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A MODEL FOR TRAINING OPTIMISATION IN A HUMAN-ROBOT COLLABORATIVE 3D PRINTING POST PROCESS

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Abstract

This study introduces a new downtime optimisation criterion in the production line of a dynamic additive manufacturing system applied to 3D printing. The focus is on post-processing activities, where an anthropomorphic robot with 6 degrees of freedom is employed. In Human-Robot Collaboration (HRC) and Human-Robot Interaction (HRI), data from a sensor system are analysed to reduce the training time of the cobot in the post-processing activities of new parts. This study proposes a theoretical criterion for planning a new cobot training cycle, which no longer follows the chronological evolution of the production cycle, but an ordered system of instruction packages based on the mono-modal command type. Each instruction is assigned to a mono-modal command based on the shortest time required to achieve optimal cobot training and then grouped into similar instruction packages. These packets identify the scheduling of a new training process in real time, and not offline, when the production of a new finished part is required.

Keywords: Human robot training; Physical human-robot interaction; Training collaborative environment; Industrial robot programming.

1. Introduction

Advances in collaboration between collaborative robots (cobots) and humans represent a significant breakthrough in the manufacturing sector. Cobots integrate human and robotic skills, combining precision and productivity with the added value of human intervention. Compared to conventional robots and automation technologies such as Computer Numerical Control (CNC) machines, cobots offer improved safety, simplified programming and flexibility without the need for isolated work cells, enabling rapid deployment. While conventional robots excel at repetitive tasks, cobots are designed to interact directly with operators, promoting creative solutions and problem-solving skills that are fundamental for customised and flexible production. These characteristics make cobots a technology that can improve the effectiveness of human activities in various production sectors. [1],[2]

As cobot-based solutions balance the benefits of advanced automation with adaptability and human decision-making, targeted design strategies are crucial. [3] These must consider systems efficiency and the human-machine interface, ensuring smooth and safe collaboration. It is essential to create working environments in which the unique capabilities of humans and cobots integrate harmoniously, maximising productivity, innovation and operational safety. With regard to safety in collaborative systems between small industrial robots and human operators, it is important to mention two main problems: the control of the human safety monitoring system and the downtime of the industrial robot during the activation of the safety system. [4] However, the automation of many industrial tasks requires significant effort due to the complexity of technical systems and lack of expertise. [5]

A further significant obstacle to automation is the lack of interoperability standards between technology providers, which complicates the process and increases costs. Maintenance engineers must manage increasingly complex automated production systems characterised by high computerisation, high-quality data acquisition in real-world environments, storage and fusion of information from different sensors and devices, and optimisation of data flow to ensure continuous interoperability in automated production. [6],[7].[8].[9],[10] This lack of standards generates intricate interdependencies between process parameters and system components, making it difficult to assess the effects of changes or replacements.

In this context, human-robot collaboration focuses on key elements such as safety, interaction dynamics in cooperative contexts and the degree of autonomy and adaptability of cobots. [11]

Robots, equipped with intelligent sensors, are designed to operate safely in close contact with humans. Cobots are able to adapt to human actions and learn new processes intuitively, without requiring complex programming. Designed to interact directly with humans and other robots, they share the workload by considering the skills and strengths of each team member. [12] In addition, they develop advanced functions such as visual perception, action recognition, prediction of intentions and safe planning in real time, avoiding collisions through specific rules. [13]

The goal is to train robots to perform tasks safely and effectively, balancing human intervention and automation to improve industrial efficiency. However, many robots are controlled by rigid codes that hinder smooth collaboration with human operators. [6] Control requires robust policies for safe and efficient operation, but their creation is often complex and costly.

It is therefore essential to develop modal or multimodal methods of communication and control, such as. Speech processing, gesture recognition and haptic interaction, to enable robots to dynamically adapt pre-planned tasks and improve interaction. [14],[15],[16],[17]

These approaches allow users to quickly train agents without advanced programming skills, facilitating smoother collaboration by reducing training time. In addition, the operator needs information from the system to orientate himself in his work. [18]

Programming industrial robots is a challenge, requiring specialised knowledge. Offline programming tools based on simulations can simplify the process, but human intervention is often necessary to optimise the programmes. [19]

A crucial aspect is the integration of cobots with sensors for real-time feedback, facilitating collaboration in hybrid environments, speeding up training and minimising downtime. [20] This article focuses on the human-robot training cycle, not production.

