Intuitive adaptive orientation control for enhanced human-robot interaction

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***Abstract*—Robotic devices can be leveraged to raise the abilities of humans to perform demanding and complex tasks with less effort. Although the first priority of such human-robot interaction is safety, robotic devices must also be intuitive and efficient in order to be adopted by a broad range of users. One challenge in the control of such assistive robots is the management of the end-effector orientation which is not always intuitive for the human operator, especially for neophytes.**

This paper presents a novel orientation control algorithm designed for robotic arms in the context of human-robot interaction. This work aims at making the control of the robot's orientation easier and more intuitive for the user, both in the fields of rehabilitation (in particular individuals living with upper limb disabilities) and industrial robotics. The performance and intuitiveness of the proposed orientation control algorithm is assessed and improved through two experiments with a JACO assistive robot with 25 able-bodied subjects, an online survey with 117 respondents via the Amazon Mechanical Turk and through two experiments with a UR5 industrial robot with 12 able-bodied subjects.

***Index Terms*—Human-Robot Interaction (pHRI), Assistive robotics, Orientation control, Rehabilitation robotics**

I. Introduction

The human body is inherently limited by its physical attributes. Robotics is seen as a key solution to circumvent such limitations. Human-robot interaction is the area of robotics that strives to achieve this goal [1, 2]. Among many others, the fields of rehabilitation engineering and industrial applications greatly benefit from the inclusion of human-robot interactions.

The field of rehabilitation robotics aims at improving the autonomy of individuals living with functional impairments [2]. This area of research includes the development of innovative robotic systems able to assist end-users in their everyday tasks. For instance, assistive robotic arms aspire to elevate the capabilities and skills of individuals living with upper limb disabilities [2]. Such robotic arms have been shown to enable their users to perform activities of daily living such as grasping objects, eating and drinking with greater autonomy [3, 4]. In the field of industrial applications, an important focus has been placed on human-robot interaction in recent years, both in research and commercial applications. In [1], the nature of human-robot interaction was defined by three main categories, namely supportive (provides support to the human), collaborative (task performed in close proximity with the robot and in collaboration where each performs its own task independently) and cooperative (direct physical contact including force interactions) such as [5, 6]. The interaction can also be performed through teleoperation [7]. In this paper, the focus is the collaborative aspect where the human controls the robot through different interfaces for completing a task, but without direct physical contact with the robot. For instance, with assistive robots in rehabilitation, user and the robot are in close proximity and will share a part of the task at different possible levels of autonomy to perform an activity such as eating. Within this context, controlling a complex robotic device is not straightforward, especially for people living with physical limitations or for operators in industries who have to control robots quickly and reliably. In fact, the mapping of the control command (i.e. the user-interface) greatly affects the operator's performance [8, 9]. In other words, intuitive control of robotic devices is important to efficiently accomplish tasks on a day-to-day basis. In this paper, an intuitive control is one that works the way the user expects it to, without having to think about it. From [10], a definition of an intuitive control for human-machine interaction is "A technical system is, in the context of a certain task, intuitively usable while the particular user is able to interact effectively, not-consciously using previous knowledge".

Different approaches have thus been proposed in the literature to improve the performance of assistive and industrial robots. For instance, much effort has been placed in the field of control interfaces in order to allow the robotic system to better understand the human intention, to enhance user performance and to extend the robot's usage to a wider range of individuals. To that end, different control interfaces have been proposed, such as interfaces based on virtual joysticks [11, 12, 13], Inertial Measurement Units (IMU) [14, 15], Electromyography [16, 17], Body Machine Interfaces (BMI) combining different sensors [18, 19, 20], touch screens [21], electrooculography [22], tongue interfaces [23], 3D hand gesture recognition [24, 25], Brain Computer Interfaces [26, 27, 28, 29], robotic skin to detect collisions [30] and eye gaze detection [31]. Algorithms were also proposed to enable the robot to perform some part of the task autonomously in order to allow the user to express his commands at a higher level while letting the system manage low-level tasks. For instance, computer vision was proposed to allow the robot to automatically detect and grasp a given object [32, 33, 34, 31]. Some algorithms have been proposed to automatically avoid limitations (joint limitations, singularities, obstacles) [35, 36], to manage the control mode switching [37] more efficiently. Other algorithms have been designed specifically for the field

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of rehabilitation (automatic position and orientation, fluidity filter, safety features, drinking mode) [38].

