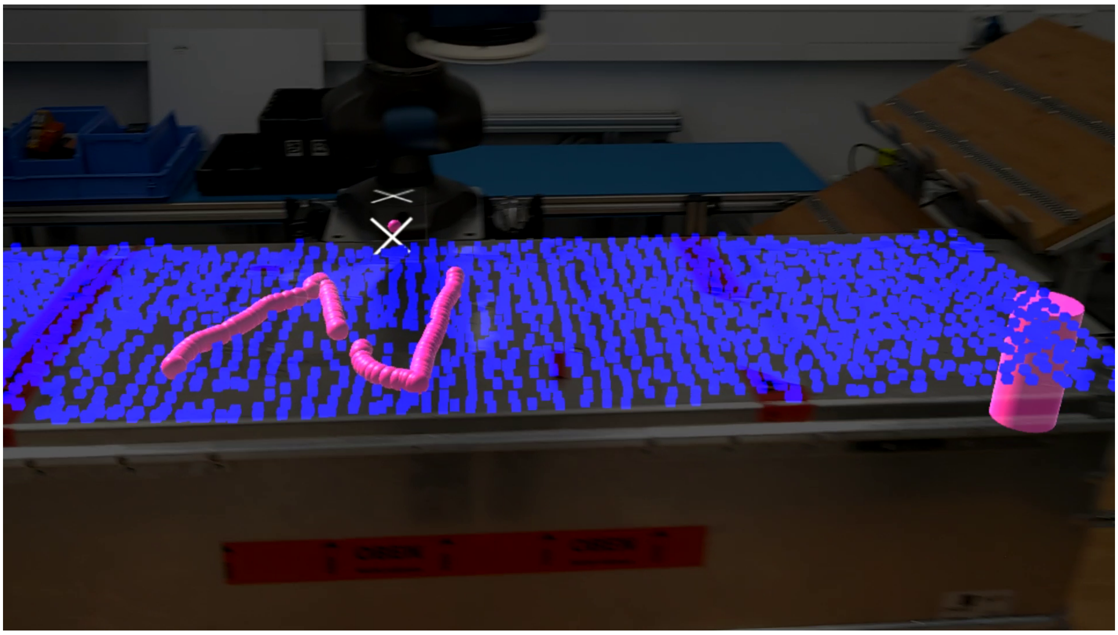


Figure 5.6: Visualisation of the demonstration feedback

surface of the point cloud. A contact point is drawn whenever the tool touches a particle of the point cloud. A pink sphere is then placed at this position of the particle, which symbolizes the contact point as in the demonstration with the robot. A more detailed description about how the drawing tool works is given in the next section 5.2.8. The marked points on the HoloLens are sent at regular intervals to the backend, from where they are transmitted to the robot. This process allows the user to perform the demonstration conveniently and intuitively on the HoloLens without having to interact directly with the robot.

The option to display additional information in the form of the segmented basic shape during the demonstration has also been implemented. In this case, the basic shape is displayed as a mesh in space.

5.2.8 Editing

Editing, especially for establishing no-go zones, is an important step in the context of our LfD system. Here, we use the same drawing tool as the tool we use during the demonstration via the interface to allow users to mark specific areas in the environment to give the robot clear instructions on how to avoid these zones.

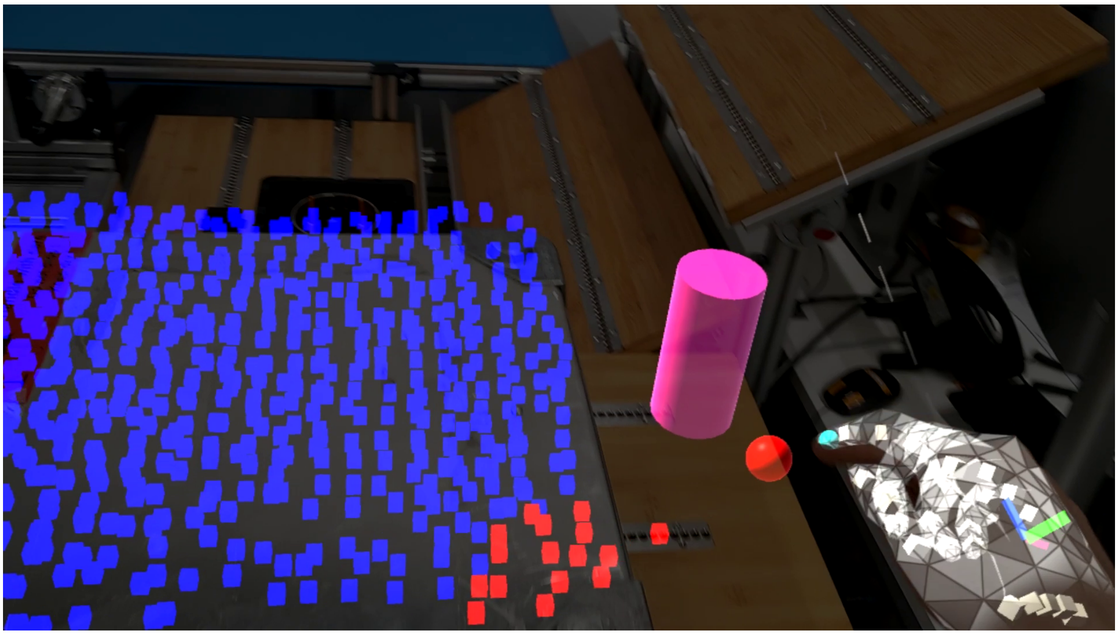


Figure 5.7: Editing No-Go Areas using the editing tool

The Drawing Tool

Our drawing tool consists of a virtual sphere attached to the user's index finger. When the user activates the editing mode, the drawing tool is launched at the same time. Due to the specific way we visualize the scanned environment with a particle system, it is not possible for us to perform collision detection in real time. Therefore, we resort to the position of the particles and the drawing tool to calculate the distance between them. If this distance is smaller than the given drawing radius, the system changes the color of the corresponding particle. In Figure 5.7 you can see the drawing tool representing the red sphere, the segmented area in blue and the edited no-go areas marked in red.

Edit and Undo

Selected locations can be deleted at any time with the click of a button, and the editing process can be restarted. This allows the user the flexibility to make changes and adjust the no-go zones as needed. The editing process is designed to be intuitive and user-friendly to ensure smooth configuration of zones.

Transfer to Backend

Once editing is complete, the user exits the editing mode and the selected points are transferred to the backend. From there, they are forwarded and passed to the robot. This step ensures that the no-go zones defined by the user can be effectively and precisely integrated into the robot's action planning.

The editing process thus plays a crucial role in the interaction between humans and robots in our application, allowing users to actively control the robot's movements and actions in their environment.

5.2.9 Execution

Execution is the final step in the LfD algorithm. At this stage, the robot's learned motions and actions are presented to the user and then executed.

Displaying the Trajectory

The first part of the execution is to show the user the planned trajectory of the robot. This trajectory is visualized as a line in space and is located on the workpiece to be machined. This step serves to give the user a clear idea of how the robot will perform the task and provides an opportunity to verify the planned motion.

Execution of the Action

After the trajectory is displayed and the user has had a chance to review it, the action is executed. The robot follows the planned trajectory and performs the previously demonstrated task. This step is the culmination of the LfD process, where the robot puts the learned behavior into practice.

After the execution has been completed, it is possible to machine additional workpieces. The "Execution" thus represents the end point where the acquired knowledge of the robot is transferred into practical application. It should be noted that the actual execution of the robot has not been implemented at this point, but the necessary infrastructure is in place. By calling the server to the robot and the execution function yet to be implemented, this step can be integrated in the future. Currently, however, this call results in an empty function.

5.3 Problem Points/Limitations

This section highlights various problem points and limitations of our system that were identified during the development process.

- **Manual Calibration:** Calibration of both Unity and HoloLens 2 coordinate systems currently requires manual adjustments. This can be time consuming and requires precise procedures.
- **Calibration Stability:** The calibration of the HoloLens coordinate system to the Unity coordinate system can shift after a reboot of the system, which can lead to inaccuracies.
- **Calibration Quality:** The quality of the calibration between the different elements of the system can have a significant impact on the accuracy and reliability of the acquired data. Especially for robotic demonstrations, accurate calibration is critical to prevent discrepancies between the demonstration points and the point cloud.
- **Vuforia tracking accuracy:** Vuforia tracking accuracy can be insufficient, leading to problems in the acquisition and placement of the robot coordinate system. An average offset in this case is about 2 cm. For this reason, a manual approach was preferred.
- **Performance:** If the number of particles is high, the performance of HoloLens can be significantly affected, which negatively impacts the user experience. For this reason, particles are sampled down before they are displayed.
- **Hardware issues:** HoloLens sensors do not function optimally in dark environments, and visibility of the real-world environment may be limited due to the brightness of the holograms, posing potential safety risks. Likewise, reflective surfaces also pose problems as they can interfere with the depth sensors, resulting in erroneous environmental information.