In this context, it is essential to explore approaches that simplify the development of control and communication policies, increasing the operational flexibility of cobots and reducing human errors. Machine learning algorithms and automatic optimisation techniques stand out for their ability to generate dynamic and adaptive solutions, facilitating programming and decreasing the need for manual intervention, thus improving the efficiency and reliability of robotic operations during training. [13],[21],[22],[23],[24],[25],[26]

Considering the different abilities and preferences of the operators, the allocation of tasks must take them into account, based on characteristics such as attention, experience and reliability. It is crucial that the robot's mental model encodes not only the sequence of necessary actions, but also expectations of operator preferences.[21],[27]. This approach allows cobots to adapt to user techniques and preferences, making collaboration in production tasks more efficient, especially during real-time adjustments. [28],[29]

The main goal is for the robot to autonomously perform tasks and learn user preferences, improving the acceptance and quality of human-robot interaction. [30]

The demand for rapid reconfiguration of production systems is growing due to frequent changes in operational requirements. Systems must adapt quickly, optimising processes and reducing reconfiguration time and costs. This implies a decrease in training or re-training time, improving learning performance through knowledge transfer between human and robot, and vice versa, as well as between robot and robot in multi-agent systems. In this context, the training programme follows the chronological order of production with multimodal interactions. Crucially, machine learning algorithms are crucial for optimising training cycles by analysing large amounts of data from multiple devices. Although machine learning and data management are not the subject of this project, some articles are cited for their contribution to the literature. [7]

Recent advances in machine learning make it possible to automate multimodal and sequential operations, but they have significant disadvantages:

- Higher margin of error due to multiple devices.
- Need for integrated configuration and ideal working environments.
- High computational costs and large data processing. [31]
- Training of operators in multiple control methods.

In dynamic production systems, these problems can cause prolonged downtime during training processes.

1.1 Scope of the paper

This research project focuses on a dynamic system in which continuous adaptation and learning are essential to manage variations in production requirements.

The paper addresses the challenge of optimising real-time symbiotic training time between a cobot and a human operator in a Human-Robot Collaboration (HRC) system during post-processing in 3D printing. The interaction is based on multiple devices and sensors, favouring modal communication (Human Robot Collaboration, HRI) instead of multimodal, without necessarily following the chronological order of production activities.

In a dynamic industrial environment with frequent new parts to be produced, the aim is to optimise cobot and operator training time as well as system set-up time. [32] When the system is up and running, the operator and cobot know their tasks; however, a change in production generates uncertainty. This study proposes a rapid reconfiguration, training and reprogramming approach to reduce downtime, with a long-term positive impact through the continuous acquisition of data and instructions. The use of machine learning algorithms will help minimise economic losses due to downtime associated with new training cycles.

In the reconfiguration phase, it is crucial to understand how the symbiotic communication between man and robot takes place to ensure fast and efficient training. Is it more advantageous to follow a sequential approach that respects the production cycle or to use intelligent algorithms that memorise instructions? Is multi-modal training more effective than a system that breaks down operations into simple single-mode instructions?

An alternative approach is to break down each activity into small instructions, identifying the fastest modal command method to achieve the optimal instruction. These instructions can be grouped into packages with homogeneous interaction modes, implementing criteria to optimise the long-term training cycle, considering the system's ability to learn autonomously. Let us put the project into context.

2. Working context

In order to test the logic of the research project, a 3D printing process of two pieces (hollow circular cylinders) on the same bed and printing process is considered. The two printed parts will then be joined and painted, resulting in a single hollow cylinder.

The project therefore concerns the automation of a production cell dedicated to the machining of a part obtained from two parts produced by 3D printing, using the FFF (Fused Filament Fabrication) or FDM (Fused Deposition Modelling) technique with PLA (Polylactic Acid) thermoplastic polymer.

