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Article

Design and Implementation of a Gesture-Controlled Robotic Platform for Applied Education in Human–Robot Interaction †

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Abstract

Industry 5.0 places humans at the center of production systems, requiring technologies that integrate operators as active components while adapting dynamically to their physical and cognitive needs. Within this context, facilitating the learning of complex concepts becomes essential, particularly through intuitive and accessible approaches. The objective of this work is to develop a hands-on educational platform for the introduction to human–robot interaction, aligned with Sustainable Development Goal 4 (SDG4). The platform is designed to support the experiential learning of key aspects of collaboration between human and robots while simultaneously familiarizing students with practical elements, including programming, hardware implementation with microcontrollers and sensors, and the use of the Robot Operating System (ROS). The developed system is based on the use of inertial measurement units (IMUs) to capture kinematic signals, enabling real-time interaction with a collaborative robot. The platform supports both translational and orientation control, with a maximum latency of 0.3 s, ensuring responsive and effective human–robot interaction. The hands-on approach will allow students to interact directly with the test bench, putting previously learned theoretical concepts into practice, according to the principle of learn-by-doing.

Keywords: SDG4; SDG9; Industry 5.0; HMI; collaborative robots; motion tracking; IMU

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1. Introduction

The transition toward Industry 5.0 aims to establish industrial environments in which technological systems are designed around human needs, emphasizing collaboration, adaptability, and operator well-being. In this context, human–robot collaboration represents a key enabling factor, requiring intuitive and efficient interaction between humans and machines [1]. However, several challenges remain open, particularly in relation to human perception, the interpretation of operator intent, and the generation of robot trajectories that can safely adapt to dynamic human behavior [2–4]. These aspects are central to the broader field of human–robot interaction (HRI), which integrates concepts from mechanics, biomechanics, computer science, and electronics, making it inherently multidisciplinary and complex [5].

Within this framework, the subject of this paper concerns the development of a robotic platform designed to support both the study and practical implementation of HRI paradigms. In particular, this work focuses on the design of a test bench that enables interaction with a collaborative robot through intuitive control strategies, allowing users to directly engage with key aspects of perception, control, and communication in human-in-the-loop systems. The proposed system builds upon and extends a previously developed platform [6], enhancing its capabilities and applicability in both research and educational contexts.

This work is driven by the challenges associated with interfacing with human behavior, which is inherently unpredictable and increases the complexity of robot control, requiring robust strategies to detect, interpret, and respond to user actions. To assess these challenges, several approaches have been proposed [7]. Therefore, there is a need to develop flexible and versatile frameworks that enable the analysis and the demonstration of different approaches. This need is particularly relevant in educational settings, where effective tools are required to support experiential learning and facilitate the understanding of complex multidisciplinary concepts through hands-on activities [8].

We propose a modular and adaptable robotic test bench that enables intuitive human–robot interaction while supporting educational objectives aligned with Sustainable Development Goals 4 (SDG4). The proposed framework allows students to explore fundamental HRI concepts, including interaction paradigms, motion tracking, safety, and communication architectures, from both hardware and software perspectives. By bridging theoretical knowledge with practical implementation, the system contributes to improving accessibility to advanced robotics topics and supports the development of expertise required in future human-centered industrial environments [9].

This paper is structured as follows: Section 2 presents the state of the art in educational robotics and human–robot interaction; Section 3 describes the architecture of the proposed system, including hardware and software components, and presents preliminary experimental validation; Section 4 discusses possible goals in education; finally, Section 5 presents the conclusions and outlines future developments.

2. The State of the Art

A literature analysis on HRI and educational robotics was conducted, mainly focusing on how hands-on and project-based approaches foster the development of technical and transferable skills and how HRI is currently treated within educational environments. Within this domain, the analyzed works address the design of robotic platforms for education.

Among the analyzed papers, refs. [8–13] investigate the effectiveness of hands-on and project-based approaches to teaching robotics.

In [8], a course that combines theoretical lectures, simulation-based exercises, and hands-on activities on multiple robotic platforms is presented. The course is integrated with group projects that require the implementation of complete hardware-based applications. The results demonstrate that the hands-on approach leads to a significant improvement in student performance, increasing outcomes in both laboratory activities and examinations while strengthening practical skills.

In [9], a course that integrates theoretical lectures on industrial robotics with parallel hands-on activities is presented. The activities include robot programming fundamentals and vision system training, to support the practical application of concepts such as kinematics, control, safety, and real-world industrial tasks. From the results, it emerges that combining theoretical lectures with practical workshops is an effective method for preparing students for modern industrial robotics.

In [10], a course is presented as a hands-on, project-based learning experience in which students, organized in teams, develop complete robotic systems (both hardware and software) for autonomous navigation through a sequence of progressively complex projects, including control, mapping, and planning. The hands-on and collaborative approach is shown to increase students' confidence, improve teamwork dynamics, and enhance project performance, highlighting a positive correlation between team effectiveness, confidence, and overall outcomes.

The authors of [11] present the design and implementation of an educational automated manufacturing work cell integrating a low-cost, 3D-printed robot; machine vision; and a conveyor system to simulate a complete workflow in a hands-on learning environment. The system leverages modular hardware and accessible software tools to enable students to develop a foundational understanding of artificial intelligence (AI), computer vision, and robotics. Similarly, in ref. [12], a modular approach to robotics education is proposed through the development of a reconfigurable mobile robot architecture based on 3D-printable components for teaching mobile robotics and AI. The reported results show statistically significant improvement in students' learning outcomes, confirming the effectiveness of the platform in reinforcing both theoretical understanding and practical competencies.