These identified problem points and limitations represent important areas for future development work and optimization. Solving these challenges will help to further improve the overall performance and usability of our application. However, for the user study, these limitations do not pose problems and therefore do not skew the results.

5.4 Summary

In this chapter, we presented and discussed our developed application in detail, focusing on the main components. At the end we also highlighted the challenges and limitations of this system, including the manual calibration of the coordinate systems and the performance aspects. This chapter provides a comprehensive look at the implementation and technical aspects of the application.

6 User Study

6.1 Structure of the User Study

To test and validate the hypotheses as described in chapter 4.3, we conducted a comprehensive user study. In this study, participants went through the process of processing a workpiece using the interface with different settings to investigate the effects of different aspects.

6.1.1 Test Description

The study involved participants evaluating the AR interface, examining different components. For this purpose, we have defined different settings, which are explained in more detail in the following description of the tests. In total, there are five different tests, each with a different setting.

Test 1: Without Feedback

The test subject performs the Lerosh process once. No visual feedback is given from the robot side. The user only performs the demonstration step. After the test, a questionnaire is filled out.

Test 2: With Feedback through the HoloLens

The test subject performs the Lerosh process with different settings a total of four times. In this process, the HoloLens is used as a feedback mechanism. The user goes through the steps of scanning, demonstration and setting up no-go zones. A questionnaire is filled out after each test.

- **Setting 1:** With feedback through the HoloLens and **continuous or discrete feedback** during the demonstration. With discrete feedback, the new state is always visualized after the demonstration is completed, while with continuous feedback, the state is already displayed during the demonstration.
- **Setting 2:** With feedback through the HoloLens and **demonstration by hand**. Demonstration is done with the drawing tool through the HoloLens.

- **Setting 3:** With feedback through the HoloLens and **visualization of the segmented primitive shape**. Here, the segmented area is displayed as a plane over the point cloud for example.

Study Design

Participants were divided into four groups, which can be seen in Table 6.1. The tests performed are listed in the respective column of each group, and the order of performance corresponds to the top-to-bottom order.

Test 1 and Test 2 were permutated differently for each group as well as setting 1.1 to obtain independent results. The setting of Test 1.2 and 1.3 were deliberately always performed at the same point of the study. While this does not give us an independent result, it does leave room for conjecture and some initial insight.

At the beginning of the study, each participant received a detailed explanation of the study procedure and the objective. This was followed by a hands-on introduction to the use of HoloLens using a demo app and an introduction to the robot setup. The main goal of each test session was to teach the robot to grind the top of a box, leaving out the corners. Participants had the freedom to perform the demonstration as many times as they deemed appropriate. In addition, they could stop the demonstration at any time once they believed the robot had sufficiently learned the task.

	Group A	**Group B**	**Group C**	**Group D**
Test 1	Without Feedback		Discrete	Continuous
Test 2	Discrete	Continuous	Continuous	Discrete
Test 3	Continuous	Discrete	Without Feedback	
Test 4	Demonstration per Hand			
Test 5	Additional Information			

Table 6.1: Group division of the user study

6.1.2 Data Collection

During testing, we actively collected data to provide a comprehensive picture of participant interactions and experiences. This data is collected in two main ways:

Questionnaire

To collect and analyze subjective results from our user study, we use a structured questionnaire. The questionnaire is used to collect demographic information of the participants and to assess intuitiveness and other relevant factors regarding the testers perceptions.

Demographic Information: In this section of the questionnaire, we collect basic demographic information from the participants. This includes:

- **Age:** The age range of the participants.
- **Gender:** Gender affiliation of the participants.
- **Profession:** The professional background information of the participants.
- **Experience with robots:** Participant's previous experience working with robots.
- **Experience with Augmented Reality:** Participant's previous experience with AR technologies.

Intuitivity Assessment: In this section of the questionnaire we accessed the intuitiveness using questions from two different question sets:

- **NASA TLX Question Catalog:** TLX stands for NASA Task Load indeX and is a questionnaire developed by NASA to specifically measure the workload at various levels [NAS]. This catalog captures: Mental Demands, Physical Demands, Temporal Demands, Performance, Effort, Frustration.
- **QUESI Question Catalog:** QUESI stands for Questionnaire for Measuring the Subjective Consequences of Intuitive Use, and measures intuitive handling through the unconscious application of users prior knowledge [NH10]. This catalog captures the subjective component of intuitive use and includes five different components: Cognitive Demand, Goal Achievement, Learning Difficulty, Familiarity, Error Rate.

Participants answer these questions after each test to capture changes in perceived intuitiveness.

Process-Understanding Questions: After each test, 5 additional questions were asked in addition to the NASA TLX and QUESI questionnaire. These questions were related to perceived knowledge discrepancy during the test and measure the user's understanding about the robot system.

In addition to these specific questions, there was also a final questionnaire which asked specific questions about each component of the AR interface. These questions aimed to gather detailed feedback and identify potential areas for improvement. Furthermore, participants were able to leave additional comments and notes to share their experiences and thoughts.

The structured questionnaire forms one of the central data collection tools in our user study. It allows us to collect quantitative and qualitative information to comprehensively evaluate the effectiveness and usability of our AR interface from a user perspective.

Application-based Data Collection

Beyond the questionnaire, we also collect data and results during the execution of the tests, which allow us to make comparisons between individual test settings. This contributes to the comprehensive investigation of our research questions, particularly on effectiveness in terms of quality. The data recorded include:

- **Contact points**, which were recorded during the demonstration.
- **Segmented areas**, which were calculated by the algorithm
- **No-Go zones**, which were marked by the user

6.2 Limitations of the Study

In this section, the limitations of the study conducted are described before the results are detailed in the next section. These limitations are important in order to adequately interpret the results of the study. The identified issues during the study include:

- **Limited number of users:** The study was conducted with a limited number of users, mainly students and engineers. This might limit the generalizability of the results and question the representativeness for real craftsmen in practice.
- **Missing subject-unrelated testers:** Some of the study participants had a great deal of prior experience with robotics and augmented reality, as they came from technical backgrounds. The absence of testers without such prior experience could mean that the results do not reflect the full spectrum of user experience.
- **Lack of opportunity for independent testing:** In some cases, certain components of the system, such as the demonstration by hand and the display of additional

information in the form of segmentation, could not be tested independently. This is because the limited number of participants and limited time made it difficult to permutate these scenarios into the study. However, the way we constructed the test provides us with an initial approach to evaluate these components.

- **Controlled Laboratory Environment:** The study was conducted in a controlled laboratory environment that does not reflect the same conditions as a real workshop or work environment. Therefore, results could vary in a real environment.
- **Lack of variation in tasks:** The tasks performed in the study were limited and may not be representative of the variety of tasks that may be encountered in the real world.

Despite these limitations, the study provides valuable insights into human-robot interaction in the context of augmented reality and can serve as a starting point for future research.

7 Evaluation of Data

In this chapter, we evaluated the data from the user study. We will describe the results of each component in detail. Here, we will consider the TLX and QUESI questionnaire data, robot-understanding questions, qualitative results about the interface, and data collected during testing. We conducted T-tests with two-sided results and paired data, as the same participants were tested in all different settings.

For better clarity, we use the following terms: "Without Feedback" for the group that, according to Test 1, did not receive any visual feedback via HoloLens. According to Test 2, Setting 1, we refer to the groups as "Continuous Feedback" and "Discrete Feedback". For "Demonstration Per Hand", we refer to Test 2, Setting 2, in which the demonstration was done manually by hand instead of using the robot. "With Segmentation" refers to Test 2, Setting 3 in which additional information is shown.

In addition to these definitions, we will only present the significant results in this chapter for reasons of clarity and because we have collected a large amount of data.

7.1 Demographic Participant Data

First, lets take a look at the demographic data of the participants. The average age of the participants was 25 years, with a standard deviation of 3.5. In total 20 people participated in this study, 16 males and 4 females. Overall, most participants had at least some experience using robotics. Specifically, 4 participants reported having no experience, 8 had little experience, and 8 had a lot of experience. In terms of experience with AR, most participants had little experience. More specifically, 11 participants indicated they had no experience with AR, 8 had little experience, and only one had a lot of experience. In terms of grinding, 12 participants reported having no experience, 7 had a little experience in recreational activities and hobbies, and one had a lot of experience.