Beyond the modality employed to control a robot, the direct mapping between the interface's input and the robot behavior is of paramount importance for creating truly intuitive human-robot interactions. However, for robotic arm guidance, current orientation control system (i.e. around which axis the end effector rotates for a specific input) have been reported as unintuitive and difficult to understand and thus, poorly suited for human-robot interaction. As such, this paper presents a novel orientation control algorithm specifically designed for intuitively controlling assistive and industrial robotic arms. The intuitiveness of an orientation control scheme was first explored in previous work with assistive robots [39] where an algorithm based on the definition of a new adaptive reference frame was proposed. This paper extends the aforementioned conference paper's work by improving and extending the previously proposed algorithm through experiments with 25 able-bodied subjects and an online survey with 117 respondents. The proposed orientation control is also adapted to industrial robots.

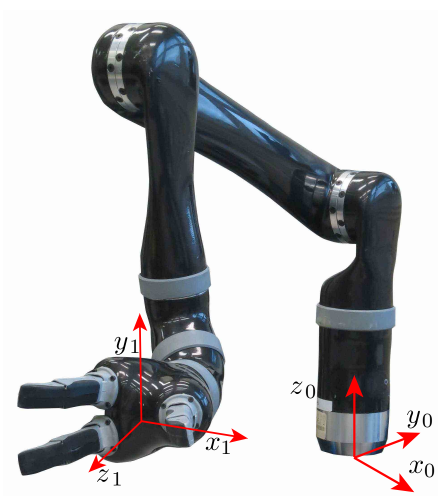


Fig. 1: Assistive robot JACO with the definition of the fixed reference frame $[x_0, y_0, z_0]$ and the mobile tool frame $[x_1, y_1, z_1]$.

The proposed algorithm automatically adapts to the robot's position and orientation, which allows the robotic arm to behave in a predictable way for the user, leading to a system that is more intuitive than existing ones. The objective of the proposed control scheme is to enable the end-user to complete tasks more efficiently and with less effort. The paper first presents existing orientation control modes along with the proposed adaptive algorithm. The proposed adaptive orientation control is then applied to a JACO assistive robot [40] from Kinova (www.kinovarobotics.com) and a UR5 industrial robot from Universal Robot (www.universal-robots.com). Experiments with able-bodied subjects are then presented with both these robots in order to assess the algorithm's performance. Finally, a qualitative assessment of the system's performance and intuitiveness is presented.

II. Orientation Control With JACO

The orientation control was first designed for the JACO assistive robot, which is a six-degree-of-freedom (6 DOF) robotic arm controlled with the wheelchair drive control (for instance a joystick). In the context of assistive robotics, JACO aims to assist individuals living with upper limb disabilities to perform activities of daily living (e.g. grabbing objects, eating, drinking). Usually, robotic arms employed one of the following two reference frames: *the fixed reference frame* and *the mobile tool reference frame*. Figure 1 presents the serial robot JACO and the position of the fixed reference frame defined by the axes $[x_0, y_0, z_0]$ with the z_0 axis pointing upward. The mobile tool frame is defined by the axes $[x_1, y_1, z_1]$ with the z_1 axis pointing out from the robot's palm.

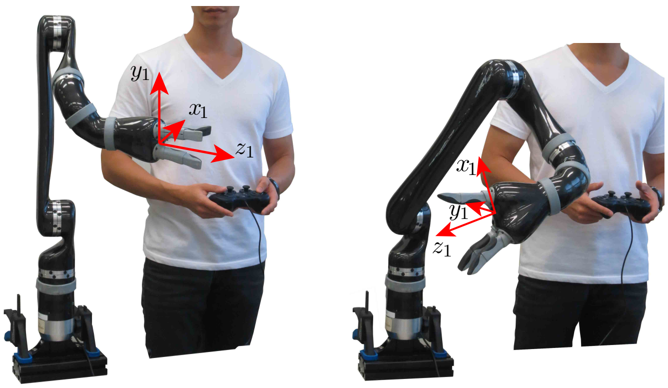
A. Fixed-frame rotation (Mode A)

One common method to define the robot's end-effector rotation is based on Euler angles. Three successive rotations of angles around predetermined axes defined by the fixed reference frame $[x_0, y_0, z_0]$ generate the final orientation of the effector. This rotation system is often employed by industrial robots for pre-programmed trajectories. However, manual control of the rotations with the Euler angles is highly non-intuitive for the operator as it is not directly defined in the task frame.