In [13], a modular EMG-based educational platform is introduced, enabling students to process biosignals and control robotic systems through reconfigurable hardware modules. The system supports hands-on, interdisciplinary learning aimed at developing design thinking and practical skills in biomedical and robotic system integration.

While these works expand the technological scope of educational robotics, they primarily focus on individual subsystems or specific innovations rather than on comprehensive human-centered interaction frameworks. However, a significant body of research has been devoted to human–robot collaboration, reflecting the growing academic and industrial interest in this field. In particular, human perception represents a key aspect investigated in HRI, as it is of fundamental importance both for ensuring operator safety during interaction [14,15] and for enabling the effective control and management of collaborative tasks [16–23].

The effectiveness of human perception is closely tied to the underlying sensing technologies. Vision-based systems are widely adopted due to their capability to capture substantial workspace information [18,20–22,24–26], although they require complex data processing pipelines. Alternatively, wearable solutions such as inertial measurement units (IMUs) offer a computationally efficient approach, enabling high-frequency data acquisition and the rapid detection of operator movements and more direct and accessible implementation [19,27–29]. Despite these advantages, their adoption in robotic educational platforms remains limited.

Overall, the analysis highlights that while advanced HRI solutions are well established in industrial applications, their integration into educational robotics is still scarce. Consequently, the lack of unified platforms combining robotics, human perception, and intuitive interaction represents a significant research gap, particularly in light of the Industry 5.0 paradigm, which emphasizes human-centricity, collaboration, and user embodiment.

To address this gap, this work proposes a robotic test bench designed to support both the understanding of robotic technologies and the exploration of human-centered interaction. The platform employs a collaborative robot controlled through gesture recognition based on wearable IMU sensors, enabling linear and rotational end-effector motions. The control architecture is implemented within the Robot Operating System (ROS), ensuring modularity and adaptability. This design supports the integration of additional sensors and facilitates the investigation of different perception and control strategies. The proposed

approach contributes to bridging the gap between current educational practices and emerging industrial requirements while also supporting the development of technologies aligned with human well-being and sustainable industrial innovation.

3. Gesture-Controlled Robotic Platform

The Remote Gesture Control and Human–Machine Interaction (HMI) test bench aims at controlling a collaborative robot through gesture-based communication. The architecture presented in [6] was redesigned to improve the simultaneous control of the translation and orientation of the robot EE.

In this extended configuration, the wearable interface was redesigned to include three IMUs, enabling a clearer functional separation between translational and rotational commands.

3.1. Hardware Architecture

The architecture consists of four boards: three peripheral units worn by the operator to detect command gestures and one central unit that wirelessly receives data from the peripherals and serves as an interface with the host PC via serial communication. The wearable sensing units are based on the IMU sensor LSM6DSR integrated within the Seeed XIAO nRF52840 Sense development board (Seeed Studio, Shenzhen, China). Each board incorporates a 6-axis IMU (3-axis accelerometer and 3-axis gyroscope) and a Nordic nRF52840 microcontroller supporting Bluetooth Low Energy (BLE) communication.

To ensure full wearability and eliminate mechanical constraints induced by cabling, each sensing board was equipped with a dedicated LiPo battery and an integrated charging circuit (Figure 1a). This configuration allows for the fully autonomous operation of each peripheral unit mounted on the user's hands and arm. The central unit aggregates orientation data streams and forwards them to the ROS-based control architecture running on a host computer. This distributed wireless design improves ergonomics, reduces setup complexity, and enhances the scalability of the sensing network.

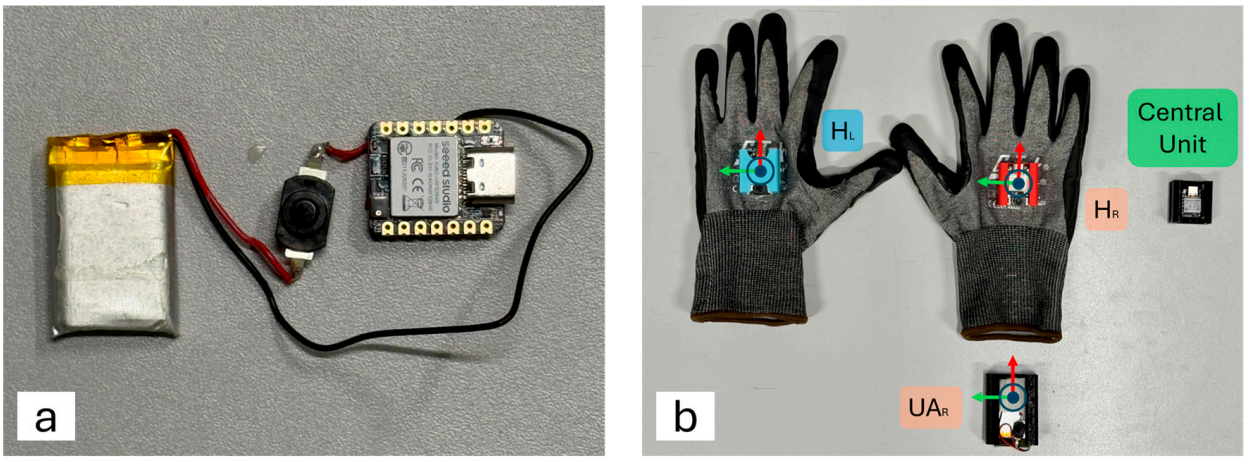

Figure 1. Hardware architecture: (**a**) The power circuit composed of a Seeed XIAO nRF52840 microcontroller, LiPo battery and a power switch. (**b**) Wearable devices developed for robot gesture control: H_L is the IMU worn on the left hand for EE orientation control; H_R and U_{AR} are the IMUs worn on the right hand and right arm respectively for controlling the translational velocity of the EE; the central unit is the device that receives data from the sensors and acts as an interface with the computer.

