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humantech

D5.5 – Scientific report on teaching control policies by teleoperation

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Acronyms and definitions

Acronym	Meaning
DMP	Dynamic Movement Primitives
APF	Artificial Potential Field
TCP	Tool Center Point
WP	Work Package
OEE	Overall Equipment Effectiveness
EEG	Electroencephalogram
GSR	Galvanic Skin Response
HR	Heart Rate

Abstract

The deliverable describes the innovative methods for "teaching by demonstration" to streamline the automation of complex tasks, eliminating the need for traditional, explicit robot programming.

This approach leverages teleoperation, where human operators can control and program heavy-duty construction robots remotely, ensuring their safety while interacting with potentially dangerous environments. The core of this method lies in moving beyond simple recording of trajectories and forces during demonstrations. Instead, it emphasizes the extraction of control "policies" from multiple human demonstrations. These policies enable the robot to not only replicate specific tasks but also adapt to varying conditions and handle uncertainties inherent in real-world environments, such as changes in materials, terrain, or sensor reliability.

This capability to generalize from learned experiences positions the robots to operate autonomously and efficiently in diverse scenarios, ultimately advancing the field of construction automation and making it more robust and flexible.

The HumanTech project

The European construction industry faces three major challenges: increase the safety and wellbeing of its workforce, improve its productivity, and become greener, making efficient use of resources.

To address these challenges, HumanTech proposes to develop **human-centred cutting-edge technologies** such as wearables for workers' safety and support and robots that can harmoniously coexist with human workers while contributing to the ecological transition of the sector.

HumanTech aims to achieve major advances in cutting-edge technologies that will enable a safe, rewarding, and digital work environment for a new generation of highly skilled construction workers and engineers.

These advances will include:

- **Robotic devices equipped with vision and intelligence** that allow them to navigate autonomously and safely in highly unstructured environments, collaborate with humans and dynamically update a semantic digital twin of the construction site in which they are.
- **Smart, unobtrusive workers protection and support equipment**. From exoskeletons activated by body sensors for posture and strain to wearable cameras and XR glasses that provide real-time workers' location and guidance for them to perform their tasks efficiently and accurately.
- An entirely new breed of **Dynamic Semantic Digital Twins (DSDTs) of construction sites** that simulate in detail the current state of a construction site at the geometric and semantic level, based on an extended Building Information Modelling (BIM) formulation that contains all relevant structural and semantic dimensions (BIMxD). BIMxDs will act as a common reference for all human workers, engineers, and autonomous machines.

The **HumanTech consortium** is formed by 22 organisations — leading research institutes and universities, innovative hi-tech SMEs, and large enterprises, construction groups and a construction SME representative — from 10 countries, bringing expertise in 11 different disciplines. The consortium is led by the German Research Center for Artificial Intelligence’s Augmented Vision department.

Contents

1. Introduction

The integration of automation into various industries has been a transformative force, driving efficiency, productivity, and safety. One of the most promising frontiers in this domain is the use of robotics in heavy-duty construction, a sector that traditionally relies on manual labour for intricate and hazardous tasks. However, the adoption of robotics in construction faces unique challenges, particularly in the programming and control of these machines. Traditional methods of programming robots often require explicit coding, which can be time-consuming, error-prone, and inflexible in dynamic environments. In response to these challenges, this deliverable explores innovative methods of "teaching by demonstration" to facilitate the implementation of automated activities without the need for explicit programming.

"Teaching by demonstration" is an intuitive approach to robot programming where a human operator demonstrates a task, and the robot learns to replicate it. This method leverages the expertise of human operators, allowing them to program robots by simply performing the tasks themselves, rather than by writing complex code. The central focus is to develop and refine techniques that enable this form of learning through teleoperation — a system where the human operator controls the robot from a safe distance. This is particularly important in the context of heavy-duty construction, where the operator must be shielded from potential hazards.

The research goes beyond simple trajectory recording, which is a common approach in robot learning. Instead, it aims to extract control "policies" from repeated demonstrations. A control policy is a set of rules or guidelines that the robot follows to achieve the desired outcome, even when faced with variations in the environment or uncertainties in its sensing systems. By focusing on policies rather than specific trajectories, the robot gains the ability to generalize across different situations. This capability is crucial in construction, where tasks can vary widely depending on the materials used, the weather conditions, or the specific design of the project.

The importance of generalization and adaptability in robotic systems cannot be overstated. Construction sites are inherently dynamic, with constantly changing variables that can affect the execution of tasks. Traditional programming methods struggle to cope with this level of unpredictability, often requiring manual adjustments or reprogramming. In contrast, a robot trained through demonstration to follow adaptable control policies can respond more effectively to changes, reducing downtime and increasing the overall efficiency of the operation.

Moreover, the use of teleoperation to demonstrate tasks offers significant safety benefits. By allowing the human operator to program the robot from a distance, the risk of accidents during the programming phase is minimized. This is especially relevant in environments where the tasks involve handling heavy machinery, working at great heights, or dealing with hazardous materials. The ability to program robots remotely without compromising the accuracy or effectiveness of the training process represents a major advancement in the field of construction automation.

In this deliverable, we will describe the methods of "teaching by demonstration" implemented through teleoperation. We will outline the process by which demonstrations are conducted by the human operator and how these are used to extract control policies. This approach not only simplifies the programming of construction robots but also enhances their ability to operate autonomously in diverse and unpredictable environments. The implications of this research extend beyond construction, offering potential applications in any field where robots must operate in complex, dynamic settings. Through the development of these methods, we aim to contribute to the broader goal of making advanced robotics more accessible and practical for real-world applications.

1.1. Learning algorithms (TECNALIA)

The construction industry is often plagued by hazardous sites that put workers at risk of exposure to unhealthy substances[1]. Even in seemingly safe environments, tasks such as bricklaying, painting, heavy lifting, and mastic application to joints can be repetitive and potentially harmful to operators' health over time. However, full or partial automation of these repetitive tasks can have a significant impact by improving worker safety, reducing musculoskeletal problems, and boosting overall productivity[2].

A significant hurdle in integrating robotics into construction sites is the dynamic nature of the environment. Unlike traditional industrial settings, where the robot's workspace

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[1] J. Wang, P. X. Zou, and P. P. Li, "Critical factors and paths influencing construction workers' safety risk tolerances," Accident analysis & prevention, vol. 93, pp. 267–279, 2016.

[2] O. Akinradewo, C. Aigbavboa, C. Okafor, A. Oke, and D. Thwala, "A review of the impact of construction automation and robotics on project delivery," in IOP Conference Series: Materials Science and Engineering, vol. 1107, no. 1. IOP Publishing, 2021, p. 012011.

remains static, construction sites are constantly changing, making it difficult to reuse programmed actions. This limitation has been well-documented[3]. However, robotic learning from demonstration techniques offers a potential solution. By enabling intuitive robot teaching methods, human expert operators can easily transfer their knowledge to robots, even without extensive robotics expertise. This collaborative approach ensures that the experience and skills of human workers are directly translated into automated systems, broadening the range of possible applications. As a result, construction projects can benefit from human-robot collaboration, preserving the valuable insights of human experts while improving safety and efficiency through robotic automation.

When it comes to transferring human demonstrations to robots, there are several approaches to consider. These include passive observation, kinesthetic teaching, and teleoperation[4] [5]. Passive observation, also known as imitation learning, involves using a motion capture system to record human movements[6]. While this method is straightforward for humans, it requires a complex mapping between human and robot movements, which can be a challenge.

In contrast, kinesthetic demonstrations involve manual guidance of the robot's gripper and joints by a human[6]. This approach eliminates the need for mapping and embodiment, as the movements are recorded directly on the robot. However, it can affect force sensing (as the human is touching robot joints), which may be problematic for robot control[4] as force readings are altered.

Teleoperated demonstrations offer an alternative, where a human operator uses a joystick to control the robot, and the movements are recorded[4]. This approach is

[3] S. A. Prieto, X. Xu, and B. Garc ́ıa de Soto, "A guide for construction practitioners to integrate robotic systems in their construction applications," Frontiers in Built Environment, vol. 10, p. 1307728, 2024.

[4] H. Ravichandar, A. S. Polydoros, S. Chernova, and A. Billard, "Recent advances in robot learning from demonstration," Annual review of control, robotics, and autonomous systems, vol. 3, pp. 297–330, 2020

[5] B. D. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration," Robotics and autonomous systems, vol. 57, no. 5, pp. 469–483, 2009.

[6] S. Calinon, "Learning from demonstration (programming by demonstration),"Encyclopedia of robotics, pp. 1–8, 2018.

particularly appealing in hazardous environments, such as underwater or nuclear settings, where physical interaction with the robot may be unsafe[7] [8].