The focus of the study is on post-processing activities, which include removing the support material, joining the parts by gluing, sanding, painting and polishing, with the aim of achieving a high-quality final part. Despite advances in 3D printing, the parts produced have surface defects that compromise their functionality and aesthetics. Post-processing operations are therefore essential to ensure the quality and reliability of the final product. [33],[34]

2.1 Production Cell

The production cell is equipped with an ecosystem of command, control and sensor devices, including a Programmable Logic Controller (PLC) and two Graphical User Interfaces (GUIs). It consists of two workstations, delimited by security fences: the Printing Station and the Post-Processing Station. [35] The two stations are connected by an Automated Guided Vehicles (AGV). The robot base can be positioned in three positions: two in the Print Station (Pos. 1 for reel replacement and Pos. 2 for loading the print bed) and one in the Post-Processing Station (Pos. 3).

Print Station (Pos. 1 and Pos. 2). The printing station consists of the 3D printer equipped with ventilation, shelving for new filament spools and print beds, and a dedicated storage tray.

Post-Processing Station (Pos. 3). The robot keeps the base in a fixed position (x3, y3, z3) except when it has to move to Positions 1 and 2. It supports and/or performs all post-processing activities on a circular workbench divided into three sections according to tasks: A: Removing and gluing, B: Sanding and polishing, C: Painting. The robot arm has 360° manoeuvrability around the Z axis of the base. The unused space of the bench is intended for the AGV system and the storage of the finished part, which will be transported out of the cell by a conveyor belt. There are two tool stands on the workbench, one for the effector and one for the operator. [28],[36]

The collaborative manipulator is an anthropomorphic robot with 6 degrees of freedom, a payload of 3 kg and an outreach of 0.58 metres. It features a built-in force/torque sensor and a dual quick-change system that does not compromise reach and extension capability even when two effectors are mounted simultaneously, allowing for automated changeover. [37] The quick-change enables two operations:

- Replacement Changeover: depositing one effector and replacing it with another.
- Rotary change: selection of the effector from the two available on the robot flange.

The system is equipped with seven connectors, such as grippers and tools, to guarantee all tasks: grippers to load and unload filament reels and print beds, grippers to move and place workpieces, a glue gun, a spindle with rotating heads for sanding and polishing, and a paint gun. [38]

The proposed layout aims to ensure quick and easy set-up or reconfiguration of the HRC workstation, in line with the goal of increasing production speed, reducing cycle time and containing costs.