For the developed prototype, custom 3D-printed mounts were designed to house the wearable electronic components while preserving user comfort and freedom of move-

ment. As shown in Figure 1b, the IMUs H_R and H_L, intended for placement on the right and left hands respectively, were integrated directly into wearable gloves. This design choice facilitates ease of use while enhancing sensor stability during operation. The UA_R IMU, positioned on the upper arm, is instead secured with an adjustable hook-and-loop strap, allowing for quick fitting and fine regulation according to the user's anatomy. The collaborative robot employed in the experimental setup is a UR3 (Universal Robots, Odense, Denmark).

In reference to Figure 2, the system is initialized in a predefined reference posture in which each sensor frame is geometrically aligned with the robot base B reference frame according to known correspondences: the H_R z-axis is oriented parallel to the B −x-axis, and the H_R x-axis is parallel to the B −y-axis; the UA_R z-axis is parallel to the B −x-axis, and the UA_R x-axis is parallel to the B −z-axis; the H_L z-axis is parallel to the B z-axis; the H_L x-axis is parallel to the B −y-axis. This deterministic initialization enables a direct and interpretable mapping between measured body rotations and commanded cartesian velocities of the robot. The resulting architecture distributes control authority across limbs, with the right side primarily being responsible for cartesian translations and the left hand governing EE orientation, thereby enhancing the intuitiveness and modularity of the human–robot interaction.

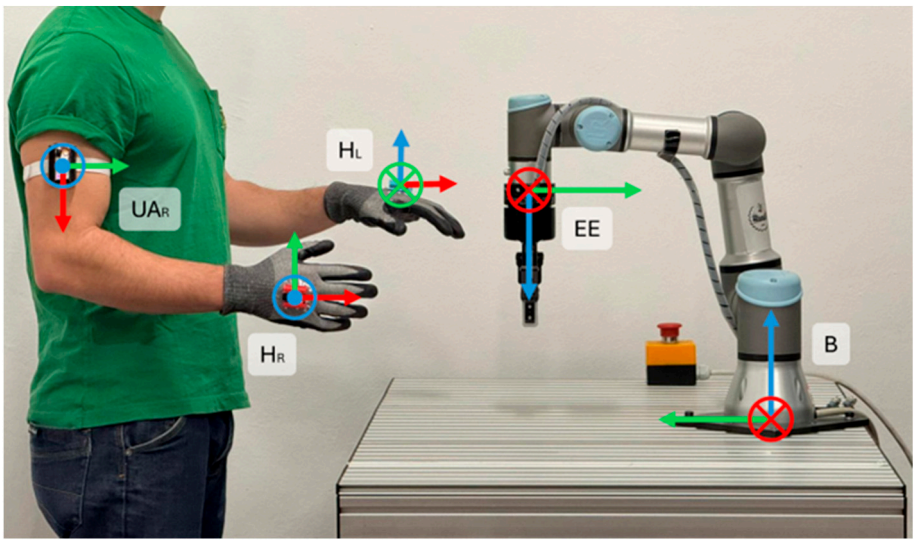

Figure 2. Prototype worn with reference frames.

3.2. Software Architecture

The software logic was developed using ROS2 middleware (Humble Hawksbill), and the architecture was designed following a modular and distributed paradigm, in order to ensure scalability and the clear separation of functionalities. The system is structured into multiple nodes, each responsible for a specific task within the sensing–processing–control pipeline. Figure 3 shows a schematic diagram of the architecture implemented on the host computer. There are three main nodes. In the node *Serial Interface*, the data transmitted by the sensors via a serial port is read and organized to create three different packets, each of which refers to a different IMU. The data packets are published on UA_R, H_R, and H_L *topics*. They are then read by the node *Data Elaboration*, which maps the IMUs' orientation angles and generates the reference signals for the translational velocity and for the closed-loop orientation control of the EE. Finally, the processed message is sent to the *Robot Controller* in the form of a six-element vector containing the set velocity information. The *Robot Controller* node acts as the communication interface with UR3 and publishes the robot's feedback information on the *Robot State topic*, which is required to close the control loop.

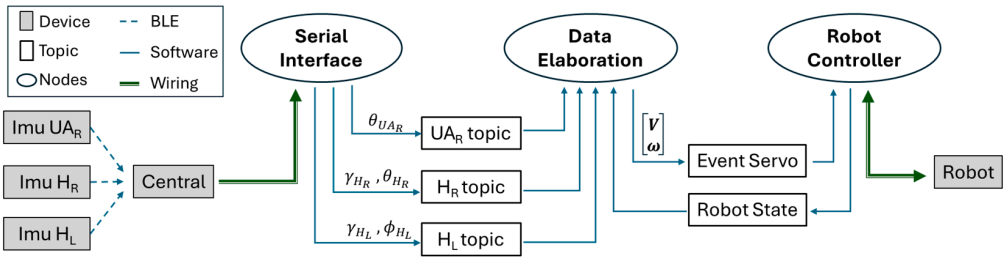

Figure 3. Schematic diagram of information flow.