B. Classic tool-frame rotation (Mode B)

The tool-frame system corresponding to $[x_1, y_1, z_1]$ in Figure 1 is more intuitive when performing tasks in the task space compared to the fixed-frame system. For instance, this frame allows a direction rotation around the tool axis z_1. This is important in practice to adapt to an object's shape (e.g. grasping a rectangular object where the length is too big for robot hand but not the width.). Moreover, a rotation around the forearm z_1 axis (which is useful in practice) would require a combination of three rotations with the fixed-frame system while it represents only a single direct command around the z_1 axis with the tool-frame system. This classical tool-frame rotation system is used for the manual operation of industrial robots and is also the default control mode for the robotic assistive device JACO.

However, while this mode is normally easier to operate than the fixed-frame rotation system, the tool-frame rotation system still has been reported as non intuitive and difficult to understand in a human-robot collaboration context. As an example, Figure 2 shows two possible configurations of the robotic arm. When the robot is in its default position (cf. Figure 2a), the device's behavior is intuitive as the user can project the robot's motion to her/his own arm. However, when the robot's wrist is not aligned with the user's arm(see Figure 2b), the tool-frame rotation system moves relative to the end-effector, lessening the control intuitivity of the system. The orientation control becomes even less intuitive when the robot's hand is purely pointing downward or upward due to the loss of the user's internal representation of the mobile tool frame.

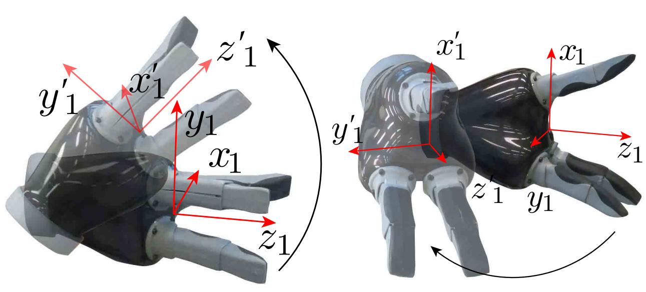


(a) Intuitive configuration of the robot aligned with the right arm of the user.

(b) Non-intuitive configuration of the robot with the palm facing outward.

Fig. 2: Different scenarios for the robot configuration.

Figure 3 shows another common issue with the classical tool frame rotation system. Regardless of the control interface, the user control the orientation of the arm through rotations about the axes x_1, y_1 and z_1. In Figure 3a, when the user sends a positive command (for instance pushing the joystick forward), the hand rotates upward, rotating around axis x_1. In Figure 3b, the hand is in the same position as previously, but has rotated 90 degrees around axis z_1. By applying the same command (i.e. pushing the joystick forward), the end-effector will still rotate around axis x_1 which will now result in a rotation to the right instead of upward as in case of the Figure 3a. In other words, to accurately predict the behavior of a robot arm employing the tool-frame system, the user has to keep track of the current end-effector's orientation, augmenting the mental load of the operator. In practice, several trial-and-error manoeuvres may be necessary in order to find the required input to achieve a given motion which is both time-consuming and requires much effort.



(a)

(b)

Fig. 3: Different scenarios showing how the tool-frame system can lead to drastically different behaviors for the same control inputs depending on the end-effector's orientation.

C. Adaptive tool-frame rotation (Mode C)

As mentioned in the previous section, the classic tool-frame system might be challenging to use since for a given command, the resulting rotation depends on the current tool orientation.