7.2 TLX Data

The overall average of the TLX score for the test evaluation is shown in Figure 7.1. The score for the individual component range from -10, with "fully disagree", to 10, which

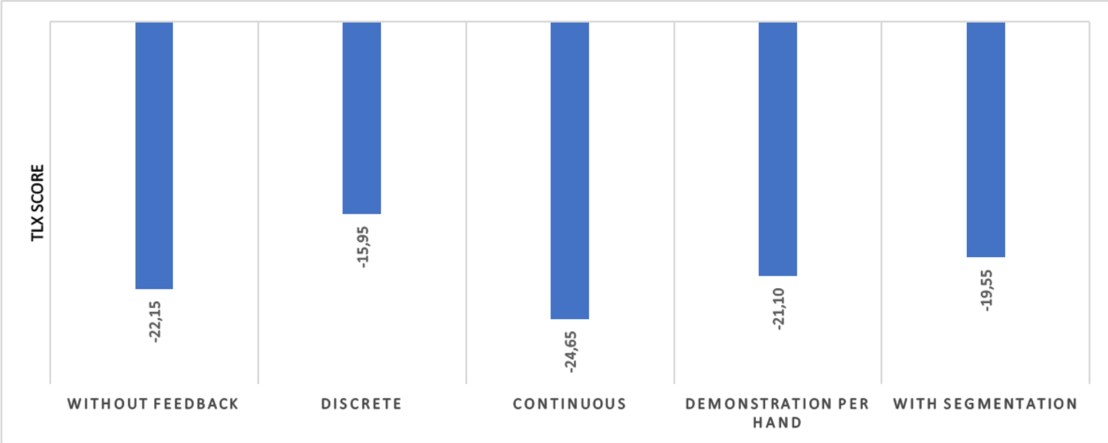


Figure 7.1: Average of the TLX-Score per Test

is "fully agree". For a user, the overall TLX score can therefore range from -60 to 60. Note that we have inverted the score of the performance component, as a higher score means a better result compared to the other components. Therefore, for the overall TLX score, a lower score for the average means a better result now. A comparison of the different configurations reveals a difference between "Discrete Feedback" (M = 15.95; SD = 21.395) and "Continuous Feedback" (M = 24.65; SD = 21.8341)(t (19) = 0.05280, $p < 0.1$). Note that the significance level is below 10%. However, this would lead to a rejection in a normal case. However, as the significance of the test is just over 5%, I mention the result here regardless, since all other comparisons did not show sufficient significance. For this reason, the individual TLX components, shown in Figure 7.2, that had significant results are analyzed below.

7.2.1 Mental Demand

In terms of the mental demand, it can be seen that "Without Feedback" (M = -6.7; SD = 3.938) has a lower mental load than "Discrete Feedback" (M = -1.35; SD = 4.922) (t (19) = 5.7E-5; $p < 0.05$), "Continuous Feedback" (M = -3.5; SD = 4.675) (t (19) = 0.01451; $p < 0.05$), "Demonstration Per Hand" (M = -2.4; SD = 5.695) (t (19) = 0.00773; $p < 0.05$), and "With Segmentation" (M = -3.15; SD = 4.509) (t (19) = 0.00226; $p < 0.05$). It also shows that "Discrete Feedback" performed worse compared to "Continuous Feedback" (M = -3.5; SD = 4.675) (t (19) = 0.04611; $p < 0.05$) and "With Segmentation" (M = -3.15; SD = 4.509) (t (19) = 0.01883; $p < 0.05$).

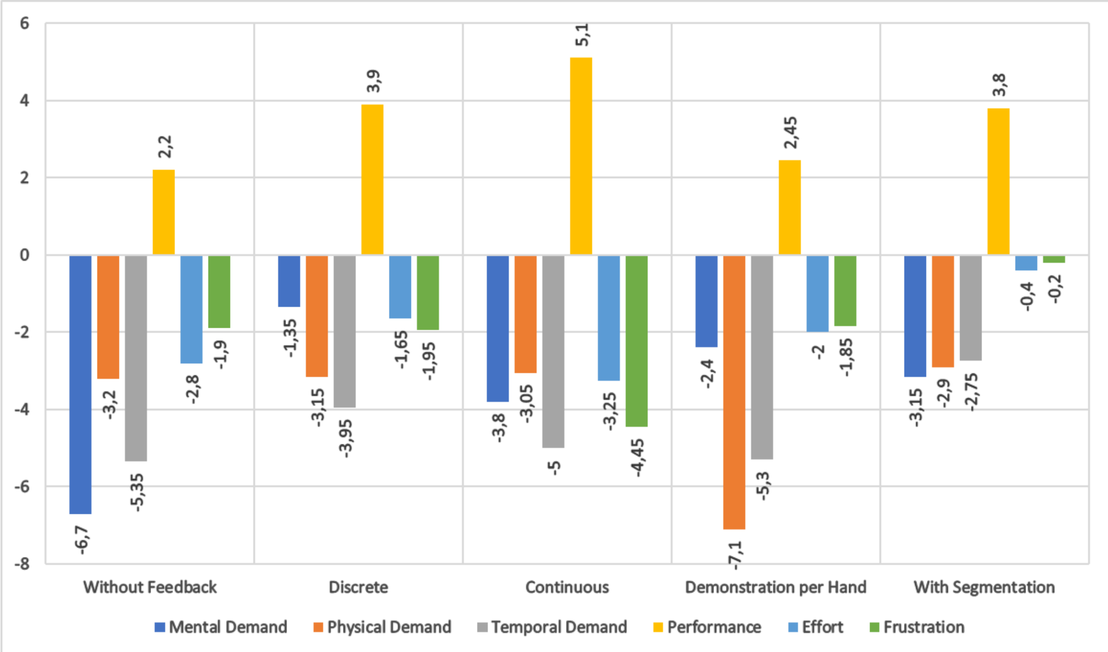


Figure 7.2: Score of TLX components per Test

7.2.2 Physical Demand

Compared to other settings, "Demonstration Per Hand" (M = -7.1; SD = 3.820) is shown to perform better than "Without Feedback" (M = -3.2; SD = 4.853) (t (19) = 0.00295; $p < 0.05$), "Discrete Feedback" (M = -3.15; SD = 4.671) (t (19) = 0.00044; $p < 0.05$), "Continuous Feedback" (M = -3.05; SD = 4.852) (t (19) = 0.00054; $p < 0.05$), and "With Segmentation" (M = -2.9; SD = 4.317) (t (19) = 0.0031; $p < 0.05$).

7.2.3 Temporal Demand

Compared to other settings, "Demonstration Per Hand" (M = -5.3; SD = 4.518) is found to perform better than "Discrete Feedback" (M = -3.95; SD = 4.5768) (t (19) = 0.02924; $p < 0.05$).

7.2.4 Performance

"Continuous Feedback" (M = 5.1; SD = 4.288) is rated as significantly better in perceived performance than "Without Feedback" (t (19) = 0.02224; $p < 0.05$).

7.2.5 Effort

No significant results were found, so this component is not included.

7.2.6 Frustration

"Continuous Feedback" ($M = -4.45$; $SD = 5.035$) showed significantly better results than "With Segmentation" ($M = -0.2$; $SD = 6.281$) ($t(19) = 0.04832$; $p < 0.05$).

7.3 QUESI Data

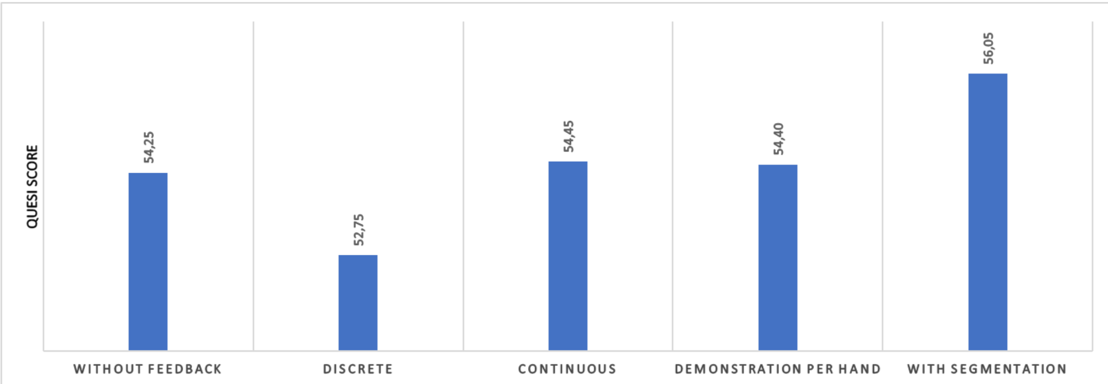


Figure 7.3: Average of Quesi-Score per Test

The mean ratings of the different settings in the QUESI questionnaire were analyzed. The results for the individual questions in the Quesi catalogue can range from 1 to 5, with the higher the score, the better the result. The overall QUESI score of a user can therefore can range from 14 to 70. The results as seen in Figure 7.3 show, that "Discrete Feedback" ($M = 52.75$, $SD = 8.9882$) received the lowest average rating, followed by the setting "Without Feedback" ($M = 54.25$, $SD = 10.821$), "Demonstration Per Hand" ($M = 54.4$, $SD = 13.116$), and "Continuous Feedback" ($M = 54.45$, $SD = 10.102$). The highest mean score was obtained in the setting with "With Segmentation" ($M = 56.05$, $SD = 8.102$).