Starting from the orientation data acquired by the IMUs, the velocity setpoints used to command the robot are computed. In particular, the generalized velocity vector comprises an open-loop velocity control for the translational components and a closed-loop control for the EE orientation. Figure 4 illustrates the implemented robot control algorithm. A Kalman filter [KF] is implemented to fuse accelerometer- and gyroscope-based estimates, thereby reducing noise and compensating for drift effects, leading to a consistent orientation estimation. The Kalman state variable is defined by two orientation angles. The prediction step is conducted by integrating the angular velocities measured by the gyroscope, while the correction step is performed using the angles computed from the accelerometer components, as described in the following. The process noise associated with the integration was experimentally tuned (1×10^{-6} rad^2), whereas the noise covariance parameters (8.4×10^{-8} rad^2) were derived from the noise density values provided in the datasheet and the sampling frequency. The orientation from the acceleration component of each IMU was estimated starting from the initial reference configuration $R^B_{IMU_0}$ by applying successive rotation transformations. The rotations applied to the reference frames of the three IMUs in order to obtain the rotation angles from the accelerometer readings are described below. Equation (1) represents the projection of the gravity vector $\boldsymbol{g}$ onto the axes of the H$_R$ IMU. The same rotational transformations were applied to the UA$_R$ IMU to extract the corresponding rotation angles

$$\begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} = R(z, \psi_{HR})\, R^B_{H_{R_0}}\, R(z, \theta_{HR})\, R(x, \gamma_{HR}) \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} -g\sin(\theta_{HR}) \\ -g\cos(\theta_{HR})\cos(\gamma_{HR}) \\ -g\cos(\theta_{HR})\sin(\gamma_{HR}) \end{bmatrix} \tag{2}$$

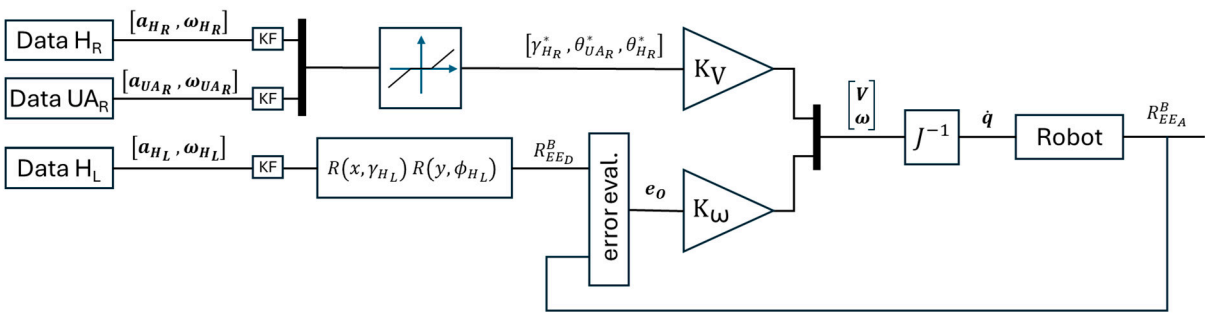

Figure 4. Robot control algorithm.

As can be observed from Equation (2), since the first rotation is applied about an axis parallel to $\boldsymbol{g}$, the projection of the vector in the IMU reference frame remains invariant with respect to ψ_{HR} rotation. The ψ_{HR} angle, in the absence of magnetometer data due to envi-

ronmental disturbances, could only be estimated by integrating gyroscope measurements, making it highly susceptible to drift over time. For this reason, it was excluded from the robot control strategy.

Similarly to Equation (1), the rotation angles θ_{UAR} and γ_{UAR} of UA_R were evaluated by coherently interpreting its initial configuration $R^B_{UA_{R_0}}$. Of the two estimated angles, only θ_{UAR} was used. The three angles extracted from H_R and UA_R worn on the right arm served as command signals for the robot translational motion.

Simultaneously, the orientation of the EE is controlled exclusively by interpreting the orientation of H_L worn on the left hand. The orientation of H_L is determined by applying different rotation matrices, as described in Equation (3).

$$\begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} = R(z, \psi_{HL}) R^B_{H_{L_0}} R(x, \gamma_{HL})\ R(y, \phi_{HL}) \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{3}$$

At each time instant, neglecting the rotation ψ_{HL}, the H_L IMU orientation is evaluated as described in Equation (4).

$$R^B_{H_L} = R^B_{H_{L_0}} R(x, \gamma_{HL})\ R(y, \phi_{HL}) \tag{4}$$

The desired orientation of the EE is defined as the mirrored configuration of the IMU orientation and is therefore computed as shown in Equation (5).

$$R^B_{EE_D} = R^B_{H_L}\ R(x, \pi) \tag{5}$$

$R^B_{EE_D}$ is then expressed in quaternion form as $\boldsymbol{Q_D} = [\eta_D,\ \boldsymbol{\epsilon_D}]$ where η_D denotes the scalar part, and ϵ_D represents the vector part of the quaternion. The actual orientation $R^B_{EE_A}$ of the EE at each time instant is obtained from the robot controller through forward kinematics and is likewise expressed in quaternion form as $\boldsymbol{Q_A} = [\eta_A,\ \boldsymbol{\epsilon_A}]$. The orientation error [30] is then computed as described in Equation (6).

$$\boldsymbol{e_O} = \eta_A \boldsymbol{\epsilon_D} - \eta_D \boldsymbol{\epsilon_A} - S(\boldsymbol{\epsilon_D}) \boldsymbol{\epsilon_A} \tag{6}$$

Here, S(·) represents the skew-symmetric operator.

A deadband of ±0.1745 rad, corresponding to ±10 deg, around zero is applied to each angle estimated from H_R and UA_R in order to stabilize the system behavior. The angle to which the deadband is applied is denoted by an asterisk superscript (*).