In HumanTech project, we focus on learning a mastic application task in construction sites. Mastic is usually applied manually on dilatation joints, either with a manual or an electric gun, but the human operator must stay bent over the joint and press the gun trigger to deposit the mastic (see Figure 1). The manual mastic application process involves adopting a non-ergonomic posture, which can lead to discomfort, pain, and musculoskeletal disorders when performed over extended periods. The potential health risks associated with repetitive tasks like this have driven the quest for innovative approaches to mastic application, with the goal of mitigating these negative consequences.

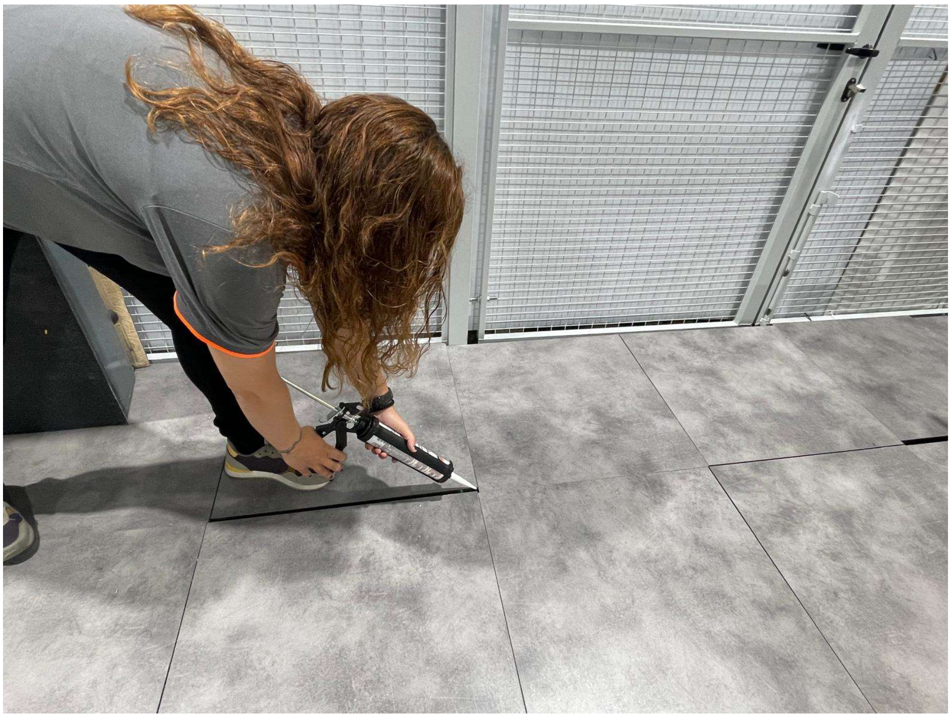


Figure 1 Human crouched down to fill a joint with mastic

In order for robots to operate autonomously in dynamic environments, they must be able to learn from a limited number of demonstrations. This requires the development of systems that can efficiently adapt to new situations and tasks with minimal guidance

[7] M. Edmonds, F. Gao, X. Xie, H. Liu, S. Qi, Y. Zhu, B. Rothrock, and S.-C. Zhu, "Feeling the force: Integrating force and pose for fluent discovery through imitation learning to open medicine bottles," in 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017, pp. 3530–3537.

[8] O. Tokatli, P. Das, R. Nath, L. Pangione, A. Altobelli, G. Burroughes, E. T. Jonasson, M. F. Turner, and R. Skilton, "Robot-assisted glovebox teleoperation for nuclear industry," Robotics, vol. 10, no. 3, p. 85, 2021.

from human instructors. By reducing the need for extensive data collection, we can accelerate the deployment of these robots beyond laboratory settings and into real-world applications.

For the automation of this task we have tested two different learning approaches. One based on Dynamic Movement Primitives (DMPs) and another one based on learning controller parameters. Both approaches share one common capacity: they are capable of generalizing and executing the task autonomously with a single human demonstration.

1.1.1 Dynamic Movement Primitives

The first proposed approach was based on DMPs. Dynamic Movement Primitives (DMPs) have been shown to possess a unique ability to learn and generalize complex robot behaviours from a single demonstration, exhibiting versatility despite their relatively simple formulation.

Generally speaking, the great potential of DMPs can be associated to several characteristics they provide:

- Generalization Capability: they can encapsulate diverse complex movements and allow robots to reproduce them.
- One Shot Learning: a single demonstration is enough to learn a desired behaviour.
- Smoothness: they create smooth trajectories which are essential for good robot control.
- Adaptability: the initial and goal positions of the learned task as well as the execution speed can be easily tuned.

DMPs can be described as a stable, second-order, nonlinear dynamical system[9]. They are composed of a second-order linear dynamical system of type mass-spring damper, in which a point is attracted towards its goal. They also have a non-linear forcing term that attracts the system towards the demonstration trajectory to be reproduced. Therefore, the forcing term is the element that has to be learned from a demonstration performed by the human. We refer the reader to Hoffmann[9] et al for the mathematical representation of DMPs.

[9] H. Hoffmann, P. Pastor, D.-H. Park, and S. Schaal, ‘‘Biologically-inspired dynamical systems for movement generation: Automatic real-time goal adaptation and obstacle avoidance,’’ in *IEEE international conference on robotics and automation*, 2009, pp. 2587–2592.

As in every other learning from demonstration approach, two phases compose a learning system based on DMP: the learning phase and the execution phase (also called rollout). In the learning phase, the desired forcing term is calculated. In the execution phase, using the calculated forcing term a new trajectory is generated with the same dynamics as the original one (with an origin and goal provided by the human).

The DMP capabilities were tested first in simulation. To enable an easy training, a graphical user interface was also built.

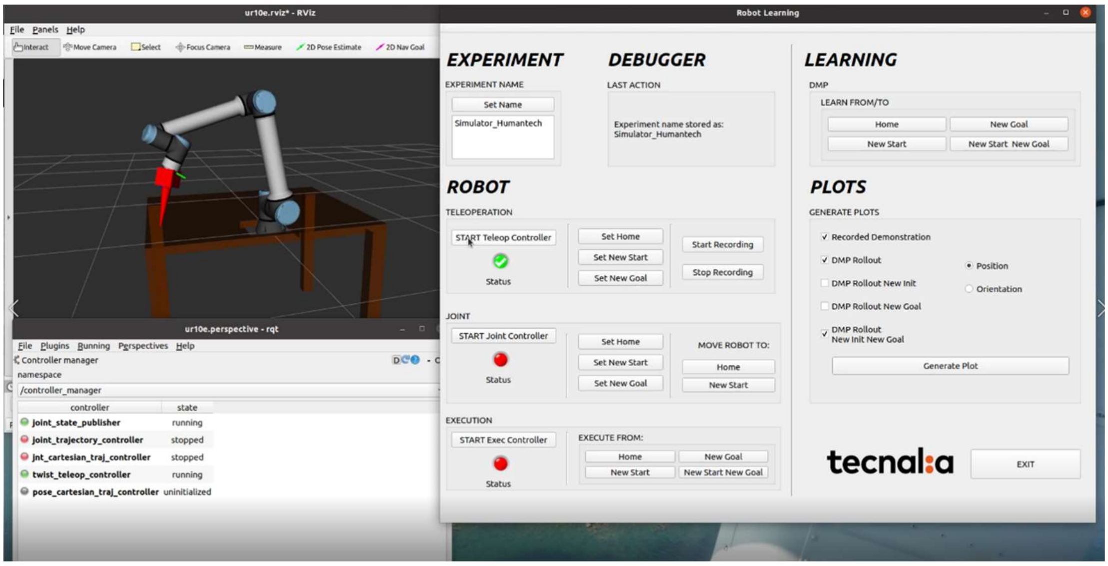


Figure 2 Graphical user interface created to test the DMP algorithm

Once the system's functioning was ensured in simulation, it was tested on a real UR10e with satisfactory results.

But for automating the mastic application task, not only the dynamics of the robots had to be learned but also the system had to be responsive to external forces or changes.

For that, the addition of artificial potential fields to dynamic movement primitives were investigated. While the investigation of the addition of artificial potential fields was fruitful, leading to a journal paper publication[10] we realized that the DMP + APF (Artificial Potential Field) combination was preferrable for tasks with more complex dynamics. The mastic application is done in straight dilatation joints, and therefore a more straightforward controller (from the dynamic perspective) could be used.

[10] Rasines, I., Cabanes, I., Remazeilles, A., & McIntyre, J. (2024). Robots adapting to the environment: A review on the fusion of Dynamic Movement Primitives and Artificial Potential Fields. *IEEE Access*.

This led us to try an admittance controller based approach for automation (note that in teleoperation[11], an admittance controller is also used).

1.1.2 Controller parameter learning

Teleoperation

The teleoperation of a robotic arm allows an operator to manipulate it from a distance using joysticks or haptic devices that could provide tactile feedback.

In this investigation, two different teleoperation approaches have been tested, position-based teleoperation, and admittance-based teleoperation. In a first attempt, a position-based teleoperation controller was implemented and tested in simulation and on the real UR10e robot. While the robot arm followed the haptic movements precisely, the robot easily entered into protective stops due to excessive forces applied against the surface.