Although these results did not show significant differences overall, individual components showed a significant difference compared to other settings. For this reason, the QUESI questions, as shown in Figure 7.4, that had significant results are analyzed per test below.

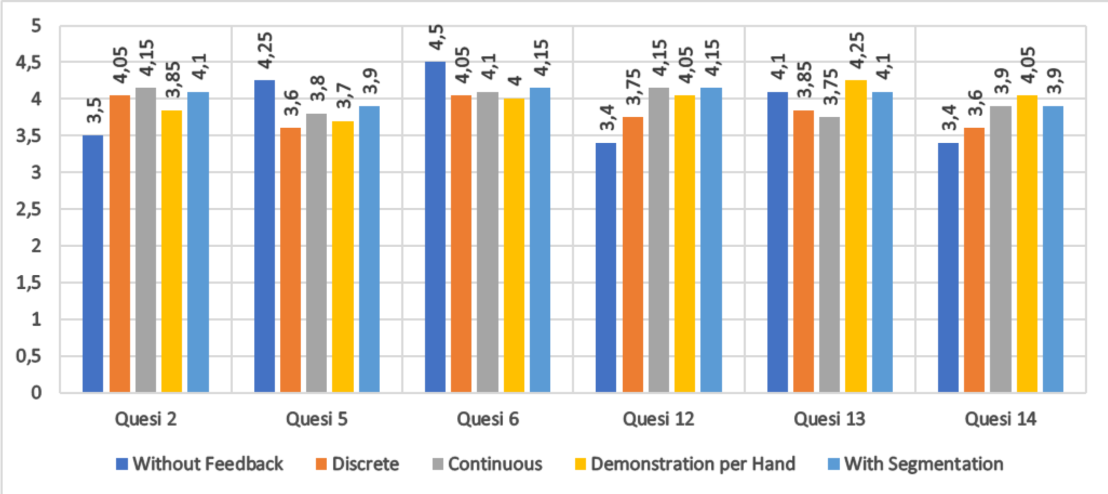


Figure 7.4: Score of the QUESI questions which showed a significant result

7.3.1 I achieved what I wanted to achieve with the system

The participants were asked whether the system had helped them achieve the goals they set out to achieve. The evaluation shows that the presence of feedback had a significant influence on the participants self-assessment. The group "Without Feedback" (M = 3.5, SD = 0.92195) was rated worse on average than the groups that received "Continuous Feedback" (M = 4.15, SD = 0.90967)(t (19) = 0.01926; $p < 0.05$) or "With Segmentation" (M = 4.1, SD = 0.88882)(t (19) = 0.03581; $p < 0.05$).

7.3.2 No problems occurred when I used the system

The participants were asked whether they encountered any problems when using the system. The evaluation shows that the presence of feedback had a significant influence on the perceived freedom from problems. The group "Without Feedback" (M = 4.25, SD = 0.887) rated problem-free significantly better than the group that received "Discrete Feedback" (M = 3.6, SD = 1.068)(t (19) = 0.11550; $p < 0.05$).

7.3.3 The system was not complicated to use

The participants were asked whether they perceived the system to be complicated to use. The evaluation shows that the presence of feedback had a significant impact on perceived ease of use. The group "Without Feedback" (M = 4.5, SD = 0.741) rated the system as less complicated to use compared to the group that received "Discrete Feedback" (M = 4.05, SD = 0.804)(t (19) = 0.03513, $p < 0.05$).

7.3.4 The system helped me to completely achieve my goals

The participants were asked whether the system helped them to fully achieve their goals. The evaluation shows that the presence of feedback had a significant impact on the perceived effectiveness of the system. The group "Without Feedback" ($M = 3.4$, $SD = 1.020$) performed worse on average than the groups that received "Continuous Feedback" ($M = 4.15$, $SD = 0.792$)($t(19) = 0.03170$; $p < 0.05$), "Demonstration Per Hand" ($M = 4.05$, $SD = 0.865$)($t(19) = 0.01519$; $p < 0.05$), or "With Segmentation" ($M = 4.15$, $SD = 0.726$)($t(19) = 0.01205$; $p < 0.05$).

7.3.5 How the system is used was clear to me straight away

The participants were asked whether the way the system was used was immediately clear to them. The evaluation shows that the type of feedback had a significant impact on the perceived clarity of using the system. The group that had "Demonstration Per Hand" ($M = 4.25$, $SD = 0.829$) rated clarity significantly higher compared to the group receiving "Continuous Feedback" ($M = 3.75$, $SD = 0.994$)($t(19) = 0.01409$; $p < 0.05$) or "Discrete Feedback" ($M = 3.85$, $SD = 0.910$)($t(19) = 0.02837$; $p < 0.05$).

7.3.6 I automatically did the right thing to achieve my goals

The participants were asked whether they automatically took the right steps to achieve their goals. The evaluation shows that the type of feedback had a significant impact on the perceived ability to automatically take the right steps. The group that had "Demonstration Per Hand" ($M = 4.05$, $SD = 0.865$) rated their ability significantly higher compared to the group "Without Feedback" ($M = 3.4$, $SD = 1.020$)($t(19) = 0.02845$; $p < 0.05$).

7.4 Process Understanding Data

After each test, participants were asked five specific questions to capture their understanding and ratings. The questions and associated results are seen in Figure 7.5.

7.4.1 Did you understand which model was learned?

The participants were asked to rate whether they understood which model was learned during the demonstration. The analysis shows as seen in Figure 7.5 that the presence of feedback had a significant impact on understanding. The group "Without Feedback" ($M = 2.35$, $SD = 1.014$) performed the worst compared to the others, while the groups

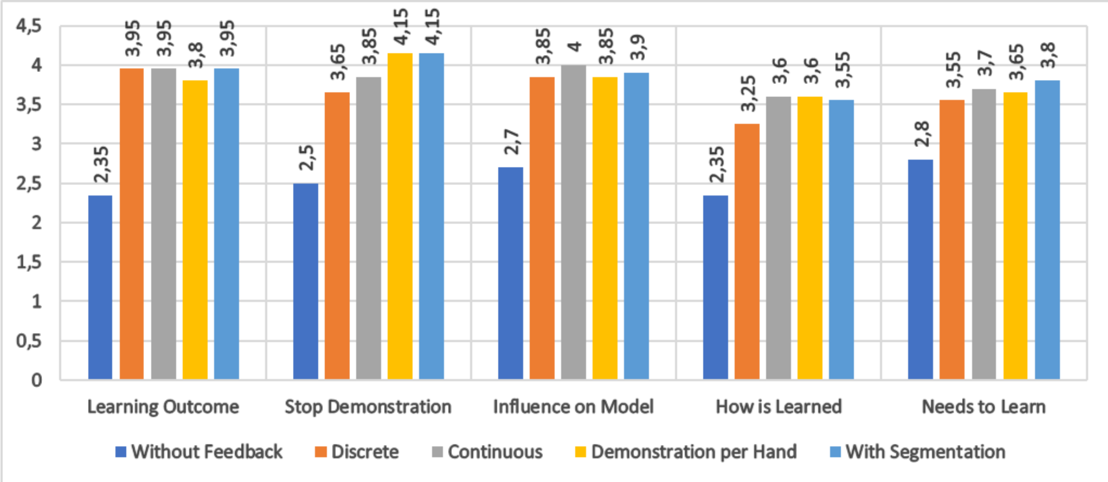


Figure 7.5: Five questions about the model understanding per Test

that received "Discrete Feedback" (M = 3.95, SD = 0.921)(t (19) = 8.5E-06; $p < 0.05$), "Continuous Feedback" (M = 3.95, SD = 0.805)(t (19) = 3E-05; $p < 0.05$), "Demonstration Per Hand" (M = 3.8, SD = 1.166)(t (19) = 0.00013; $p < 0.05$), or "With Segmentation" (M = 3.95, SD = 0.921)(t (19) = 7.8E-05; $p < 0.05$) had significantly higher mean scores.