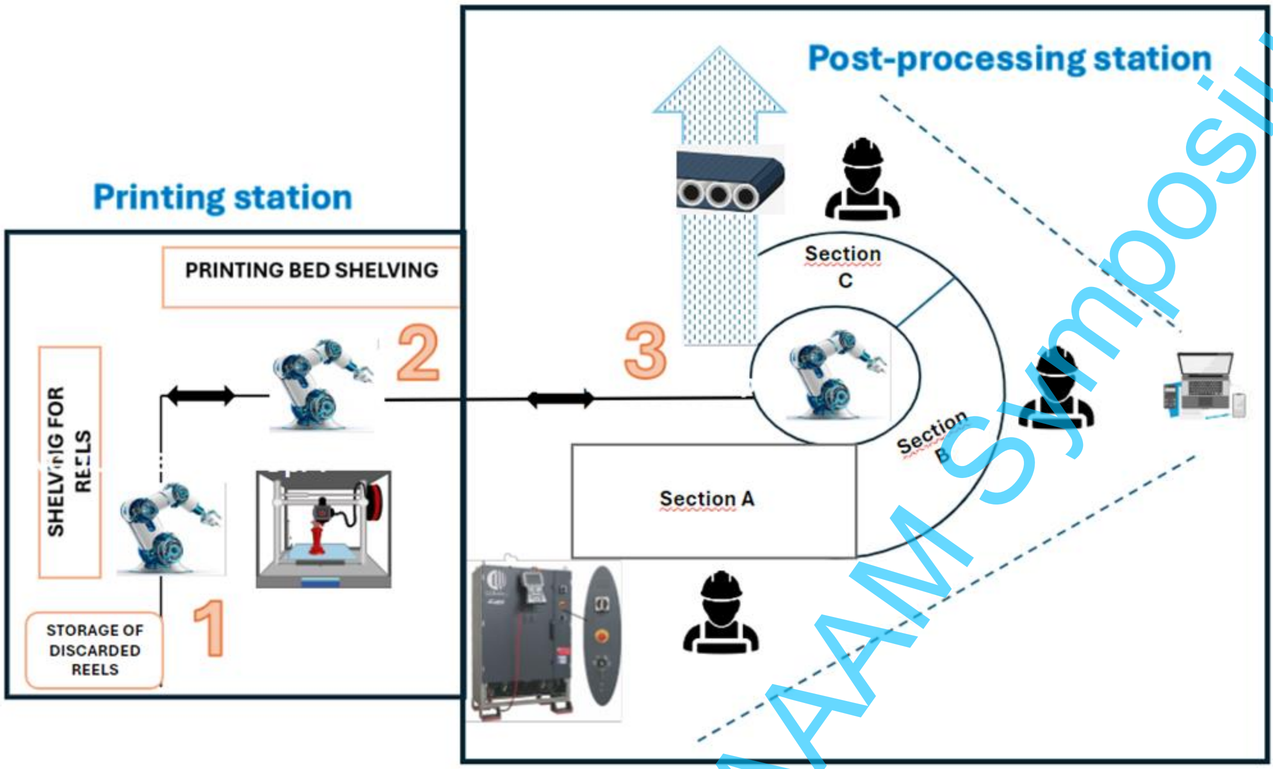

Fig. 1. Layout production cell

2.2 Human-Robot Interactive Ecosystem

Our system is a generalised unified model for active and passive resources, including humans, robots, printers and structures, as well as a system of sensing devices. [39] The latter captures arm, body, hand and finger movements, as well as sonic detections during training, providing valuable data for machine learning and enabling cobots to self-train for future tasks. [13]

The project's HRI ecosystem hardware, crucial for sensing, visualisation, command and control, enables eleven (11) types of interaction as is illustrated below, enabling real-time training between human and cobot. [22],[40],[41]. The interaction modes required for training and related devices are classified according to the degree of virtualisation:

Real:

- Leap Motion optical sensor for hand gestures.
- Technological gloves for tactile and precision interaction.
- Visual instructions via joypad, touch pendant and monitor/tablet.
- Voice recognition with Audio Science Review (ASR) microphones mounted on head and positioned in the cell.
- Manual guidance with direct robot control, force/torque sensing for precision and safety.
- Manual guidance without direct robot contacts via joypad or touch pendant.
- Real-time instruction via interactive video tutorials on monitor/tablet.
- Man-to-man training with direct learning.

Semi-Real:

- Monitor/tablet with touch controls and 2D vision for Augmented Reality (AR).
- 3D HDM (Head-Mounted Display) helmets for virtual controls in augmented reality (AR).

Virtual:

- RV helmets in 3D for virtual commands through virtual reality (VR) viewers.

A unified communication language has been implemented, enabling the integration and use of all components and services within the device architecture, based on a three-tier Service Oriented Architecture (SOA). As a Reconfigurable Manufacturing Systems (RMS), the system respects fundamental characteristics such as modularity, integrability, customisation, convertibility, scalability and diagnostics. [24],[32],[42],[43],[44] This architecture is designed to be service-oriented, ensuring compliance and interoperability between autonomous systems. By emulating our system through a virtual Digital Twin, we have identified a structure organised on three distinct levels, which are subject to constraints and operating parameters, and which communicate bilaterally and share common information. [45],[46],[47]

1.System and technological/production conditions:

- System: production times and volumes, progress, downtime reduction, technological requirements, training, working conditions and safety regulations, etc.
- Product: PLA material, weight, dimensions, cooling, handling, etc.

- Economic efficiency: resource costs, energy, hourly costs, installation, filament and technologies, etc.

2.Tasks:

- Human performance: hazards, workload, ergonomics, fatigue, physical characteristics and experience, etc.
- Robot performance: speed, reach, load, safety, graspability, etc.
- Human-robot team: control, trust, monitoring and feedback on robot performance, etc.

3.Human-robot communication:

This layer includes a two-way Human-Robot/System channel, using interface devices and sensors to transmit data and targets between the operator and the system. This allows visualisation of pending and ongoing tasks, robot trajectories and notifications of events and results of operations. Communication devices, such as augmented reality and tablet interfaces, HD (High Definition) monitors and VR or HMD RA helmets, are adaptable to the operator's preferences through the knowledge base ontology.