The generalized velocity vector used to command the EE is therefore defined as Equation (7).

$$\begin{bmatrix} \boldsymbol{V} \\ \boldsymbol{\omega} \end{bmatrix} = \begin{bmatrix} \gamma^*_{H_R} K_v \\ \theta^*_{UA_R} K_v \\ \theta^*_{H_R} K_v \\ \boldsymbol{e_o} K_\omega \end{bmatrix} \tag{7}$$

Gain K_v is set equal to 1.25×10^{-2} in order to obtain a translation speed of 1 m/s when the angle (*) is 80 deg. K_ω is set equal to 10 in order to guarantee a stable but fast response of the EE orientation. From the current configuration, the Jacobian matrix is evaluated, and the generalized velocity kinematic information is mapped into motor space velocity commands. As can be inferred from Equation (7), UA_R commands the translation of the EE in the B y-axis direction (Figure 5a), while H_R commands the translation in the B z-axis direction (Figure 5b) and x-axis direction (Figure 5c). IMU H_L is therefore adopted to control the angular velocity of the EE to guarantee the orientation (Figure 5d).

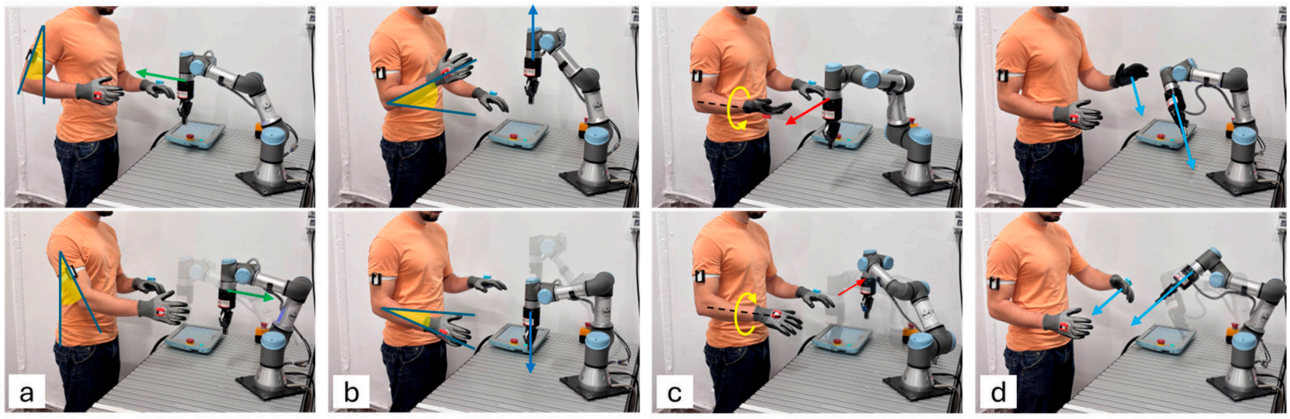

Figure 5. Robot command modalities: (**a**) EE translation along the B y-axis; (**b**) EE translation along the B z-axis; (**c**) EE translation along the B x-axis; (**d**) EE orientation control.

This hybrid architecture combines open-loop cartesian velocity control for translations with closed-loop proportional control for orientation, ensuring intuitive command generation while preserving stability and consistency in rotational motion.

3.3. Experimental Test

The experimental tests were carried out to verify the correct operation of the system and to evaluate its performance. Using a dedicated ROS function, set and feedback values were acquired from the relevant topics throughout the entire duration of the trials. The testing procedure includes two acquisitions.

The first acquisition focused on the verification of translational commands, the accuracy of velocity control, and the correct implementation of the deadband. The devices involved in this stage were H_R and UA_R. The robot was commanded to perform multiple EE displacements along the B y-axis (Figure 6a), B z-axis (Figure 6b) and B x-axis (Figure 6c). During the test, the IMUs were tilted at varying angles to assess different motion velocities. The inclinations measured by the sensors were then compared with the linear velocities reached by the EE during motion, and the results are shown in Figure 6.

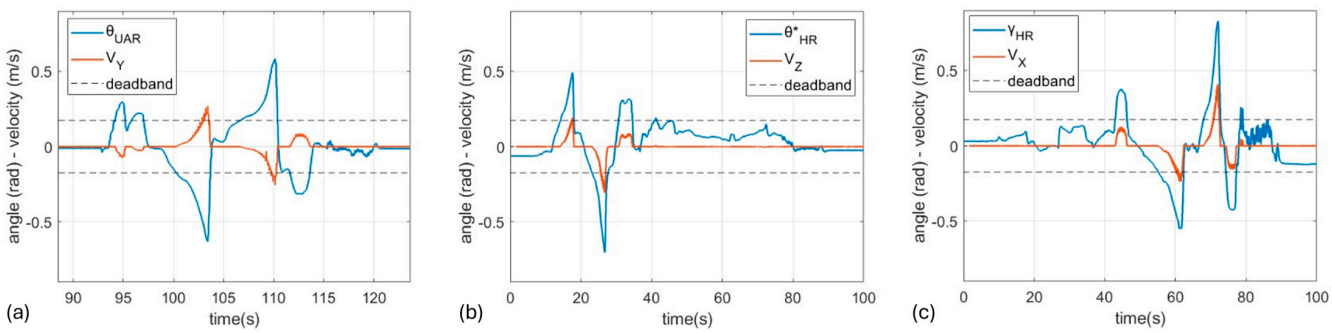

Figure 6. A comparison between the values of the inclination angles and the calculated values of the linear velocity of the EE: (**a**) EE translation along the B y-axis; (**b**) EE translation along the B z-axis; (**c**) EE translation along the B x-axis.