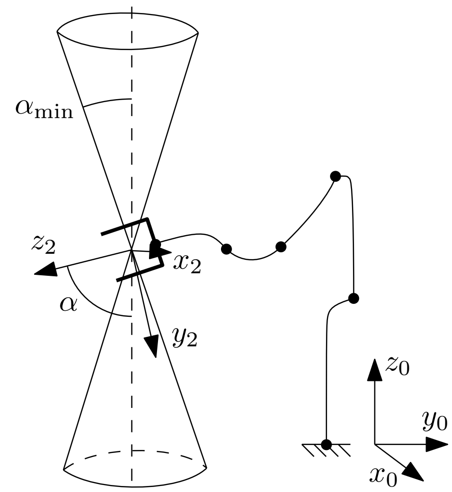


Fig. 4: Presentation of the anti-singularity cones defined to prevent the miscalculation of the vector $\mathbf{e}_{x2}$. The direction of the x_2 axis is parallel to the horizontal plane whereas the y_2 axis is inverted for a more intuitive control with the left/right joystick.

This paper proposes to solve this problem by defining a new rotation frame $[x_2, y_2, z_2]$, as shown in Figure 4. The definition of this system of rotation axes is as follows: The z_2 axis is first defined as the axis pointing out of the tool (or hand) and is the same as z_1 axis from the classical tool-frame as this axis of rotation is important in practice.

The unit vector $\mathbf{e}_{x2}$ corresponding to direction of the x_2 axis is obtained using

$$\mathbf{e}_{x2} = \frac{\mathbf{e}_{z0} \times \mathbf{e}_{z2}}{||\mathbf{e}_{z0} \times \mathbf{e}_{z2}||}. \tag{1}$$

where $\mathbf{e}_{z0}$ and $\mathbf{e}_{z2}$ are the unit vectors corresponding to their respective axes. The geometrical interpretation of Eq. (1) shows that the x_2 axis is perpendicular to the fixed axis z_0, that is pointing upward, and perpendicular to the mobile axis z_2, that is pointing out of the robot's palm. Therefore, the x_2 axis is always defined in the horizontal plane while remaining orthogonal to the axis pointing out of the robot's hand (cf. Figure 4). In comparison, the direction of the x_1 axis of the classical tool-frame system changes depending on the other rotations around the axes y_1 and z_1, and can even point upward as shown in Figure 3b. Consequently, the ambiguity in the tool-frame orientation control depicted in Figure 3 is solved using the proposed method since the x_2 axis is always defined in the horizontal plane.

Unfortunately, using the adaptive tool-frame rotation, vector $\mathbf{e}_{x2}$ is undefined when the axes z_0 and z_2 are co-linear, namely when the hand of the robot is pointing upward or downward. In order to obtain an expression of $\mathbf{e}_{x2}$ at these singular orientations, the angle α between the vectors $\mathbf{e}_{z0}$ and $\mathbf{e}_{z2}$ is calculated as follows

$$\alpha = \cos^{-1}\left(\mathbf{e}_{z0} \cdot \mathbf{e}_{z2}\right). \tag{2}$$

If the angle α is below the threshold $\alpha_{\min}$, then vector $\mathbf{e}_{x2}$ is equal to vector $\mathbf{e}_{x0}$, which defines the direction of the axis

x_0, namely

$$\text{if } \alpha < \alpha_{\min} \text{ then } \mathbf{e}_{x2} = \mathbf{e}_{x0}. \quad (3)$$

$\alpha_{\min}$ describes two symmetrical and vertical cones at the robot's hand as shown in Figure 4. The modification of the frame due to the singular configuration occurs when the user stops the motion (when the joystick is released or the motion direction is reversed) while being in the cone. If she/he maintains the movement through the cone, the switch does not occur.

Finally, the direction of the vector $\mathbf{e}_{y2}$ completes the frame of reference of the new orientation method, namely

$$\mathbf{e}_{y2} = \mathbf{e}_{z2} \times \mathbf{e}_{x2}. \quad (4)$$

Our hypothesis is that this novel orientation control mode is more intuitive than the fixed-frame and classic tool-frame. Both the classic tool-frame and the proposed adaptive tool-frame allow a rotation about an axis pointing out of the hand (z_1 and z_2). However, with the proposed adaptive tool-frame system, a rotation about axis x_2 will lead to a rotation about an axis parallel to the $x_0 - y_0$ plane (i.e. the effector will rotate upward or downward). On the other hand, with the classic tool-frame, the result of a rotation about axis x_1 or y_1 will depend on the actual orientation of the tool, which is very confusing and often difficult to infer for the user.