7.4.2 Did you understand when to end the demonstration?

The participants were asked if they understood the right time to end the demonstration. The analysis shows that the presence of feedback had a significant impact on understanding. The group "Without Feedback" (M = 2.5, SD = 1.162) performed the worst, while the groups that used "Discrete Feedback" (M = 3.65, SD = 1.352)(t (19) = 0.00015; $p < 0.05$), "Continuous Feedback" (M = 3.85, SD = 1.276)(t (19) = 0.00026; $p < 0.05$), "Demonstration Per Hand" (M = 4.14, SD = 1.014)(t (19) = 3.9E-05; $p < 0.05$), or "With Segmentation" (M = 4.15, SD = 1.108)(t (19) = 2.8E-05; $p < 0.05$) received a significantly higher mean score.

7.4.3 Did you understand how to influence the model through actions?

The participants were asked if they understood how they could influence the model through their actions. The analysis shows that the presence of feedback had a significant impact on understanding. The group "Without Feedback" (M = 2.7, SD = 1.229) performed the worst, while the groups that used "Discrete Feedback" (M = 3.85, SD = 0.910)(t (19) = 0.0009; $p < 0.05$), "Continuous Feedback" (M = 4.0, SD = 1.183)(t (19) =

0.00061; $p < 0.05$), "Demonstration Per Hand" (M = 3.85, SD = 1.152)(t (19) = 0.00015; $p < 0.05$), or "With Segmentation" (M = 3.9, SD = 0.889)(t (19) = 0.00140; $p < 0.05$) had significantly higher mean scores.

7.4.4 Did you understand how the robot learns?

The participants were asked if they understood how the robot works during the learning process. The analysis shows that the presence of feedback had a significant impact on understanding. The group "Without Feedback" (M = 2.35, SD = 1.062) performed the worst, while the groups that received "Discrete Feedback" (M = 3.25, SD = 0.766)(t (19) = 0.00030; $p < 0.05$), "Continuous Feedback" (M = 3.6, SD = 0.917)(t (19) = 0.00010; $p < 0.05$), "Demonstration Per Hand" (M = 3.6, SD = 0.970)(t (19) = 1E-05; $p < 0.05$), or "With Segmentation" (M = 3.55, SD = 0.805)(t (19) = 4E-05; $p < 0.05$) had significantly higher mean scores.

7.4.5 Did you understand what the robot needs to build a model?

The participants were asked if they understood what requirements the robot needed to meet in order to build a model. The analysis shows that the presence of feedback had a significant impact on understanding. The group "Without Feedback" (M = 2.8, SD = 1.249) performed the worst, while the groups that used "Discrete Feedback" (M = 3.55, SD = 0.740)(t (19) = 0.00390; $p < 0.05$), "Continuous Feedback" (M = 3.7, SD = 1.145)(t (19) = 0.01190; $p < 0.05$), "Demonstration Per Hand" (M = 3.65, SD = 0.963)(t (19) = 0.01100; $p < 0.05$), or "With Segmentation" (M = 3.8, SD = 0.927)(t (19) = 0.00160; $p < 0.05$) had significantly higher mean scores.

7.5 Qualitative Results

This section discusses the results of the qualitative interviews conducted at the end of the study. With the help of word clouds, we highlight key words from the participants feedback in order to present the most important findings in a summarized manner.

7.5.1 Did you prefer the process with the robot only or with hololens?

In this study, a clear result as shown in Figure 7.6 emerged in which all participants preferred the Hololens-based solution. This preference pattern was particularly justified by the visual feedback provided by the Hololens. Users found this visual feedback to be extremely helpful and intuitive. The real-time display of additional information

Figure 7.6: Did you prefer the process with the robot only or with hololens?

and the ability to detect errors were also rated positively. In addition, setting up no-go zones was perceived as a useful feature.

7.5.2 What did you think about the visualization of the Pointcloud?

Figure 7.7: What did you think about the visualization of the Pointcloud?

The participants opinions on the visualization of the point cloud were mixed as can be seen in Figure 7.7. While the point cloud was perceived as accurate, users expressed concerns about the distance between points, which they felt was too large. The edges of the point cloud were also too indistinct for users. Furthermore, occlusion, where the point cloud interfered with the view of the real world, was rated negatively. A striking feature was the disagreement about whether the point cloud was actually helpful in performing the task or not.

7.5.3 Which type of update rate during the demonstration did you prefer?

Figure 7.8: Which type of update rate during the demonstration did you prefer?

Regarding the update rate during the demonstration, participants opinions were clear, see Figure 7.8. All participants felt that "Continuous Feedback" was the better option. They particularly emphasized the benefits of direct feedback, as it helped them to immediately understand the impact of their actions. Some participants also emphasized that "Continuous Feedback" allowed them to adjust their actions in real time, which provided an increased level of confidence. Overall, comments on the "Continuous Feedback" updating were positive.

7.5.4 What did you think of the additional information in the form of the segmentation vizualization?

The participants opinions on the segmentation visualization were mostly negative as seen in Figure 7.9. The majority of users found it unhelpful and confusing or distracting, which led to the focus being diverted from the main task. Thus, they did not experience segmentation as a positive additional benefit. However, it is worth mentioning that

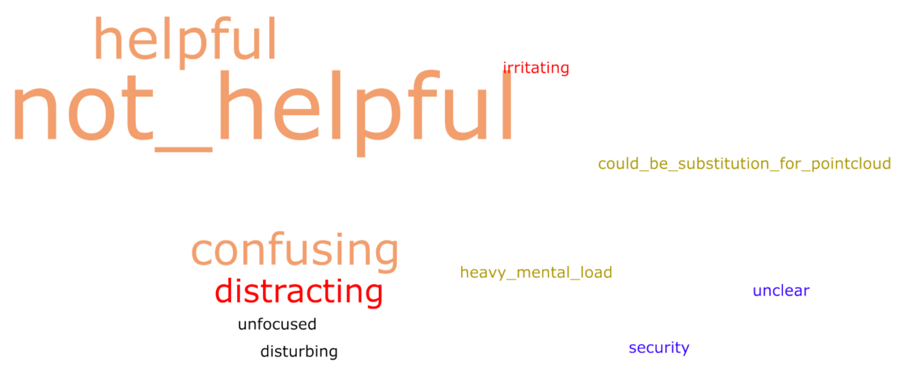


Figure 7.9: What did you think of the additional information(segmented shape) in form of the green plane?

a single user emphasized that the segmentation gave them a certain level of security. It was also mentioned that one user suggested using the segmentation instead of the point cloud.

7.5.5 What kind of demonstration approach did you prefer?

The participants were asked for their opinion on the two demonstration approaches: demonstration with robot or demonstration by hand. The results showed that 12 participants preferred the robot variant as seen in Figure 7.10, while 8 participants favored demonstrating by hand as seen in Figure 7.11.

The results on the robot variant was more positive overall. Participants described it as more natural, smoother, and more intuitive. They also highlighted the quality of the feedback. However, it was also noted that the robot variant was perceived as bulky and could be physically demanding.

The demonstration per hand variant was described as easier and more natural. However, some disadvantages were also mentioned, including the blurriness of the movements, the lack of intuitiveness, and problems such as the Hololens freezing while using the editing tool and the lack of haptic feedback.

Figure 7.10: What kind of demonstration did you prefer? - Answer: Demonstration per Robot

Figure 7.11: What kind of demonstration did you prefer? - Answer: Demonstration per Hand

7.5.6 Which aspects did you particulary like?

Several aspects of the interface were positively highlighted by participants as the results show in Figure 7.12:

- Intuitiveness and ease of use: many participants found the interface intuitive and easy to use. These features made it easier to use and contributed to the positive

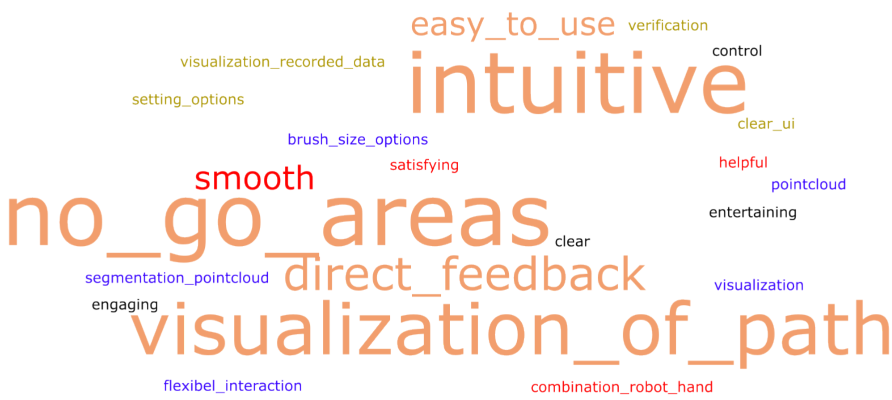


Figure 7.12: Which aspects did you particulary like?

user experience.