The HRI ecosystem will be constrained by specific metrics and constraints related to device combination (multimodal) and modal level (unique) functionality associated with each device.

- A combinatorial/multimodal level: reliability, robustness and cognitive load.
- A modal level (single device): extent of use, flexibility, wearability, connectivity and durability.

Durability: time required to interpret and execute the instruction, estimated numerically. This value is derived from the time identified for the human or robot to complete the optimal instruction in the training process. We can identify technologies with specific applicability for instructions/operations with shorter response times than others. For example, the use of a joypad will take longer than manual guidance with robot arm contact in a positioning instruction. [16],[28],[48]

3. Approach

Analysing the entire production process examined in this study, eight main activities were identified: three in the printing station and five in the post-processing station. [35],[49],[50] To simplify the conceptual analysis, we will focus on four post-processing activities, ordered chronologically: removal, gluing, sanding, and coating. The study explores different scenarios of human-robot interaction, as shown in Tables 1 and 2, highlighting specific characteristics, contributions, and tasks for each activity. It should be emphasized that the interaction in the backing material removal and gluing activities is collaborative human-robot, avoiding a fully automated system, which is not suitable for the demonstration purposes of this study.

Location and Workstation	Activities	Level of interaction	Human task	Cobot task	Joint effort
Pos.3_Post-processing	Substrate Removal	Assistance. Man - Robot Collaboration	Man manually removes material	Robot grabs and holds workpieces at a fixed position and manages their weight	Yes
Pos.3_Post-processing	Past Processing	Assistance. Man - Robot collaboration	Man distributes glue and glues the workpiece via Robot effector	Robot maintains glue gun with orientation and position of workpiece controlled by man	Yes
Pos.3_Post-processing	Levelling	Robot programmed and man can intervene	Man supervises activity from close range	Robot smoothes surface, moving parallel to it automatically	Man supervises
Pos.3_Post-processing	Painting	Fully programmed robot	None	Robot sprays the surface automatically	No

Table 1. Human-robot collaborative interactions and scenarios, contributions and characteristics 1

Location and Workstation	Activities	Physical contact	Mode of operation Robot	Type of workspace	Working tools and instruments	Safety conditions
Pos.3_Post-processing	Substrate Removal	Required	Required	Adaptive	Cutter, sandpaper, workpiece gripper	Robot is moved manually
Pos.3_Post-processing	Past Processing	Required	Adaptive	Shared	Glue gun, workpiece gripper	Robot is moved manually

Pos.3_Post-processing	Levelling	Allowed	Maximum speed / Full stop on approach Man	Shared with side barriers	Sanding spindle, workpiece gripper	Robot stops when Man enters work section
Pos.3_Post-processing	Painting	Excluding	Maximum speed / Full stop on approach Man	Not shared	Sprayer Spray, workpiece clamp	Robot stops when Man enters work section

Table 2. Human-robot collaborative interactions and scenarios, contributions and characteristics 2

The total of these four activities requires a total of thirty-four (34) operations. If we decompose these operations into instructions, we obtain fifty-seven (57) instructions. [51] Of the fifty-seven instructions, many coincide, leading to the identification of seventeen (17) basic instructions distinct from each other in the four observed post-processing activities. At this point, we pose the question as to which method of communication, using a single mode for each instruction, allows the optimal level of execution during training to be achieved in the shortest possible time. To answer this conceptually, we imagine various interactions were tested in the laboratory, assigning numerical values to each communication mode associated with a single instruction. The interaction with the shortest duration was then chosen, always guaranteeing optimal execution. The main criterion is to use a single communication mode for each instruction, applying a single device for each basic instruction. Therefore, each of the 17 instructions will be assigned a specific type of human-robot, robot-human or human-robot interaction (robot-robot, if it were a multi-agent system). Similar instructions with the same interaction mode can be grouped into packages, classified according to the single-mode command mode with the shortest execution time in the training process. In the following table, the result obtained considering the four selected post-processing activities is summarised.