D. Orientation Control Mapping

Regardless of the interface used to control the assistive robotic arm (e.g. joystick, Sip-and-Puff system, buttons, IMU, EMG), the lack of intuitivity of the actual orientation control systems remains the same. In this paper, the control interface used is shown in Figure 5.

Arbitrary rotation of the end-effector requires at least three degrees of freedom, thereby the upward/downward movement of the left joystick, the lateral movement of the left joystick and the upward/downward movement of the right joystick are used in order to map the orientation of the effector. Positive rotation refers to a counter clockwise rotation according to the right-hand rule.

The directional pad is employed to map the forward/backward and the left/right translations in the Cartesian space of the end-effector whereas two triggers on top of the controller are used in order to map the upward/downward translations.

The orientation control using the classic tool frame $[x_1, y_1, z_1]$ —hereafter referred to mode B— is as follows:

- Upward or downward movement of the left joystick rotates the effector around the x_1 axis.
- Left or right movement of the left joystick rotates the effector around the y_1 axis.
- Upward-Downward movement of the right joystick rotates the effector around the z_1 axis.

The control of the orientation with the new proposed adaptive frame of reference $[x_2, y_2, z_2]$ —hereafter referred to as mode C— with the controller pad is defined as follows:

- Upward or downward movement of the left joystick rotates the effector around the x_2 axis.

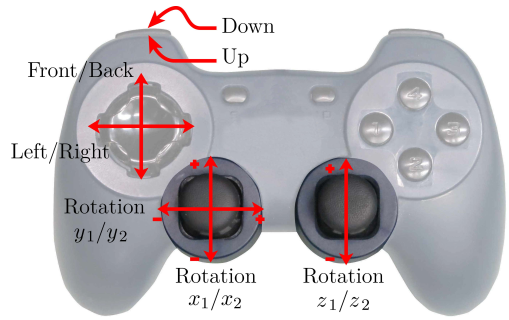


Fig. 5: Control map of the robot's movement with the controller pad.

- Left or right movement of the left joystick rotates the effector around the y_2 axis.
- Upward-Downward movement of the right joystick rotates the effector around the z_2 axis.

An important advantage of the proposed adaptive tool-frame rotation system is that the control can be explained to the participants with simple instructions. This is especially important because the users are typically not experts in robotics. The orientation control can thus be resumed in the following terms:

- Upward and downward movement of the left joystick rotates the effector upward and downward respectively.
- Left and right movement of the left joystick rotates the effector to the left and to the right respectively.
- Upward-Downward movement of the right joystick rotates the end-effector in a screw-driver motion (i.e. around the z_2 axis, counter-clockwise or clockwise).

The experimental validation is presented in Section IV.

III. Orientation Control With UR5

The objective of this section is to adapt the proposed orientation control to industrial robots, namely a UR5 robot from Universal Robot. Figure 6 presents the position of the fixed reference frame defined by the axes $[x_0, y_0, z_0]$ with the z_0 axis pointing upward. The adaptive tool frame is defined by the axes $[x_2, y_2, z_2]$ with the z_2 axis pointing out from the robot's palm. One major difference is that assistive robot users are always in the same position relative to the robot (the robot is installed on the user wheelchair) while industrial robot users might move around the robot. The objective was also to perform experiments with other robots to confirm the intuitivity of the method.

Before the implementation of the proposed orientation control on the UR5 robot, the algorithm was further assessed for possible improvements. To that end, a questionnaire was designed to determine what rotation would be the most intuitive for a given command. The survey was sent to the *Amazon Mechanical Turk* and completed by 117 participants. Only users who had previously completed at least 5 000 surveys with an acceptance rate of 97% or more had access to the survey. This was done to reduce/remove possible noise from bot users. Participants were paid 1.50*US$* for completing the survey.