This issue has been corrected by implementing an admittance-enabled teleoperation controller, in which the external forces perceived by the force sensor are used to adjust the motion commands. This controller receives the target pose and velocity as a command and computes the robot motion which tracks this input while simultaneously reacting to external forces with:

$$v_d = K_p \Delta(x_t, x_c) + v_t + K_a f_{ext}$$

Where K_p and K_a are position-tracking and admittance gain matrices respectively, $\Delta(x_t, x_c)$ is an operator computing the position error between the target and current position of the robot as a twist vector, v_t is the target twist (from the haptic device) and $f_{ext}$are the measured contact forces.

The resulting v_d is mapped to the robot joint spaces sent to the robot using a custom direction-preserving pseudoinverse matrix. From a practical perspective, it can be summarized that in teleoperation, the controller listens to haptic movements and commands the robot accordingly taking into account the force that is being applied against the environment.

This type of control in the force domain allows to provide the user with an idea of the exerted forces against the environment. Transmitting measurements of the force/torque sensor of the UR10e robot directly to the haptic device leads to an unstable

[11] D5.2 – Scientific report on hybrid haptic-visual feedback mechanisms for efficient teleoperation of demolition robots - https://zenodo.org/communities/humantech_heurope/

system. The force feedback used here is proportional to the difference between the desired and current robot poses $\Delta(x_t, x_c)$.

Automation

Since proper application of the mastic requires ensuring a stable contact between the tip of the extruder and the bottom of the joint, an admittance control scheme like the one described above for teleoperation has also been used.

For automatic reproduction, the user input is replaced by a synthetic motion parameterized from the user demonstration as follows. Since this study is concerned with filling linear joints, the controller is designed to produce a constant linear velocity until the signal to stop is received. Since there's no absolute position to track here, the K_p proportional tracking gain matrix is set to zero, effectively removing its associated term from the controller.

Also, since the orientation of the extruder is to be kept constant throughout the filling motion, the lower three rows of K_a and v_t are all zeroed out, resulting in a null rotational velocity component in v_d.

The translation-related components of both of K_a and v_d are treated separately to achieve a combination of velocity and force control. For the next explanations, it must be considered that the reference frame in which the controller components operate is defined in such a way that the Z axis is perpendicular to the (XY) plane containing the joint to be filled (see the red axis in Figure 3).

Figure 3 Frame reference (red) located at the base f the robot

Velocity control in XY plane

First, the XY components of K_a are used to produce the desired dynamic response if the extruder laterally collides with the walls of the joint. The related XY components of v_t are used to generate a motion with the desired magnitude and aligned with the joint's longitudinal axis.

Force control in Z axis

The Z component of both K_a and v_t are adjusted in a combined way to result in a stable contact where the steady state force applied by the extruder against the joint matches the values obtained from the experimental demonstrations.

Learning from Unstructured Demonstrations

During the demonstrations through teleoperation, the following data is recorded:

- Tool Center Point (TCP) position and orientation
- Sensed forces and torques
- Pedal status
- Mastic gun status

In order to use the demonstration as a reference to learn the task, the recorded data has been carefully processed following these steps:

a. Remove the information when the mastic applicator is not used: the data collected when the mastic gun is off is discarded.
b. Discard the information when the robot is not moving.
c. Recalculate the time vector: after removing sections of the demonstration, the timeline of the trial is unstructured and has to be updated accordingly.
d. Filter force data: the recorded forces and torques are filtered in order to remove noise. In this case, a fourth order Savichky-Golay filter[12] has been used.

The force data filtering is a crucial step. It is probable that the non-expert teleoperators may not make fluent translation of the tool. Each jump of the tool and contact with the floor or surface will influence the force readings and therefore the output of the forces may be noisy as it is observed in the left side of the Figure 4. The right side of the Figure 4 shows the results of eliminating the non-desired information of the demonstration (steps a-c in the list) and the filtering afterwards. As it can be observed, the clean demonstration (right) is shorter, and the signals are smoother compared to the original data (left):

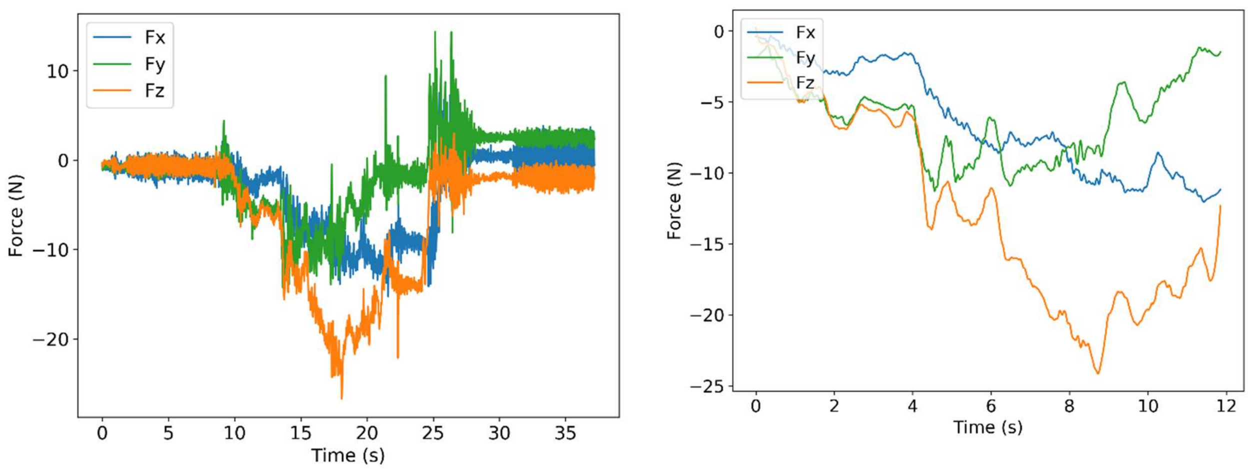


Figure 4 Original force data (left) and filtered data (right)

The next step consists of extracting the controller parameters from the human demonstration.

[12] Savitzky, A.; Golay, M. J. E. Smoothing and differentiation of data by simplified least squares procedures. Anal. Chem. 1964, 36, 1627– 1639, DOI: 10.1021/ac60214a047

To extract the desired velocity in X and Y directions, it has to be taken into account that the human demonstration is not made at constant velocity, and it changes over the demonstration.

So in order to extract the adequate velocity we follow the next procedure: split the trial in 1 second windows, calculate the mean velocity in each window and keep the maximum velocity of the calculated ones in each dimension.

Mathematically, we have that, for windows of size α, we have that per window k:

$$x_k = \{x_t | t \in [(N-1)+\alpha, N+\alpha]\}$$

$$y_k = \{y_t | t \in [(N-1)+\alpha, N+\alpha]\}$$

Being N the number of windows. For each window the velocity is calculated as:

$$v_{x,k} = \frac{\delta x_k}{\delta t_k} \; v_{y,k} = \frac{\delta y_k}{\delta t_k}$$

And finally the maximum velocity among windows:

$$V_{x,max} = \max\{v_{x,0}, v_{x,1}, \dots, v_{x,N}\}$$

$$V_{y,max} = \max\{v_{y,0}, v_{y,1}, \dots, v_{y,N}\}$$

These values are going to be the values of v_t of the admittance velocity controller described in this section.

But maintaining the contact forces during the execution is also crucial for an adequate task performance. From a clean demonstration it is straightforward to calculate the mean force applied normal to the surface and then this force has to be translated into a velocity in the Z plane for the controller to be configured. In the admittance velocity controller, the velocity command is directly proportional to the force: $K_a * f_{ext} = -v_t$.

The calculated control parameters will be provided to the controller and using them the automatic execution will start. The proposed approach leads us to have the following learning schema:

- First, the demonstration will be performed by the human, via teleoperation.
- As this demonstration can be un-structured and the data may contain noise, the demonstration will go through a data preprocessing step.

- Once the data is clean, the learning block will extract the parameters for the controller.
- Finally this parameters will be fed to the controller to enable an adequate automatic execution.