In the plots, the blue curve represents the sensor inclination angle, while the red curve denotes the translational velocity of the EE. The dashed black lines indicate the IMU angular deadband region. When the IMU angle exceeds this deadband threshold, a velocity reference command is generated for the EE.

From the three graphs, it can be noted that the EE translational speed linearly depends on the IMU inclination. Moreover, in Figure 6a, it can be noted that the velocity component

along the B y-axis moves in the opposite direction to the command imposed by the rotation of θ_{UAR}. This is due to the mirrored position of the user with respect to the robot.

The second acquisition was carried out to assess the control of the EE orientation, using H_L as the only device involved. In this case, the IMU was tilted in different directions and varying angular velocities to evaluate the robot's responsiveness. The orientations of the IMU and EE were compared at each time instant, as shown in Figure 7.

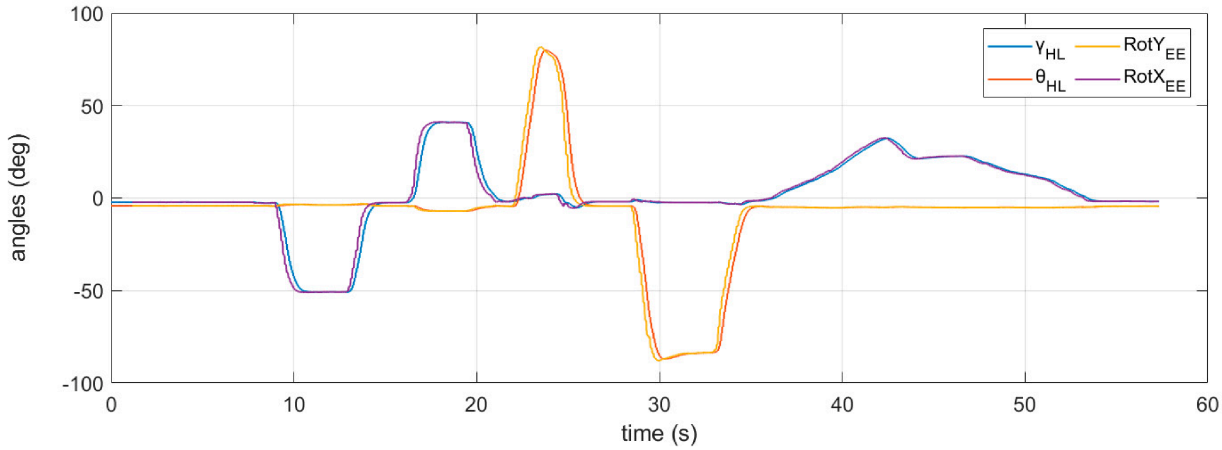

Figure 7. A comparison between the orientation of the H_L IMU and the orientation of the EE.

The graphs show how the control algorithm is able to consistently follow the movements imposed by the user. To evaluate system performance, the maximum delay error was computed for both translational control and orientation control by measuring the time interval between input reference signals and motion feedback data. For translational motion, a maximum delay of 0.02 s was observed, consistent with the controller's internal processing time, indicating that no significant delay is introduced during data processing. For orientation control, the delay is higher due to the dynamics needed to reach the desired orientation regulated by the proportional gain K_ω. The maximum delay evaluated is 0.3 s, compatible with human–robot interaction applications. Higher gain values would reduce delay; however, they would also increase the responsiveness of the robot, potentially leading to more oscillatory or less stable behavior. Other sources of error may arise from the inaccurate estimation of IMU orientation angles, as well as from excessive latency or packet loss in wireless communication. Since the control does not involve high-dynamic movements, the angular estimation accuracy of the IMU sensors was experimentally evaluated under static conditions using a stereophotogrammetric system, yielding an accuracy of ± 1 deg. Following these quantitative tests, eight subjects tested the platform to qualitatively assess the intuitiveness of the control and to evaluate its effectiveness within an educational context, with a view to the future integration into innovative teaching activities in the robotics course. Informed consent for participation was obtained from all subjects involved in this study.

4. Discussion

The key outcome of this work is the implementation of the test bench enabling the teaching of human–robot interaction through a hands-on approach, in line with the effectiveness of hands-on and project-based methodologies highlighted in [8–10].

Although recent research extensively explores HRI, existing works on education often focus on robot modeling, computer vision, autonomous navigation, and other key aspects of robotics [8–12]; they rarely provide unified frameworks focusing on the HRI concepts that combine perception, control, and interaction in a cohesive learning environment. The

proposed platform addresses the gap between advanced HRI solutions and their limited adoption in hands-on educational approaches.

The platform provides a modular and adaptable framework that connects theoretical knowledge with practical implementation in human-centered robotics, coherently with the modular and reconfigurable approaches presented in [11,12], while extending them toward integrated HRI concepts. It enables students to explore the complete HRI loop within a real-time system, including aspects of perception and control typically addressing industrial applications [16–23]. The system allows for direct engagement with motion tracking and reference frame transformations concepts while encouraging students to infer control logic through experimentation and thus deepen their understanding of cartesian and joint space control and sensor–actuator relationships.

The ROS-based architecture further supports this process by introducing distributed systems, real-time communication, and multi-rate processing. The use of wearable IMUs, differently from the existing educational platforms [8–13], ensures a simple and accessible solution for high-frequency motion capture with reduced computational complexity, aligning with the advantages of wearable sensing technologies discussed in [19,27–29] while offering an alternative to more complex vision-based systems [18,20–22,24–26]. This makes the platform suitable for educational contexts while remaining aligned with industrial HRI paradigms, providing a scalable tool for both teaching and preliminary research in collaborative robotics.