- No-go areas: The ability to define no-go zones was positively evaluated by users. This contributed to better control and safety when using the editing tool.
- Visualization of the path: The visualization of the path was appreciated by the users. It helped to better understand the progress and movements and contributed to the improvement of spatial orientation.
- Direct feedback: the interface provided direct feedback, which was perceived positively by the users. This direct feedback helped users understand and adjust their actions immediately.

7.5.7 Which aspects of the interface did you not like?

Some aspects of the user interface were rated negatively by participants as the results show in Figure 7.13:

- Accuracy of the no-go zones: The accuracy in defining the no-go zones was found to be problematic.
- Lag and Delay: The application was described as laggy, indicating delays and unresponsiveness.
- Need to move the robot: The requirement to physically move the robot has been criticized by some users.

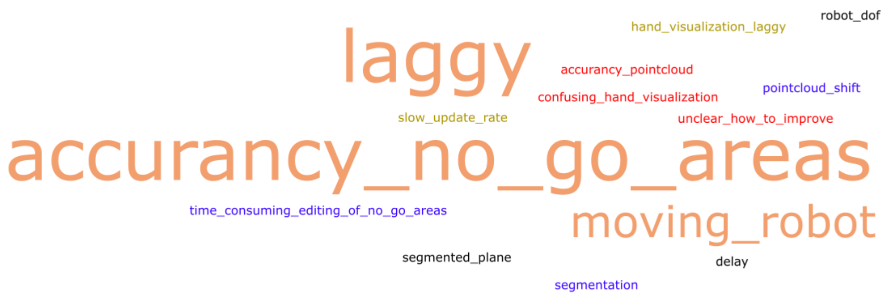


Figure 7.13: Which aspects of the interface didn't you like?

7.6 Quality of the Demonstration

In this section we analyse the data collected during the tests.

7.6.1 Accurancy of the Segmentation

In order to be able to evaluate the quality of the demonstrations, the deviation of the corner points from the ground truth was used as a measure. The segmented surface was solved in the form of a plane equation to obtain X, Y and Z coordinates. The X and Y coordinates were obtained from the corner points of the ground truth, while the Z coordinate was derived from the segmented area. Note that we are using the robot coordinate system here. By calculating the difference between these values and the z-value of the established ground truth segmentation, we were able to determine four values that were used to evaluate the demonstrations between users. We have summed the 4 values obtained and the average deviation per test can be seen in Figure 7.15.

The results show that "Discrete Feedback" ($M = 0.073$; $SD = 0.043$) performs worse on average than "Without Feedback" ($M = 0.042$; $SD = 0.024$)($t(19) = 0.00428$; $p < 0.05$). "Demonstration Per Hand" ($M = 0.030$; $SD = 0.020$) performs better than "Discrete Feedback" ($M = 0.073$; $SD = 0.043$)($t(19) = 0.00054$; $p < 0.05$), "Continuous Feedback" ($M = 0.052$; $SD = 0.029$)($t(19) = 0.000981$; $p < 0.05$) and "With Segmentation" ($M = 0$ $.052$; $SD = 0.031$)($t(19) = 0.00727$; $p < 0.05$)

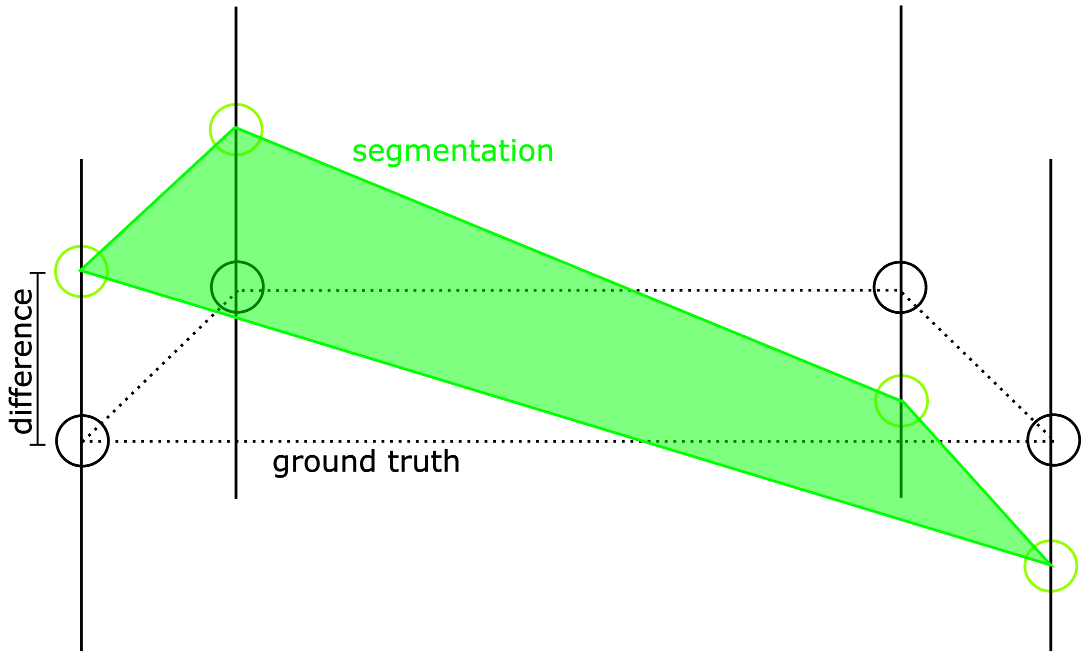


Figure 7.14: Calculation of the corner point deviation

7.6.2 Contact Points

We have determined the average value of the recorded contact points per test. The results can be seen in Figure 7.16.

The results of the contact points show that the hand variant had the lowest contact points recorded. The "Demonstration per Hand" group (M = 337; SD = 183.043) shows the lowest number of contact points compared to "Without Feedback" (M = 676; SD = 310.834) (t (19) = 2.133E-05; $p < 0.05$), "Discrete Feedback" (M = 683; SD = 410.391) (t (19) = 0.000453; $p < 0.05$), "Continuous Feedback" (M = 803; SD = 309.112) (t (19) = 1.251E-06; $p < 0.05$) and "With Segmentation" (M = 776; SD = 297.070) (t (19) = 2.028E-06; $p < 0.05$). Furthermore, there is a moderately significant result with more contact points in "Continuous Feedback" (M = 803; SD = 309.112) compared to "Without Feedback" (M = 676; SD = 310.834) (t (19) = 0.05913; $p < 0.1$).