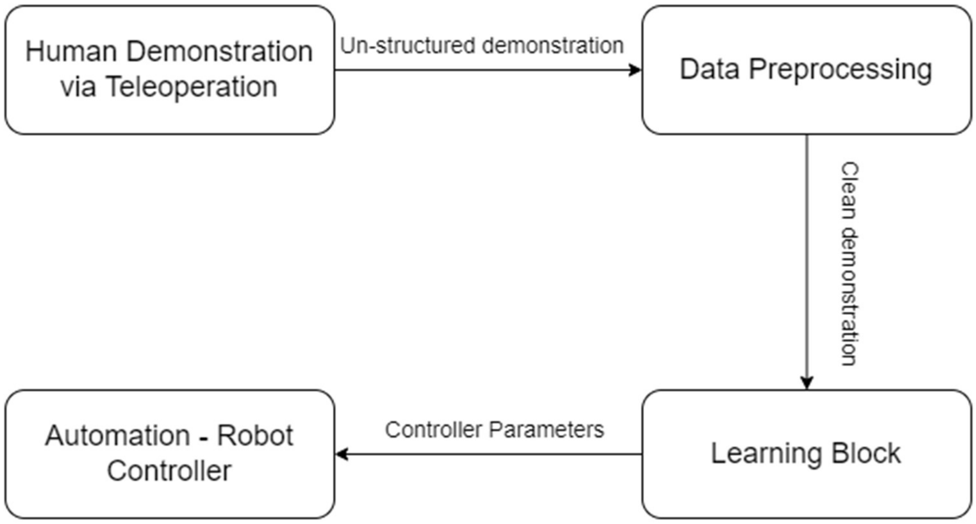


Figure 5 Learning schema

To validate this setup, a laboratory setup was built in TECNALIA prior to on site evaluation.

1.2. User expectations

User expectations play a critical role in shaping the development and adoption of new technologies. Users — ranging from construction site managers to skilled operators — anticipate that these robotic systems will not only enhance productivity but also simplify the programming and operational processes. One of the key expectations is ease of use. Users expect that the methods of "teaching by demonstration" will allow them to program robots without needing in-depth technical expertise in coding. The teleoperation-based approach should provide an intuitive interface where operators can demonstrate tasks naturally, without extensive training on the robotic system itself.

Safety is another paramount expectation. Users working in heavy-duty construction environments expect that the introduction of teleoperated robotic systems will significantly reduce their exposure to hazards. This expectation extends to the reliability of the systems—users require that the robots function consistently and predictably, even in the face of environmental variability and sensor uncertainty. The extracted control policies must enable the robots to handle these uncertainties, ensuring safe and effective operation in diverse scenarios.

Lastly, there is an expectation for adaptability and efficiency. Users anticipate that robots trained through demonstration will be capable of generalizing from the demonstrated tasks to new, unforeseen situations. This adaptability is crucial in the construction industry, where no two projects are exactly alike. The robots must be able to learn from demonstrations and apply that learning to similar, but not identical, tasks without requiring additional programming or significant human intervention. Meeting these expectations will be key to the successful deployment and widespread adoption of robotic systems in construction and other dynamic environments.

In the following, industrial partner ACCIONA brief about different needs that are to be addressed.

1.2.1. Requirements of ACCIONA

Productivity Improvement

- Speed and Efficiency: The conventional process of filling an expansion joint is manual which are found to be monotonous by an average worker. These tasks may also be prone to errors due to physical exhaustion of workers from maintaining certain body postures maintained while performing them. The robotic arm should therefore be able to perform these repetitive or mundane tasks quickly and efficiently as compared to conventional manual process.

- Continuous operation: Ensure the robotic arm can operate continuously for long hours with minimal downtime, equipped with features like automatic recharging or quick-change battery systems.
- Multi-tasking capabilities: Ability to switch between different types of joints (figure 6 & 7) and materials seamlessly without requiring extensive reconfiguration.

Ease of use for unskilled operators

- User-friendly interface: Design a simple, intuitive interface that requires minimal training.
- Automated calibration and customized setup: The system should automatically calibrate for customized set ups based on the type of joint and material specifications to reduce dependency on skilled technician.
- Remote operation: Enable remote operation capabilities, allowing operators to control the arm from a safe distance, thus simplifying the task for unskilled workers.

Workers' Health and Safety

- Ergonomic design: Ensure the interface and control devices are ergonomically designed to reduce strain on operators.
- Safety features: Incorporate safety features such as emergency stop buttons, collision detection, and automatic shut-off systems to prevent accidents.
- Reduced exposure: By using teleoperation, reduce workers' exposure to hazardous environments and substances involved in mastic application.

Addressing labour shortage

- Labour cost reduction: Highlight how the robotic arm can reduce the reliance on skilled labour, which is becoming scarce and expensive.
- Scalability: The system should be scalable, allowing for deployment in multiple sites with minimal additional costs, thereby maximizing the utility of available labour.

Quality and Consistency

- Precision and accuracy: The robotic arm should ensure precise application of mastic with consistent quality, reducing the likelihood of human error.
- Quality control systems: Include integrated quality control systems that monitor and adjust the application process in real-time to maintain high standards.

Flexibility and Adaptability

- Compatibility with different joints and materials: The system should be adaptable to various joints in building and construction environments, from civil to commercial to residential projects.
- Customizable settings: Allow for customizable settings to adjust for different mastic types, joint sizes, and application conditions.

Maintenance and Support

- Ease of maintenance: Design the robotic arm for easy maintenance with readily available spare parts and straightforward troubleshooting protocols.
- Comprehensive support: Offer robust customer support and training programs to ensure smooth operation and quick resolution of any issues.

Environmental considerations

- Energy efficiency: Ensure the robotic arm operates efficiently to minimize energy consumption.
- Eco-friendly materials: If possible, use sustainable and eco-friendly materials in the construction of the robotic arm.

Integration with existing systems

- Seamless integration: The robotic arm should easily integrate with existing construction management systems and workflows.
- Data connectivity: Include data connectivity features for real-time monitoring, reporting, and analytics to help in optimizing operations and maintenance schedules.

Future proofing

- Upgradability: Design the system to be easily upgradable, allowing for future enhancements and technological advancements without significant overhauls.
- Compatibility with Emerging Technologies: Ensure compatibility with emerging technologies such as integration with BIM models, self-positioning and

autonomous movement using GPS, and machine learning for potential future integration.

1.2.2. Testing and validation

To ensure the developed teleoperated robotic arm meets requirements as stated above, a comprehensive testing phase has been designed. This phase will simulate real-world conditions and compare the performance of the robotic arm against traditional manual methods.

Test set-up:

A floor slab has been constructed with three types of slots (5mm, 10mm, and 15mm wide) representing three different kinds of floor joints mostly seen in a building and construction industry (Figure 6 and 7).

Figure 6 3D model of the floor slab (rendered)

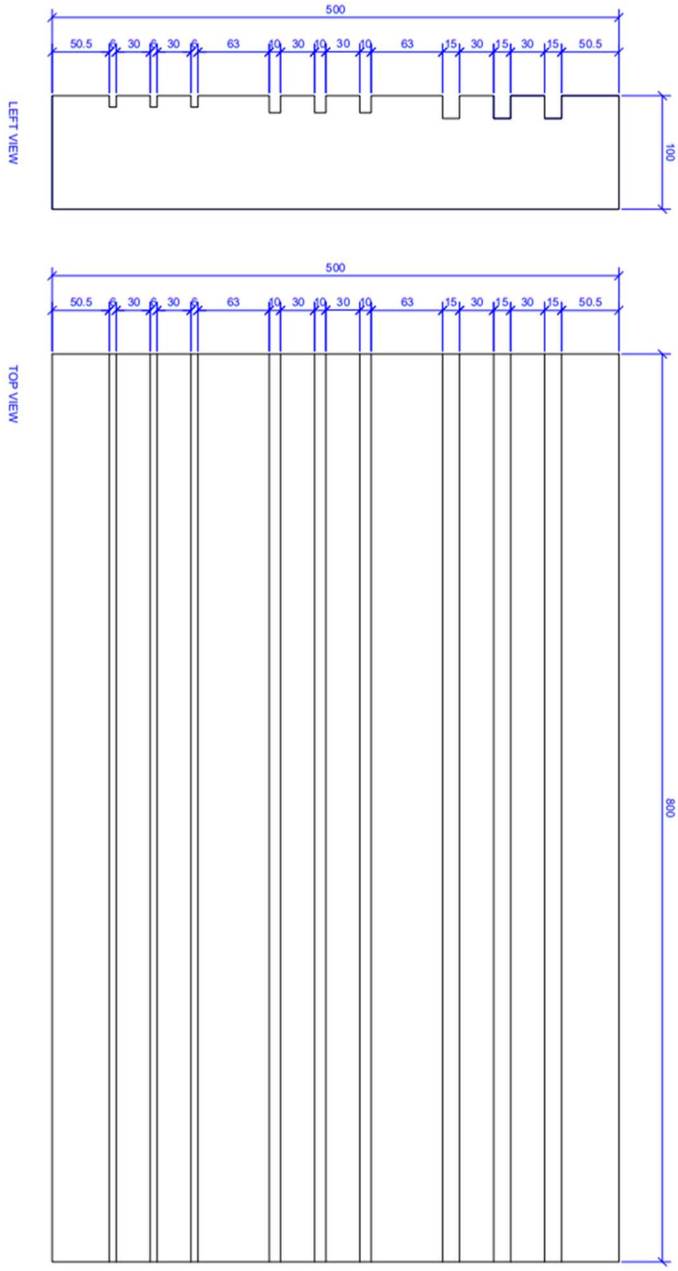


Figure 7 2D drawing of the floor slab with details of each of the three types of slots

Validation is a critical component of the development process for robotic systems. The success of these systems hinges on their ability to accurately and reliably replicate the tasks demonstrated by human operators, and to generalize these tasks across varying conditions. To ensure that the control policies extracted from demonstrations are robust and effective, rigorous validation processes must be implemented.