However, some limitations affect the current implementation. The absence of a magnetometer in the IMU system leads to drift in absolute orientation estimation, limiting the completeness of motion tracking and requiring a constant predefined relative orientation between the user and the robot. This constraint reduces the flexibility of interaction and deviates from fully unconstrained human motion. Furthermore, the lack of a graphical user interface necessitates direct interaction with low-level code to modify control parameters, which may hinder usability, especially for users with limited programming experience. Although the platform enables the introduction and hands-on experience of some fundamental HRI concepts, its effectiveness still needs to be experimentally and systematically validated, similarly to the validation approaches adopted in [8–10,12]. These limitations highlight areas for future improvement, particularly in enhancing sensor fusion, user interface design, and learning effectiveness validation.

Overall, the results suggest that human-centric interaction frameworks can be effectively translated into educational platforms, providing a solid foundation for understanding and developing collaborative robotic systems in line with emerging industrial paradigms.

5. Conclusions

This work presented a robotic test bench that enables intuitive HRI through wearable IMU-based gesture control. The system, implemented within the ROS, demonstrates how human sensing and actuation can be integrated into a robot control modular architecture suitable for both educational and experimental purposes.

The primary contribution lies in the development of an accessible and scalable platform that bridges theoretical knowledge and practical implementation in collaborative robotics for educational purposes following the principle of SDG4. Moreover, by combining wearable sensing, gesture-based interaction, and a distributed software architecture, the proposed approach provides a concrete tool for exploring human-in-the-loop systems in alignment with the principles of Industry 5.0. The platform also supports the acquisition of multidisciplinary competencies relevant to modern robotics, integrating aspects of mechanics, control, and software engineering within a unified environment.

To address the identified limitations, a user-friendly graphical interface will be developed to facilitate programming for non-expert users. Furthermore, integrating the platform into experimental activities within a robotics course will enable a systematic evaluation of its effectiveness in supporting students' understanding of fundamental HRI concepts. An interactive laboratory activity is planned, in which students will use the platform and understand its operation in order to complete assigned tasks. This innovative educational activity, intended for a master's degree robotics course, will require students to reconstruct gesture-based control architecture starting from pre-programmed functions, to be used as a block-based programming tool. These enhancements aim to make the platform more comprehensive and impactful in an educational context, laying the foundations for further developments.

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References

1. Dhanda, M.; Rogers, B.A.; Hall, S.; Dekoninck, E.; Dhokia, V. Reviewing Human-Robot Collaboration in Manufacturing: Opportunities and Challenges in the Context of Industry 5.0. *Robot. Comput. Integr. Manuf.* **2025**, *93*, 102937. [CrossRef]
2. Fant-Male, J.; Pieters, R. A Review of Personalisation in Human-Robot Collaboration and Future Perspectives Towards Industry 5.0. In *Proceedings of the IEEE International Workshop on Robot and Human Communication, RO-MAN*; IEEE Computer Society: New York, NY, USA, 2025; pp. 223–230.
3. Bonci, A.; Cheng, P.D.C.; Indri, M.; Nabissi, G.; Sibona, F. Human-Robot Perception in Industrial Environments: A Survey. *Sensors* **2021**, *21*, 1571. [CrossRef] [PubMed]
4. Wang, T.; Zheng, P.; Li, S.; Wang, L. Multimodal Human–Robot Interaction for Human-Centric Smart Manufacturing: A Survey. *Adv. Intell. Syst.* **2024**, *6*, 2300359. [CrossRef]
5. Bounouar, M.; Bearee, R.; Siadat, A.; Benchekroun, T.-H. On the Role of Human Operators in the Design Process of Cobotic Systems. *Cogn. Technol. Work.* **2022**, *24*, 57–73. [CrossRef]
6. Crivellari, F.; Cornagliotto, V.; Polito, M.; Pastorelli, S. A Hands-On Platform for Learning Human-Robot Collaboration Using Gesture-Controlled Robotics. In *Proceedings of the I4SDG Workshop 2025—IFToMM for Sustainable Development Goals*; Springer: Cham, Switzerland, 2025; pp. 199–207.
7. Ajoudani, A.; Zanchettin, A.M.; Ivaldi, S.; Albu-Schäffer, A.; Kosuge, K.; Khatib, O. Progress and Prospects of the Human–Robot Collaboration. *Auton. Robots* **2018**, *42*, 957–975. [CrossRef]
8. Ackovska, N.; Kirandziska, V. The Importance of Hands-on Experiences in Robotics Courses. In *Proceedings of the IEEE EUROCON 2017—17th International Conference on Smart Technologies*; IEEE: New York, NY, USA, 2017; pp. 56–61.
9. Wendt, T.M.; Lamm, J.; Stiglmeier, L. Advancing Robotics Education with Novel, Practical Teaching Approaches. In *Proceedings of the 2025 International Symposium on Accreditation of Engineering and Computing Education (ICACIT)*; IEEE: New York, NY, USA, 2025; pp. 1–5.
10. Du, X.; Fowler, R.; Alford, L. Student Teamwork Experience in a Hands-on Robotics Course. In Proceedings of the 2025 ASEE Annual Conference & Exposition, Montreal, QC, Canada, 22–25 June 2025.
11. Thinh, D.P.; Han, v.T.N.; Thinh, N.N.; Huy, N.V.D.; Thuan, T.Q.; Duy, H.N.; Dat, P.T.; Hieu, V.C.; Cong, V.D. Development of an Educational Robotic Platform with Dual Control Interfaces and Intelligent Computer Vision-Based Interaction. *FME Trans.* **2026**, *54*, 93–106. [CrossRef]
12. Balbuena, J.; Sinche, J.; Quiroz, D.; Arce, D.; Villota, E. PlatROB: An Open-Source, Modular, and Low-Cost Hardware Platform for Mobile Robotics and AI Education. *HardwareX* **2026**, *25*, e00747. [CrossRef] [PubMed]