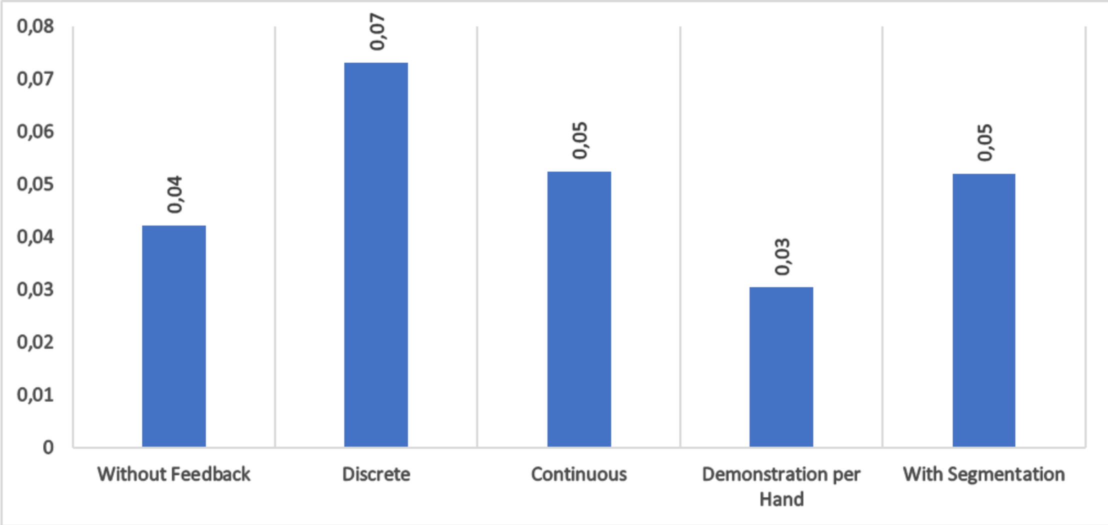


Figure 7.15: Sum of the deviation of the corner points from the ground truth

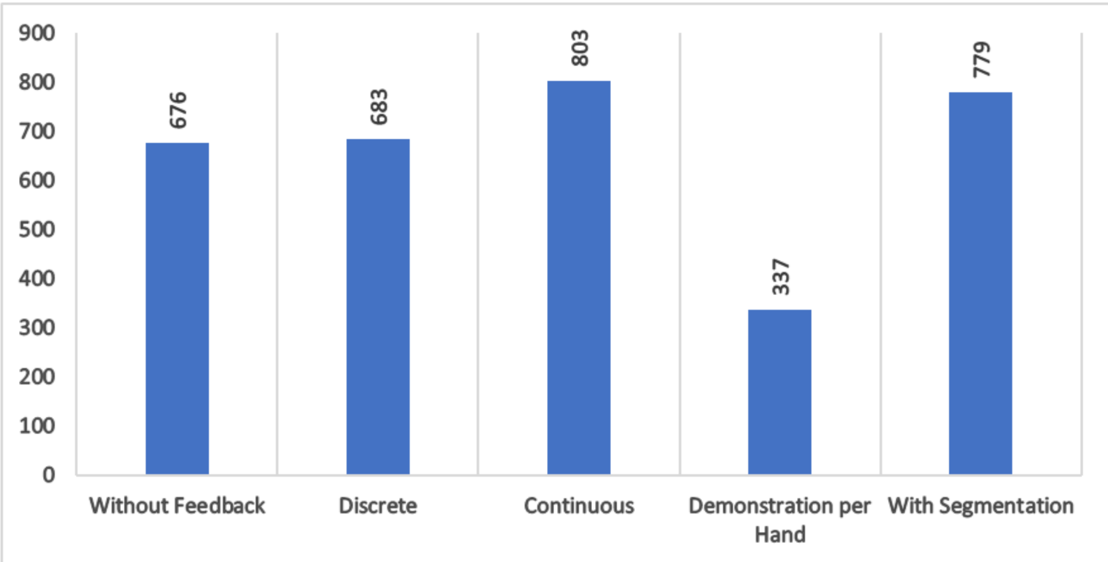


Figure 7.16: Average number of contact points per test

7.7 Summary

In this section, we have analyzed in detail the data collected during our user study. In doing so, we have taken a closer look at the various elements, including TLX data, QUESI data, process understanding data, qualitative results, and information collected during testing. In the next chapter, we will discuss these results.

8 Discussion and Conclusion

In this chapter, the results of the study are discussed and organized according to the different hypotheses.

8.1 Discussion

H1: The use of the AR interface leads to an increased intuitive handling of the LfD robot compared to the use without interface

The results of hypothesis H1 suggest that the use of the AR interface does indeed lead to increased intuitive handling of the LfD robot compared to use without an interface. The results show that the variants with feedback perform better in terms of physical demand during the Demonstration per Hand and the perceived performance during continuous feedback. This indicates that the AR interface is perceived as less physically demanding and performance-enhancing when the appropriate demonstration mode and update rate are selected.

However, an interesting finding is that the mental demand is lower for the test "Without Feedback". This could indicate that some users find the AR interface more mentally demanding. This could be because the interface needs a more visuall attention from the user than the variant without visual feedback. It is important to note that mental load is an important factor in usability and should be further explored in future work. It should also be crucial whether the mental load is still within a tolerable range or is overwhelming for the user. Nevertheless, especially the Quesi questions and in particular the question whether the system helped me to achieve my goals and whether I automatically did the right things to achieve my goals, showed that the intuitiveness is increased when using the interface compared to without the interface.

When we asked the user directly about their thoughts about the interface, users showed a clear preference for the AR interface. Many participants found the editing tool intuitive and easy to use, which contributed to a positive user experience. The visualization of the path was also appreciated by the users, as it helped to better understand the progress and movements and contributed to the improvement of spatial orientation.

However, there were also mentioned some negative aspects. Some users described the interface as "laggy" and "buggy", indicating technical problems. Interaction with the robot was described as "bulky" by some users, indicating usability challenges.

Overall, the results suggest that the AR interface has the potential to improve the intuitive handling of the LfD robot, but technical issues and mental load should be considered in further development.

H2: Visualization of the process helps increase the efficiency of the demonstrations in terms of accuracy, compared to situations without visualization

The results with regard to hypothesis H2 show that the visualization, in terms of how we visualise the process, has an impact on the accuracy of the segmentation. For this purpose, the deviation of the segmentation from the ground truth was taken as a measure. In particular, the Discrete variant performs worse compared to the situation without feedback and to the variant with Demonstration per Hand.

A possible explanation for this could be that the feedback in the discrete variant demands too much of the users mental capacity, which leads to increased deviations. Here, the users concentrate on the feedback, which, however, only comes after the demonstration, and no longer concentrates on the task itself. This would need to be investigated further to rule out the possibility that this is an accidental error.

It is also interesting to note that the Demonstration per Hand variant has the lowest number of contact points compared to the other variants. This could be due to the way contact points are recorded by the Demonstration per Hand variant, as it only allows the recording of contact points that are present on the point cloud. In contrast, more contact points can be recorded with the robot.

These results do not confirm the hypothesis that visualization of the process increases effectiveness. Whether this is related to the relatively simple data and process is unclear. Future research should test more complex workpieces, which may allow the results from the different settings to have greater variation.

H3: The use of visual feedback allows to reduce the existing knowledge gap between humans and machines

The evaluation of the user ratings for hypothesis H3 shows that the use of visual feedback has a positive influence on the understanding and knowledge gap between humans and machines.

In all the aspects of process understanding examined in chapter 7.4, the feedback variants performed better than the variant without feedback. Users indicated that feedback gave them a better understanding of the robot's model. They were better able to assess when to stop the demonstration, how their actions affected the model, and how the robot learns and builds a model. This suggests that visual feedback helps to reduce the perceived knowledge gap.

However, it is important to note that users disagree on whether certain visual elements, such as the point cloud and segmented area visualization, are helpful. Some users criticized aspects such as the resolution and accuracy of the point cloud. The visualization of the segmented area was found to be confusing and distracting by most users. This could be due to the Field of View (FoV) and the way it was displayed. A possible solution could be to implement a thumbnail view to improve the visual representation of the area.

Overall, the evaluation shows that visual feedback reduces the perceived knowledge gap between humans and machines from the users perspective. Whether the knowledge gap was actually closed could not be confirmed by the achieved quality of the segmentation results. In this respect, further more complex user tests are needed, which show an increased knowledge discrepancy. It is also important to continue working on improving the visual display elements to ensure an optimal user experience.

H4: Compared to discrete feedback, continuous feedback while the demonstration is still in progress can increase effectiveness in terms of quality

The results of hypothesis H4, which examines the influence of continuous and discrete feedback on the quality of demonstrations, show clear trends in terms of feedback type.

Analysis of the TLX questions shows that discrete feedback performs significantly worse compared to continuous feedback. This suggests that continuous feedback is perceived by users as more effective and of higher quality.

The results of the QUESI questions confirm this tendency. Users indicated that the system with continuous feedback (which was the default in the tests) was better at helping them achieve their goals compared to situations without feedback. Also, the system with discrete feedback was rated as significantly more complicated than the system without feedback. The perception that the goal was achieved was also more positive for the continuous feedback variants.

The corner point deviation of the segmentation showed that discrete feedback produced worse results compared to the variant without feedback. This result is controversial and would imply that a poor feedback method can produce worse results than without feedback method.

The direct question about the preferred update rate resulted in a unanimous vote for continuous feedback. Users clearly preferred continuous feedback during the demonstration.

In summary, the results confirm the hypothesis that continuous feedback increases effectiveness in terms of usability and intuitiveness of the system compared to discrete feedback. Users appreciated the immediate feedback and preferred the continuous updating of information to adjust their actions in real time.

Hypothesis H4 cannot be confirmed in terms of quality, that continuous feedback is better than discrete feedback. Nevertheless, the results emphasize the importance of continuous feedback of the system for the user. In future research, it may be of interest to perform more complex tasks to determine whether users can indeed adjust their actions accordingly with continuous feedback. Because the task performed was comparatively simple, we were unable to draw any final conclusions about whether users actually adjusted their actions in real time.

H5: Targeted use of AR technologies can further improve the LfD approach and make it more intuitive

The results of the study related to hypothesis H5 indicate significant differences that prove the superiority of the hand method in various aspects. The deviation of the corner points of the segmentation shows that the hand method achieves better results compared to the variants without feedback, discrete feedback, and continuous feedback. This is due to the fact that the contact points in the hand method are precisely located on the point cloud and are not affected by possible inaccuracies in the calibration of the robot.