In the following, validation of the requirements in Section 1.2.1 are detailed.

Productivity improvement

Performance Metrics:

Measure the time taken to fill each slot type by:

- A traditional worker

The same traditional worker with using the teleoperated robotic arm

- Robotic arm alone

Outcome goals:

Aim for the robotic arm to reduce the time taken compared to manual labour, while maintaining or improving the quality of the fill.

Ease of use for unskilled operators

User experience evaluation:

Assess the ease with which unskilled operators can use the robotic arm compared to traditional methods. This will include:

- The time required for an unskilled worker to be trained on the new system.
- The simplicity and intuitiveness of the interface.

Usability testing:

Collect feedback from the workers on the ease of use and any challenges faced during operation.

Workers' Health and Safety

Ergonomic assessment:

Evaluate the ergonomic benefits by comparing the physical strain on workers using traditional methods versus the robotic arm.

Safety metrics:

Monitor the safety incidents or near-misses during the testing phase, emphasizing the reduction in risk with the robotic arm.

Addressing labour shortage

Labor efficiency:

Demonstrate how the robotic arm allows fewer workers to perform the same amount of work, helping to address the labour shortage.

Skill level analysis:

Show that unskilled workers can achieve near-expert results using the robotic arm, highlighting the potential for upskilling the workforce.

Quality and Consistency

After filling each slot, conduct a thorough quality inspection to compare the consistency and precision of the mastic joint filled by:

- A traditional worker
- An expert using the teleoperated robotic arm
- A worker using the new developed technology

Consistency Metrics:

Measure and record the uniformity of the fill, adherence to specified dimensions, and absence of defects.

Flexibility and Adaptability

Adaptability testing:

Assess how well the robotic arm adapts to the three different slot widths without requiring extensive reconfiguration.

Versatility metrics:

Evaluate the system's ability to handle different joint types and floor conditions during the testing phase.

Maintenance and Support

Maintenance simulation:

During the testing phase, simulate maintenance scenarios to ensure the system is easy to maintain and troubleshoot.

Support evaluation:

Gather feedback on the support provided during the setup and testing phase to ensure it meets user needs.

Material usage

Assess the material wastage and efficiency during the filling process.

Integration with existing systems

Ensure the robotic arm integrates smoothly with existing construction management systems and workflows during the testing phase.

2. Laboratory testing

In this following, we focus on learning how to fill a dilatation joint with mastic via teleoperation using the robotic setup described in the next subsection, in a controlled laboratory environment.

2.1. System overview

The robotic system is composed of different elements for the mastic application task: the haptic interface, the robot, the mastic gun and a foot switch as it can be observed in the next figure.

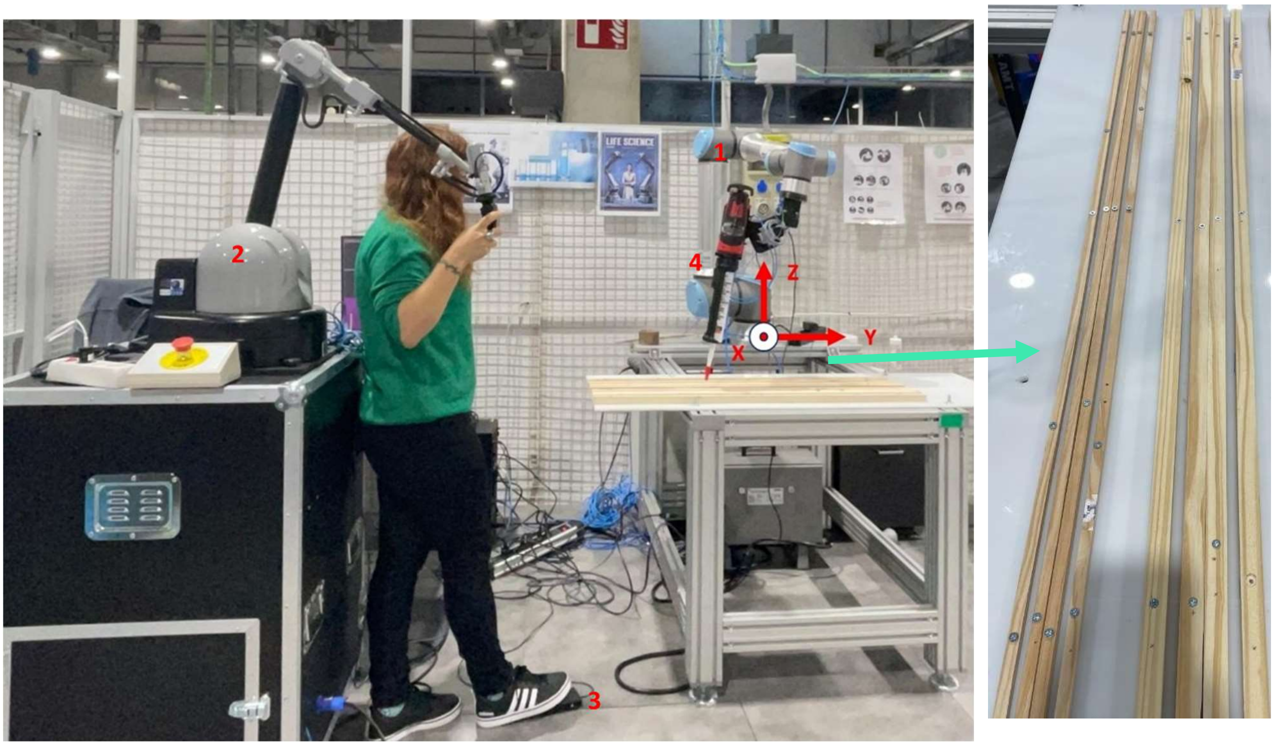


Figure 8 Laboratory robotic setup

2.1.1. UR10 and teleoperation system

1) The Universal Robots UR10e is a collaborative robot (cobot) known for its versatility, ease of use, and safety features. It has a 10 kg payload and an embedded force sensor in its wrist which allows direct interaction characterization.
2) Haptic Device: The haptic interface that it is used is a Haption Virtuose 6D. This device has been selected due to its large workspace and because it can transmit higher forces and torques than other commercial devices. It also presents three programmable buttons that are used for controlling the activity of the mastic gun.

3) Foot switch: The teleoperation console has a foot switch used to engage the coupling of the haptic motions with the robot movements. It also considered as a security measure, as the robot can only move if, and only if, the foot switch is pressed.
4) Mastic gun: A commercial automatic mastic gun is attached to the robot, using a 3D printed coupling device. To enable the mastic deposition from the haptic device, an Arduino is attached to the gun and the main PC. It activates a pneumatic button that presses the physical trigger of the gun.

The axis of reference is located in the robot's base. It is painted in red overlayed to the setup image. There is also a joint mock-up is attached to the profile table where the robot is mounted. The haptic device and pedal are close to the robot but at a safety distance to avoid robot-human collisions.

The functioning of the mastic applicator will be extended in the following subsection.

2.1.2. Mastic applicator

For the mastic applicator a standard battery driven adhesive gun from Milwaukee was chosen as a start point. This tool is meant for manual use but has been adapted for automatic use. The following sections documents the build-up and functionality of the mastic applicator.

There are three basic ways of controlling the adhesive gun automatically, pulse width modulation (PWM) control of electric motor, variable voltage control (replacing enabling switch) and mechanism pushing the enabling switch. Out of the three the last is considered safest, because it can be achieved without manipulating the electronics of the adhesive gun. The two other methods would need more investigation on exactly how the electronic circuitry of the chosen adhesive gun works, the benefit of choosing one of these methods is the possibility to control the rate of deposition. With the proposed mechanical solutions there is a static rate of deposition.

Hardware

The mastic applicator consists of several components. Assembly of the applicator is shown in Figure 9 and an exploded view in Figure 10.