N. OF BASIC INSTRUCTIONS	SIMILAR INSTRUCTION PACKET	N° OF INSTRUCTIONS / PACKAGE	MONO MODALITY CONTROL MODE
1	TILE piece 1	4	Gestures with Sensors
2	TILE piece 2	3	HDM for RA
3	COLLOC piece 1	3	Gestures with Sensors
4	COLLOC piece 2	3	HDM for RA
5	MOOVE Flange piece 1	11	Manual guide with force/torque
6	MOOVE Flange piece 2	10	Glove Handling
7	STOP flange position	2	Visual instruction
8	Man Separates with Nylon piece 1	2	Man - Man
9	Man Removes support piece 1	2	Man - Man
10	Man clears table	1	Man - Man
11	New effector assembly	1	Visual instruction
12	Replacement effector	4	Visual instruction
13	Rotational effector change	7	Vocal Instruction
14	Man distributes glue with guidance	1	Manual guide with force/torque
15	Man glues 1b onto 1a with guide	1	Manual guide with force/torque
16	Robot smoothes workpiece	1	Virtual simulation VR helmets
17	Robot sprays paint onto workpiece	1	Manual guide with force/torque

Table 3. Packing similar instructions according to a single mode of interaction

In this table, piece 1 refers to one of the two cylindrical pieces 1a and 1b obtained simultaneously by the printing process 3, and piece 2 to the part obtained after the gluing activity of the two pieces 1.

Considering this methodology, we do not follow a human-robot training in a chronological order related to production time; instead, we contemplate a training cycle aimed at optimising and distributing a set of similar instruction packages requiring the same type of interaction. The Figure 2 shows the flowchart of the logical steps of this proposed study, representing the generic planning of the training cycle.

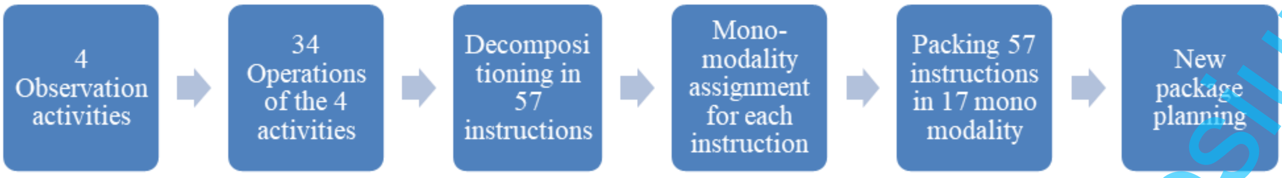

Fig. 2. Generic planning of the training cycle.

During the training cycle, all obtained optimal instructions related to human-robot interaction are stored and subsequently reassigned to the original activities and operations, following the planned chronology of the production cycle. This process, guaranteed by an intelligent decision-making algorithm, contributes to task planning between man and cobot in the production phase. [52] In other words, all activities already broken down into individual instructions are sent to a planning algorithm, which returns the result to the activity management system once the instruction is completed. If the instruction is executed correctly during training, it proceeds to the next one; in the event of an error, it is repeated until the instruction has been executed perfectly. [29]

4. Discussion

Due to the vastness of the content, it was necessary to identify a structure of assumptions that would keep the concept of this proposed approach consistent and avoid dispersion of information. In this section, we present these assumptions and system limitations in a clear and concise manner.

A significant limitation was the difficulty in collecting information from the companies involved. The survey found that cobots are mainly used for simple tasks and long cycles, with limited flexibility and reusability. Training, still focused on traditional robotics, lacks standardization and requires specific skills for each cobot model. Although the interfaces are intuitive, advanced programming requires the support of specialized engineers. Therefore, training focused exclusively on cobots is needed. These are chosen for their low cost, space savings, and safety, but their potential remains underutilized.

Another limitation was and the lack of a laboratory to perform the necessary experiments, making it impossible to validate through practical tests the “Duration” parameter of the instruction to achieve optimal execution. However, the approach presented in this study remains conceptually sound, as the numerical value of the “Duration” parameter can still be estimated through specific tests. Moreover, the exact accuracy of this numerical value is not essential for understanding the content of the article. In this study therefore, the only analysis metric considered is “Duration”. Although other metrics may influence the choice of the most appropriate mode of interaction in real-world scenarios, we assume that all these variables and constraints have already been analysed and evaluated in the three levels of our digital twin model (System, Tasks and Communication). Therefore, the decision criterion is based solely on the “Duration” constraint/metric.