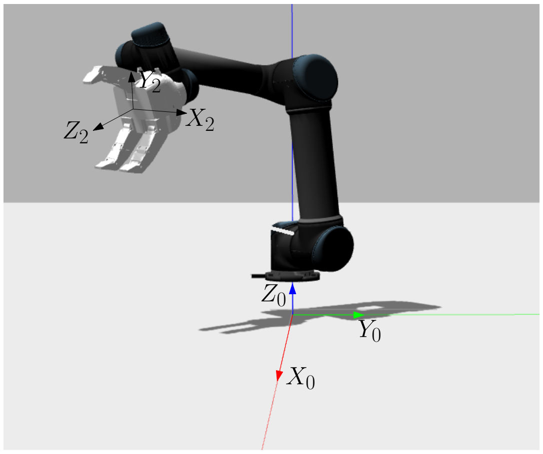


Fig. 6: UR5 robot from Universal robot with the definition of the the reference frame $[x_0, y_0, z_0]$ and the adaptive tool frame $[x_2, y_2, z_2]$.

Eight pictures of the UR5 robot were taken in different configurations and participants were asked to assert which movement would result from a given joystick command. To reduce bias, only the possible inputs of the joystick (see Fig. 7) were given to the respondent as prior instruction. Fig. 8 gives an example of the questions asked in the survey[1].

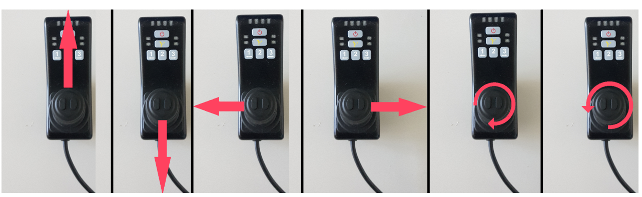


Fig. 7: The six possible joystick input given to the Amazon Mechanical Turk participants. From left to right: Upward, Downward, Left, Right, Clockwise, Counter-Clockwise.

For each of the eight questions, the most popular answer amongst the 117 participants was consistent with the axis rotation that the proposed adaptive orientation system would have employed. The direction of the rotation on the axis was however split amongst the respondents (e.g. moving the end-effector upwards or downwards, from a user's point of view, when inputting the upward motion on the joystick). This result suggests that while the proposed control scheme behavior does intuitively define around which axis the end-effector should rotate given a specific input, the direction of movement around said axis is a personal preference that the user should be allowed to set. Table I presents the percentage of respondents who selected the same behavior as the proposed orientation control (mode C) along with mode A and mode B (independently of direction for each mode) for each questions.

As shown by Table I, the majority of respondents selected the rotation axis given by the system. The only exception is

[1]The totality of the survey's questions are available here: https://robot.gmc.ulaval.ca/fileadmin/Membres/AlexCampeauLecours/Papers/QuestAmazon_IntuitiveAdaptiveOrientation.pdf

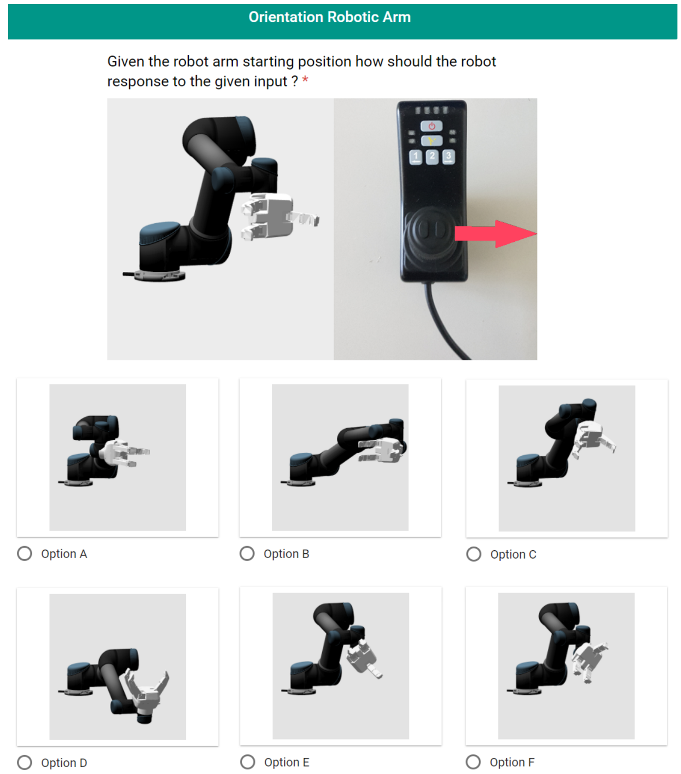


Fig. 8: One of the eight question asked in the survey (Question 3). In this case, 44.4% answered with option B (behavior of the proposed system) and 35.0% with option A (behavior of the proposed system but in the opposite direction).

from Question 1 where the answers were divided uniformly between the three proposed rotation axes. This suggests that the clockwise rotation input is not intuitively associated, at least without prior knowledge, to a specific control of the robotic arm.