- Adhesive gun from Milwaukee
- Arduino Uno
- Solid state relay (5 V control, 24 Volt switching)

- 3-way solenoid Valve (24 Volt)
- Linear pneumatic actuator
- Holder for all electronics and adhesive gun
- Wires
- Pneumatic hoses
- 24 Volt supply

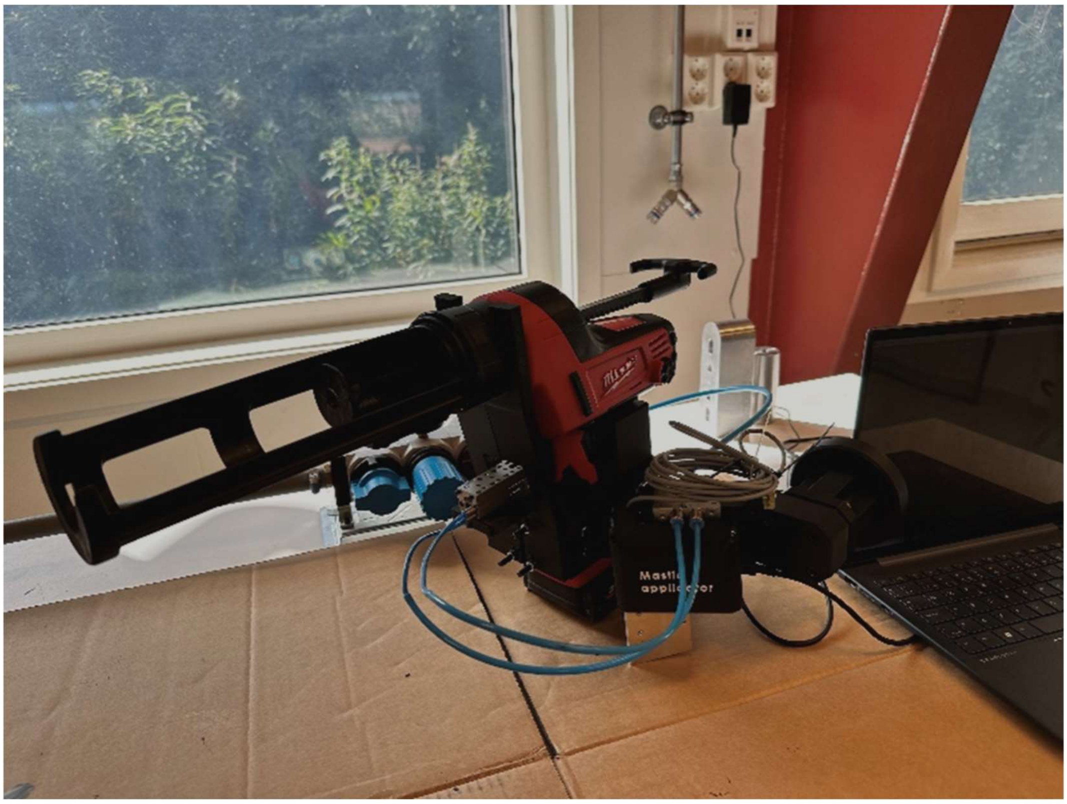


Figure 9: Matic applicator

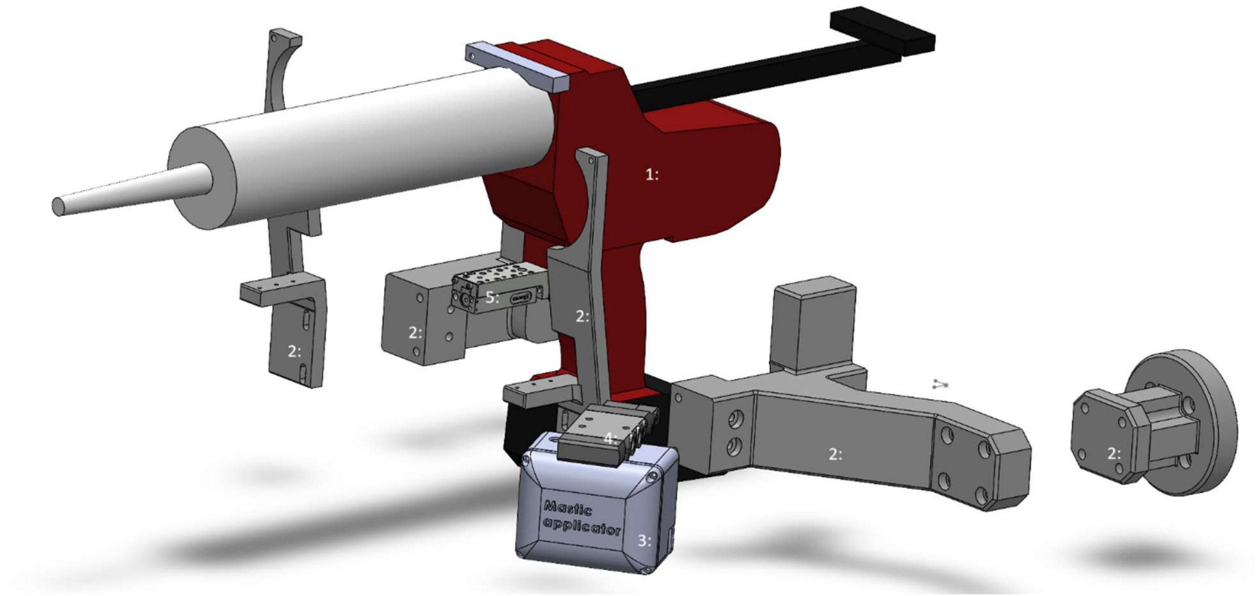


Figure 10: Exploded view of hardware components

Functionality

Figures 11 and 12 shows diagrams of how both pneumatic lines and electronics are coupled. The electronics control a 3-way solenoid valve, this is done by activating a digital out from the Arduino board. But since the solenoid valve needs 24 V to operate, a solid-state relay is used to either give 24 V supply or break the circuit. The effect on the valve is that when the digital output is low, the air flows from port A to B on the valve, which results, that the pneumatic actuator is sent to back position, and there will be no action from the adhesive gun. When the digital output is high air flows from port A to C, this results in the linear actuator being pushed to its forward position, this engages the adhesive gun. To enable or disable the digital output from an external system, there is a simple protocol that uses the USB-interface of the Arduino board. controlled by sending a package over a standard serial connection. The package is either “1” or “2”, representing disable and enable. In return the Arduino sends an acknowledgement package, stating if the digital output has been enabled or disabled. If no acknowledgment, the package has been misinterpreted by the Arduino or lost.

Tables 1 and 2 shows pseudo code for communicating with the Arduino.

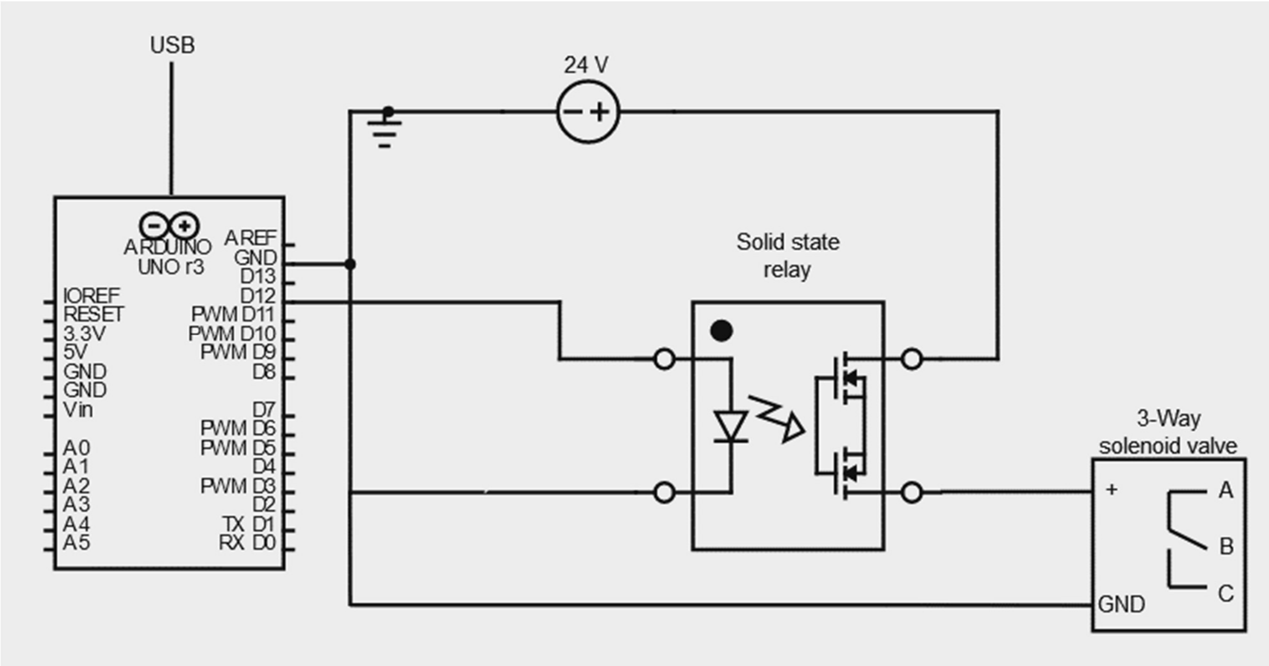


Figure 11 Wiring diagram

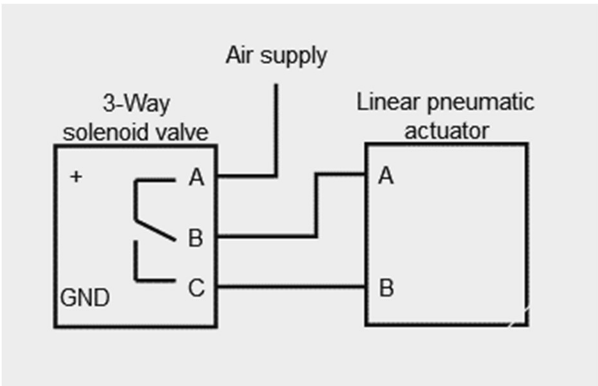


Figure 12 Pneumatic diagram

Table 1 Start mastic

Procedure 1 Start Mastic

```
procedure start_mastic(port)
    ser = Serial(port=port, baudrate=9600)
    ser.write("2") # encoding "ascii"
    ser.read() # returns "1"
end procedure
```

Table 2 Stop mastic

Procedure 2 Stop Mastic
1: **procedure** stop_mastic(port)
2: ser = Serial(port=port, baudrate=9600)
3: ser.write(“1”) # encoding “ascii”
4: ser.read() # returns “1”
5: **end procedure**

2.2. Learning from human operators

2.2.1. Experimental data

Two human subjects have taken part to these preliminary tests. The protocol is composed of three steps: the task demonstration via teleoperation, the model training and the automatic task execution.