Another result of this hypothesis is the significantly lower number of recorded contact points with the hand method. This is explained by the dependence of the recording of a contact point on the resolution of the point cloud. Due to the limited resolution of the point cloud, the hand method was not able to record as many contact points as the robot method. There was no significant difference in the recorded contact points for the other variants, suggesting that the variant does not affect them. However, this could also indicate that users understand better when to stop the demonstration when using the Demonstration per Hand variant. This would be an interesting research topic for the future but would require both interaction methods to be able to enter the same number of contact points in order to continue.

The results of the QUESI questions indicate that the hand method was perceived as significantly clearer, and users were able to identify the correct steps more intuitively. Additionally, the hand method was rated as significantly better at supporting goal achievement and reducing physical effort. The time burden was also perceived to be lower compared to the discrete feedback.

User-friendliness was rated positively overall, as confirmed by the users QUESI and TLX ratings.

It is interesting to note that the users qualitative assessment provided mixed results. User preferences for the type of demonstration showed that 12 users preferred the robotic application, while 8 users favored the handheld method. The users who preferred the robotic application described the interaction as more natural, fluid, and intuitive. However, some users found the robotic application bulky and physically demanding. Other criticisms of the robot application related to the need to physically move the robot.

The hand method was also described as natural and perceived as easier. However, it is worth noting that some disadvantages of the hand method were also mentioned, including inaccuracies, freezing, and the lack of haptic feedback. The assessment of whether the hand method was perceived as intuitive or not varied. No clear user preference can be determined from the mixed nature of these results.

In summary, the results of this hypothesis demonstrate that the hand method is superior in several aspects such as precision, user-friendliness, and physical effort, while the robotic application is compelling in terms of more natural interaction. This highlights the potential of AR technologies to improve the LfD approach and make it more intuitive, with the hand method considered superior in only some aspects. This highlights the importance of user preferences and requirements when developing AR interfaces for LfD systems.

8.2 Conclusion

This study investigated the application of AR technologies in the LfD Approach and the impact on intuitive handling, efficiency, the knowledge gap between human and machine, feedback influence, and improvement of the LfD approach. Based on the results and discussions, several conclusions can be drawn:

Regarding the first hypothesis H1, the results showed that using the AR interface increased the intuitive handling of the LfD robot compared to using it without an interface. Users positively evaluated the intuitive elements as well as the increased process understanding through the AR interface , although some technical problems and a increased mental load were mentioned.

The results related to the second hypothesis H2 suggest that visualization of the process affects the accuracy of the demonstrations. The discrete feedback variant performed worse compared to the no feedback variant, indicating usability challenges. The hypothesis could not be confirmed.

Hypothesis H3 could be confirmed, as the visual feedback reduced the perceived knowledge gap between humans and machines. However, the question remains whether an actual knowledge gap can also be reduced with this interface.

The fourth hypothesis H4 could not be confirmed, but showed that continuous feedback increased the usability of the demonstrations compared to discrete feedback.

Users valued immediate feedback and preferred continuous updates.

In conclusion, hypothesis H5 could be confirmed as the results showed that the targeted use of AR technologies can improve the LfD approach and enable intuitive adaptations. The hand method showed superior results in terms of precision and usability, while the robotic application scored in terms of more natural interaction.

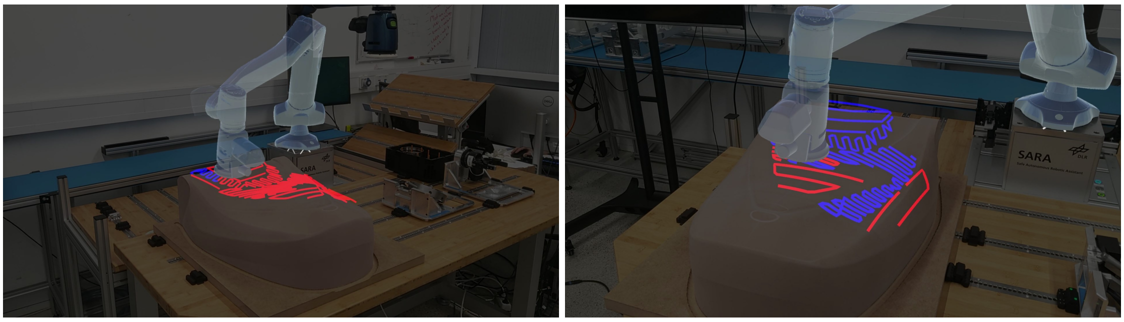
These findings highlight the enormous potential of AR technologies to enrich LfD methodology and improve human-machine interaction and enable its use in workshops. Nevertheless, technical challenges and user preferences must be considered to develop optimal solutions. This underscores the importance of continued research and development of AR-supported LfD systems for a wide range of use cases.

8.3 Further Changes

In response to the results received from the user study, we made changes to the interface. This was primarily due to user feedback and a misunderstanding that was identified. It became clear that the users did not understand that the segmented point cloud was not available from the beginning, but was generated by their input and the LfD algorithm. To communicate this concept more clearly, we developed an animation that illustrates the progress of generating the surface. In this animation, the segmented point cloud builds up circularly in an interval from the last contact point.

Furthermore, we integrated a simulation of the robot's execution into the HoloLens. This allows users to perform the planned action. In this simulation, the trajectory that still needs to be executed is displayed in red, while the trajectory that has already been completed appears in blue.

These adjustments made are intended for future testing and should improve the user experience. Unfortunately, it was no longer possible to test them with another user study as part of this thesis.



(a) Execution through the virtual model of the SARA Robot

(b) Trajectory status. Red line: Pending trajectory. Blue line: Completed trajectory

Figure 8.1: Additional changes based on the feedback received

9 Summary and Future Work

9.1 Summary of the Thesis

This thesis was dedicated to the investigation of how a feedback mechanism for the Learning from Demonstration approach can be designed and to what extent it adds value. To this end, an AR interface combining the Microsoft HoloLens 2 and the SARA robot was developed. This interface allowed users to receive visual feedback and track the status of the robot during the LfD process. A comprehensive user study with 20 participants was conducted to evaluate the effectiveness of the AR interface.

The results of this study indicate that the AR interface is a promising method to improve human-robot interaction and collaboration. Users were able to gain a better understanding of the robot's knowledge state with the help of the interface. In addition, the user experience was positively affected as the visualization of the process and the ability to monitor progress helped improve spatial orientation. The results also confirm that visual feedback reduces the perceived knowledge gap between humans and machines.

However, it was difficult to confirm qualitative improvements in terms of the quality of the demonstrations. Some technical challenges, such as delays and errors in the AR interface, clouded the user experience. In addition, mental load was slightly increased when using the AR interface, which could be due to visual complexity.

In addition, we have made further changes to the interface, which should further improve the user-friendliness. This meant a visualisation which should clarify the change of the point cloud, as well as two approaches to visualise a grinding process state with a digital twin, as well as the trajectory which is being executed.

9.2 Future Outlook

Several promising perspectives for future research emerge from this work, either to continue research at this interface or to try new approaches to gain further insights:

Userstudy with the Changes Made to the Interface: The adjustments made should be subjected to a more detailed examination in a further user study. Here, the focus should be on re-examining the understanding of the robot process and evaluating the usefulness of the visual feedback. Does the feedback help the user to better understand the process?

More Complex Tasks: In this study, a comparatively simple task with a box as the workpiece was used. For a deeper understanding of the potential of the AR interface, more complex workpieces should be considered in the user studies. Organic shapes and more difficult fits could provide a better understanding of the actual performance of the AR interface.

Different Display Methods: It might be useful to explore different display and visualization methods to represent the robot's knowledge state in a more effective way. This could include the development of thumbnails, alternative user interfaces, or improved augmented reality integration. An explicit exploration of a projector-based interface and a comparison with the created HoloLens interface could provide more insight into user preferences. A projector-based approach would be more natural for the FoV and free the user from the additional weight of the HMD.

Different Interaction Methods: It would be interesting to explore different interaction methods, particularly with respect to more naïve users. Here, approaches such as gesture control, voice control, or incorporating virtual reality could be included in the studies. In the context of the projector-based interface just proposed, new interaction and visualization methods will be required. Users could interact directly with the workpiece by drawing on it, and new visualization techniques could project 2.5-dimensional views onto the workpiece.

The presented thesis has shown that AR technologies are a promising tool to improve the LfD approach. With future developments and research, this potential can be further exploited to enrich and optimize the interaction between humans and robots in a variety of application domains.

Abbreviations

LfD Learning from Demonstration

AR Augmented Reality

PbD Programming by Demonstration

HMD Head-Mounted Display

HHD Hand-held Device

FoV Field of View

UI User Interface

DLR German Aerospace Center

MRTK Mixed Reality Toolkit

SARA Safe, Autonomous Robotic Assistant

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