The project focuses on proximal, online and real-time communication technologies, excluding default scheduling systems in offline or remote virtual environments.

The system analysed involves the optimal implementation of devices for human-system interaction, adopting a multi-view configuration that ensures robustness against occlusions, blurring and lighting variations, accurately detecting both visual and acoustic attributes. Each device operates without interference, ensuring optimal execution of instructions, operations and activities.

At the level of system structure and layout, analyses regarding compliance with safety standards or the technologies needed to ensure them are not considered, as they are beyond the scope of this study.

In addition, human-human interactions and self-training are considered, in addition to human-cobot/system interactions, as the latter may be among the most effective in terms of quality and instruction execution time. This choice aims to make the study scenario more generic and representative of reality.

5. Conclusion

Through the analysis of this new training criterion, two fundamental conclusions emerge.

1. Training of instruction packages according to mono-modality.

- The human operator, by repeating very similar instructions through the ‘Learning by Demonstration’ method, would quickly attain sufficient mastery to execute all optimal instructions in a single session. This applies not only to the four post-processing tasks in our case study but could extend to the entire production cycle.
- As this is a mono-mode rather than multi-mode instruction block, the system is able to process a reduced data flow. This approach decreases the number of errors, reduces delays caused by latencies and interface updates, and lowers computational costs. Looking into the future, and considering the dynamic nature of the system, we are processing many similar data and commands, allowing the system to self-learn more quickly and easily, facilitating optimised instruction execution and reducing deviations, in accordance with a Gauss curve.

- The mono-mode characteristic of instruction packages allows for continuity of training without the need to reconfigure the system until switching to another package classified with a different mode of interaction. This has a positive impact on the training cycle of the entire production process.

2. Planning instruction packages and optimising the training cycle.

Once the instruction packages characterised by mono-modality have been identified, it is necessary to define the execution sequence of these packages. We can consider various parameters and constraints, such as:

- Technological flexibility of the device-mode. It is possible to use the device for other instructions, reducing the hardware setup time. For example, sequencing manual force/torque guidance to execute the instructions 'MOVE Flange piece 1' and 'Man distributes glue with guidance" could facilitate technological reconfiguration.
- Physical device proximity and wearability. If the sensor for gesture recognition is mounted on the robot base, and the microphone for speech recognition is also placed on the robot base, the training packages could be executed in succession to optimise the process.
- Margin of error: Although RV helmets may offer shorter execution times, they have a larger margin of error. Therefore, the operator could adopt a training logic that involves "first the complex activities and then the simpler ones", ordering the packages from the most difficult to the simplest.

In addition, the adoption of other parameters could be considered, one of them being machine learning algorithms that, based on historical data from previous production and training orders, are able to recognise the optimal sequence for training packages or individual instructions.

5. Future works

The method presented is an important step toward integrating human and robot operators in shared workspaces, with the goal of assigning tasks dynamically. However, it has not yet been tested experimentally, so aspects remain to be further investigated. Artificial intelligence, particularly potential machine learning algorithms (Supervised Learning, Unsupervised Learning, Semi-supervised Learning, Reinforcement Learning, and Deep Learning) has not been considered. Future studies could explore which algorithm is best suited for each instructional package. For example, Supervised Learning is ideal for simple instructions, while Reinforcement Learning is better suited for complex instructions, especially an already trained system. In the long run, this approach may accelerate the self-learning process.

Another aspect to consider concerns the possible adaptation of the algorithms as the system's learning progresses. The planning algorithm, at a higher level, could optimize the sequence of instruction packets and, in the future, fully automate planning, reducing the need for human supervision. As technology evolves, it is expected that human-robot interaction tools will become more performant, and machine learning will play a crucial role in managing and optimizing data streams, fostering continuous system improvement.

6. Declaration of conflicts of interest

The authors declare that they have no known financial conflicts of interest or personal relationships that could have influenced the work reported in this article.

7. Acknowledgments

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