1) Perform teleoperated demonstration: In the first step, each participant fills a part of the joint using the teleoperated system. During this demonstration, the time spent to fill the joint, the positions and orientations of the extruder tooltip, the forces measured in the robot's force sensor and the extruder's activations are recorded.
2) Model training from demonstration: Once the demonstrations are gathered, the proposed learning approach is carried out and the controller configuration parameters are inferred from the demonstration. These parameters are stored and used by the controller in the next step.
3) Task automation evaluation: Once the training is completed, an empty joint portion of the same dimension is filled in a fully automated manner. The tooltip moves 25 cm along the joint. The run time and the amount of joint cm filled are noted. Besides, the positions, orientations, forces and activations of the mastic gun during this process are also measured.

2.2.2. Evaluation

The automatic joint filling is performed three times per each type of joint to ensure the repeatability and stability of the results.

In the result tables, the values for these 3 demonstrations are shown in the 'Automation Filled Length' rows. Regarding the demonstration, the two subjects did not fill completely the joint (see result tables). Also the teleoperated demonstration duration differs. The most experienced teleoperator (User 1) is the fastest, compared to the less experienced user (User 2). For both, the demonstration of the two joint fillings last less than two minutes. User 2 has also filled more cm in the demonstration compared to user 1 in both joints.

During the automatic mastic filling, and for the two types of joint, the robot is requested to process 25 cm of the joint. The tables indicate that the automatic executions have not filled the whole section. This is due to the lag observed between the order being sent to the extruder to start the mastic deposition, and the gun being activated. In the thinner joint (Table 3), as the translation velocity is high, the tooltip advances more centimetres before the mastic gun starts working. This leads to less cm of the joint being filled. In the larger joint (Table 3) this problem is reduced due to the decrease of the velocity.

Regarding the difference of the controller parameters extracted from demonstration, we see the influence of the force in the amount of the cm filled. As more force is applied, the real velocity of the system is slowed down, which means the lag of the extruder affects to less centimetres of the joint. User 1 applies less force in both demonstrations compared to User 2.

The joint is located in robot's y direction and this is correctly extracted from the demonstration as the v_x is always zero and v_y varies. Comparing the obtained values of v_y in joints of different sizes, it is observable that for larger joints (joint 2) the velocity is slower than thinner joints (joint 1) for both users.

Table 3 Result tables

TABLE I

RESULT TABLE FOR JOINT 1 (THIN JOINT)

	User 1	User 2
Teleop Time (s)	31	52
Teleop Filled (cm)	15	24
Controller Velocity parameter Vx (m/s)	0	0
Controller Velocity parameter Vy (m/s)	0.029	0.031
Controller Force parameter Fz (N)	- 15.8	- 4.2
Automation Filled Length (cm)	19.9-20.5-21	19-18-19.2
Human errors	0	0
Robot errors	0	0

TABLE II

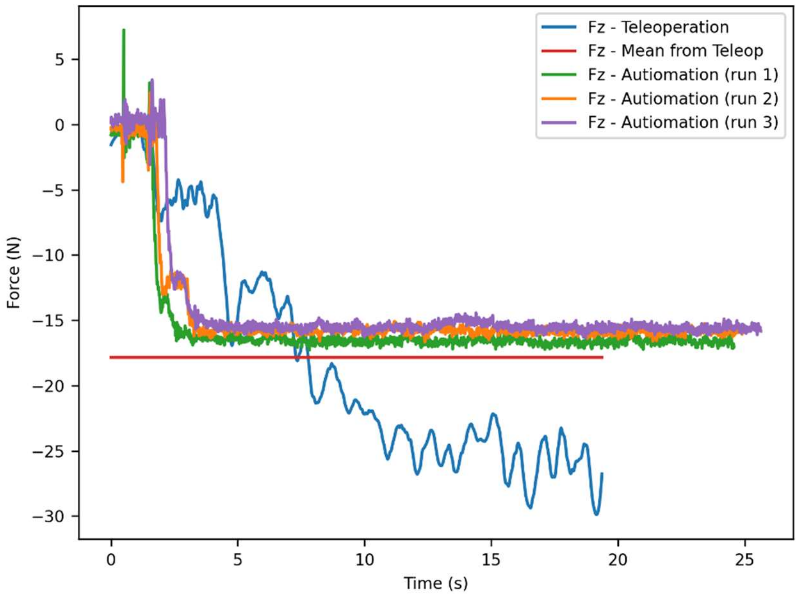
RESULT TABLE FOR JOINT 2 (LARGE JOINT)

	User 1	User 2
Teleop Time (s)	40	63
Teleop Filled (cm)	12.5	18
Controller Velocity parameter Vx (m/s)	0	0
Controller Velocity parameter Vy (m/s)	0.017	0.013
Controller Force parameter Fz (N)	- 17.5	- 7.2
Automation Filled Length (cm)	23.8-23.5-23.9	24-24.5-24.5
Human errors	0	0
Robot errors	0	0

Figures 13 and 14 show how the different control parameters affect to the automatic execution.

In Figure 14 is observed how the real velocities in automation (green, orange and purple) are slower than the command sent (red), due to the contact forces with the surface.

The recorded forces in automation (see Figure 13, green, orange and purple lines) are slightly lower than the controller force but remain in the order of magnitude and very similar over automated trials.



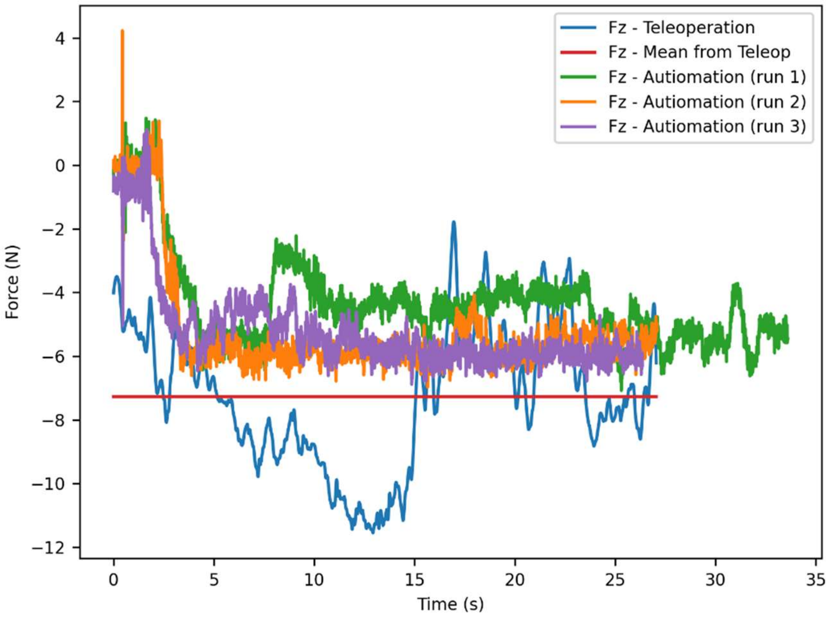
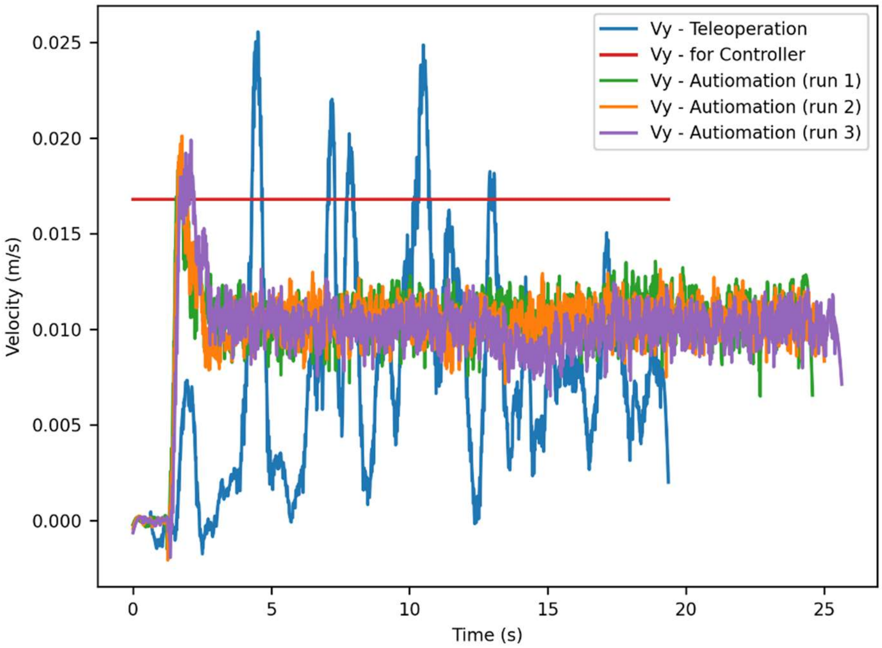