13. Hattori, T.; Nakada, K.; Tsunematsu, M.; Kihara, T. A Custom Module Type EMG Interface for Augmenting Self-Embodiment: Its Design Concept and Educational Applications to Practical Exercises. *J. Robot. Mechatron.* **2026**, *38*, 152–165. [CrossRef]
14. Safeea, M.; Neto, P.; Bearee, R. On-Line Collision Avoidance for Collaborative Robot Manipulators by Adjusting off-Line Generated Paths: An Industrial Use Case. *Rob. Auton. Syst.* **2019**, *119*, 278–288. [CrossRef]
15. Mohammed, A.; Schmidt, B.; Wang, L. Active Collision Avoidance for Human-Robot Collaboration Driven by Vision Sensors Active Collision Avoidance for Human-Robot Collaboration Driven by Vision Sensors. *Int. J. Comput. Integr. Manuf.* **2017**, *30*, 970–980. [CrossRef]
16. Krüger, J.; Lien, T.K.; Verl, A. Cooperation of Human and Machines in Assembly Lines. *CIRP Ann.* **2009**, *58*, 628–646. [CrossRef]
17. Kaplanoglu, E.; Nasab, A.; Erdemir, E.; Young, M.; Dayton, N. Hand Gesture Based Motion Control of Collaborative Robot in Assembly Line. In *Proceedings of the 2021 International Conference on Engineering and Emerging Technologies (ICEET)*; IEEE: New York, NY, USA, 2021; pp. 1–4.
18. Angelidis, G.; Bampis, L. Gesture-Controlled Robotic Arm for Small Assembly Lines. *Machines* **2025**, *13*, 182. [CrossRef]
19. Ateş, G.; Kyrkjebø, E. Human-Robot Cooperative Lifting Using IMUs and Human Gestures. In *Proceedings of the Annual Conference Towards Autonomous Robotic Systems*; Springer: Cham, Switzerland, 2021; pp. 88–99.
20. Andrusyshyn, V.; Židek, K.; Ivanov, V.; Pitel', J. Novel Gesture-Based Robot Programming Approach with the Ability of Code Reuse. *Machines* **2024**, *12*, 217. [CrossRef]
21. Filiatrault, S.; Cretu, A.-M. Human Arm Motion Imitation by a Humanoid Robot. In *Proceedings of the 2014 IEEE International Symposium on Robotic and Sensors Environments (ROSE) Proceedings*; IEEE: New York, NY, USA, 2014; pp. 31–36.
22. Zelensky, A.; Zhdanova, M.; Voronin, V.; Alepko, A.; Gapon, N.; Egiazarian, K.O.; Balabaeva, O. Control System of Collaborative Robotic Based on the Methods of Contactless Recognition of Human Actions. *EPJ Web Conf.* **2019**, *224*, 04006. [CrossRef]
23. Soyguder, S.; Abut, T. Haptic Industrial Robot Control with Variable Time Delayed Bilateral Teleoperation. *Ind. Robot* **2016**, *43*, 390–402. [CrossRef]
24. Halme, R.J.; Lanz, M.; Kämäräinen, J.; Pieters, R.; Latokartano, J.; Hietanen, A. Review of Vision-Based Safety Systems for Human-Robot Collaboration. *Procedia CIRP* **2018**, *72*, 111–116. [CrossRef]
25. Duarte, L.; Polito, M.; Gastaldi, L.; Neto, P.; Pastorelli, S. Demonstration of Real-Time Event Camera to Collaborative Robot Communication. In *Proceedings of the 5th International Conference of IFToMM ITALY*; Springer: Cham, Switzerland, 2024; pp. 351–358.
26. Melchiorre, M.; Scimmi, L.S.; Mauro, S.; Pastorelli, S.P. Vision-Based Control Architecture for Human–Robot Hand-over Applications. *Asian J. Control* **2021**, *23*, 105–117. [CrossRef]
27. Di Vincenzo, G.; Digo, E.; Cornagliotto, V.; Gastaldi, L.; Pastorelli, S. A Comprehensive Narrative Review of Abrupt Movements in Human–Robot Interaction. *Appl. Sci.* **2026**, *16*, 3350. [CrossRef]
28. Digo, E.; Cereatti, A.; Gastaldi, L.; Pastorelli, S.; Caruso, M. Modeling and Kinematic Optimization of the Human Upper Limb for Collaborative Robotics. In *Proceedings of the 4th International Conference of IFToMM ITALY*; Springer: Cham, Switzerland, 2022; pp. 577–585.
29. Digo, E.; Polito, M.; Pastorelli, S.; Gastaldi, L. Detection of Upper Limb Abrupt Gestures for Human–Machine Interaction Using Deep Learning Techniques. *J. Braz. Soc. Mech. Sci. Eng.* **2024**, *46*, 227. [CrossRef]
30. Differential Kinematics and Statics. In *Advanced Textbooks in Control and Signal Processing*; Springer: London, UK, 2010; pp. 105–160. [CrossRef]

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