Figure 13 Force F_z in teleoperation and automatic execution for User 1 (up) and User 2 (down)



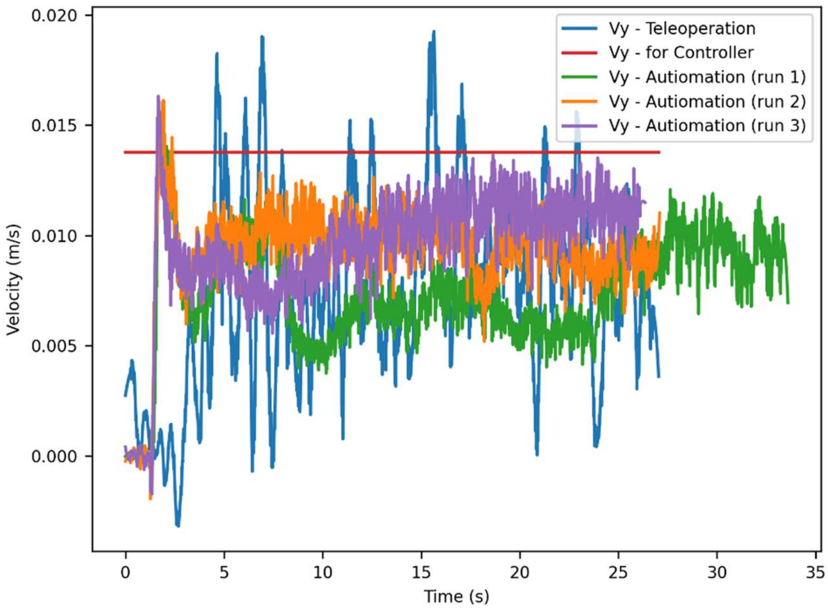


Figure 14 Velocity Vy in teleoperation and automatic execution for User 1 (up) and User 2 (down) for joint 2

Regarding the comparison the filling capacity with different controllers extracted from different users, Figure 15 left (User 1) and right (User 2) show the teleoperated partial joint filling and one of the automatic runs. In figure 15 left (User 1), the upper irregular mastic line is the demonstration made by the user. There are jumps in the mastic and it has not been applied homogeneously.

Figure 15 right provides a closer look of the same task for User 2. The teleoperated demonstration (above) is irregular while the automatic deposition obtains a constant mastic flow on the joint.

Figure 15 Real joint filling. Teleoperated demonstration above, automatic filling below for joint 2. User 1 left and User 2 right

The results of this study provide insights into the efficacy of the proposed one-shot learning from teleoperated demonstration to fill dilatation joints.

The results shown in Table 3 indicate that even with different controller parameters extracted from the demonstration, the automatic filling is successful (Figure 15).

The data also indicates that the real velocity and forces are always smaller to the ones of the controller due to the friction forces with the environment, which also affects the duration of the automatic runs. This is due to the initial position and orientation of the tooltip over the joint hole. If the tooltip is placed close to one of the walls, the friction with it will happen, which will not be the case if the tooltip is cleanly located in the middle of the hole. Therefore, the initial positioning of the joint can affect the results of the filling. If the tool is slowed down, being the mastic flow constant, this will lead to overfilling of the gap.

Regarding the teleoperated demonstrations, a small demonstration is enough for the learning algorithm to extract adequate parameters for the controller. In real life scenarios, this will help ensuring human engagement with the system as there is no need for extensive data gathering.

Finally, the proposed method for controller parameter extraction is promising although it needs more experimentation in real life environments out of the laboratory.

3. Towards Pilot V: Mastic Application

3.1. Requirements

This laboratory setup will be transformed to be applied on construction site. In HumanTech project, Pilot V is focusing on the technology presented in this deliverable and will be the validation use-case. Thanks to previous on-site integration efforts, where the preliminary tests were done, we have created a smaller robotic base to help the robot reach the floor. The haptic device will be located over a table (or flat surface) for the operator to manipulate it.

Figure 16 Image for the robotic setup on site during the integration workshop

Besides, ACCIONA will build several (around 15) concrete blocks with three different joint sizes for the user tests.

Figure 17 Real concrete block with 3 different joint sized built for user experiments

This user tests will be carried out in October 2024 in ACCIONA's building in Alcobendas (Madrid, Spain). In them, up to 10 construction workers will test the proposed system and the results will be evaluated based on different aspects (that will be described in the next section (3.2)).

Although the user tests are mainly related to WP6 and WP7 of HumanTech project, researchers of WP5 have been actively collaborating with other WPs in order to generate the needed documentation for the ethics committee, which has approved the upcoming tests.

3.2. Validation method

Generally, validation of an automation solution requires a function specification that sets both demands and restrictions of the autonomous solution. For robotic solutions these functions that need to be validated are connected to health and safety of said solution, accuracy, repeatability and stability of the solution.

Validation of health and safety is normally carried out thorough risk assessment, a key component in this assessment is health and safety of human operators and the danger robotics solutions pose for serious injury or worse.

Accuracy, repeatability and stability of a solution is closely tied to the solution demands, validation of this requires a series of test. Accuracy and repeatability is tied both to hardware and software, the hardware often gives an indication of what the repeatability is and accuracy is mainly due to programming of the equipment, i.e. a robot trajectory can have a high repeatability, but if the trajectory points is off in regards to the trajectory demand the accuracy will be low.

For laboratory testing, stability is not much of a problem, but in an operational environment the equipment needs to be stable. How long will an adhesive gun last, if it fails every other time the stability is low. The needed stability is often tied to the overall effectiveness (OEE) of the given solutions.

In this pilot usability study of a robotic system to fill dilatation joints both quantitative and qualitative evaluations will be carried out.

For the qualitative analysis, various questionnaires will be used, which participants will be asked to complete, and a brief interview will be conducted to gather their impressions.

For the quantitative analysis, psychophysiological signals from users will be measured while they perform the task, as well as the time needed for different modes and their quality. Additionally, information from the robotic system itself will be collected (positions, orientations, forces, robotic and extruder/pistol activations).

Regarding the measurement of psychophysiological signals, electroencephalographic (EEG) signals, galvanic skin response (GSR) and heart rate (HR) will be recorded.

Besides, during both the teleoperation demonstration phase and the automatic filling phase, the following information will be collected from the robotic system:

- Positions, orientations, and velocities measured on the robot
- Forces measured on the robot
- Situation of the pistol and pedal
- Possible errors of the complete robotic system

This collected information about the robot will be used to improve its development. This study will evaluate:

- The quality of filling using the robotic system
- The efficiency of the robotic system
- The efficiency of the trained learning models
- The percentage of failed executions will be calculated

Additionally, demographic data will be requested to draw conclusions related to the profiles of the participants.

4. Conclusion

The development of methods for "teaching by demonstration" marks a significant step forward in the field of construction robotics, offering a promising alternative to traditional robot programming. By allowing operators to program robots through teleoperation, this approach not only enhances safety but also makes the programming process more accessible and intuitive. The focus on extracting control policies rather than merely recording trajectories is particularly noteworthy, as it equips the robots with the ability to adapt to new and unpredictable situations—an essential requirement for dynamic construction environments.

Through repeated demonstrations, these robots learn to generalize their tasks, ensuring they can perform reliably even when faced with variations in their environment or uncertainties in sensor data. This ability to generalize and operate autonomously across diverse scenarios is expected to reduce downtime, increase efficiency, and ultimately lead to safer and more productive construction processes.

In conclusion, the methods and technologies developed within the frame of HumanTech represent a significant advancement in the automation of construction activities. They not only address the current limitations of robot programming but also pave the way for broader applications of robotics in complex, real-world settings. The technology presented in this deliverable is the basis for the pilot use-case, called Pilot V: Mastic Application, where on-site test will be carried out and validation of the technology will take place. As these systems continue to evolve and be validated, they hold the potential to transform the construction industry, making it safer, more efficient, and more adaptable to the challenges of the modern world.