Based on these results, and the analysis of the 25 participants who performed the experiments with the assistive robot JACO (see section IV), the algorithm was improved. One of the major improvement was to allow the user to choose if the direction of rotation around the x_2 axis should be inverted or not. Indeed, making the upward movement of the joystick leading to the end-effector pointing upward or downward, depending on the user's choice, simplified the learning process. For the same reason, e_{x0} (eqn. 3) was replaced by $-e_{x0}$, if the user preferred the inverted control. It was also observed that the rotation about the y_2 axis is much dependent on the operation position relative to the robot (for instance in front or behind the robot). It was thus suggested to measure the operator orientation relative to the robot by placing a magnetometer both on the control pad and on the robot base and to change the rotation direction depending on the user position (for instance, a right movement of the joystick leading to a clockwise rotation when standing in front of the robot but to a counter-clockwise rotation when standing behind the robot). As such, eqn. 3 is modified in an adaptive manner where e_{x0} is replaced by a combination of e_{x0} and e_{y0}. For instance: $-e_{x0}$ if standing behind the robot, e_{y0} if standing to

TABLE I: Percentage of respondents that selected the behavior of mode A, B or C (regardless of the direction). The input given by the joystick is written within the parentheses.

	Question 1 (Clockwise)	Question 2 (Upward)	Question 3 (Downward)	Question 4 (Left)	Question 5 (Downward)	Question 6 (Left)	Question 7 (Right)	Question 8 (Upward)
Mode A	**33.3%**	19.7%	7.7%	20.5%	6.8%	27.4%	12.8%	**72.7%**
Mode B	**33.3%**	19.7%	**79.4%**	**58.1%**	7.7%	19.7%	12.8%	**72.7%**
Mode C	**33.3%**	**62.4%**	**79.4%**	**58.1%**	**85.5%**	**72.9%**	**70.9%**	**72.7%**

the right of the robot.

IV. Experimental validation with JACO

In order to evaluate the intuitiveness and the performance of the proposed orientation control system two experiments were conducted with JACO. The first experiment assesses how easy it is to predict the behavior of mode B (classic tool-frame) and mode C (adaptive tool-frame) while the second experiment evaluates both modes in a complex control task with the joystick. 25 participants aged between 22 and 41 were recruited for the experiments. Each participant started with the mode that the previous participant finished with. The first mode use by the first user was selected randomly. Instructions about how to operate the corresponding modes were given to the participant while they were getting accustomed to the controller pad for five minutes.

A. Experiment 1: understanding the orientation system

The first experiment aims to evaluate if participants can predict the behavior of mode B (tool frame $[x_1, y_1, z_1]$) and C (novel adaptive tool frame $[x_2, y_2, z_2]$). To that end, the participants were shown the robot in five positions in succession as shown in Figure 9.

For each position, the participants were asked which direction the robot's hand would face if given a specific command. The user was evaluated on the time to give an answer and on the validity of her/his answers. One point was granted if the given orientation was correct, half a point if the opposite direction was given (i.e. correct rotation axis, but wrong direction) and no point otherwise. Therefore, the maximum number of errors (incorrect answers) is five.

Figure 10 shows the results of the experiment. For each participant, the number of errors is depicted in the vertical coordinate whereas the average time taken to answer is depicted in the horizontal coordinate. As such, lower and to the left is better. The crosses are centered on the corresponding class average and the bars represent the standard deviation. When mode B is utilized (classical tool frame), the average number of errors is 2.7 with an average time of 7.5 sec to answer. When mode C is utilized (proposed tool frame), the average number of errors is 0.3 and the average time to answer is 3.2 sec. The standard deviations with mode B are $\sigma_{\text{time}B1} = 4.55$ sec for the time and $\sigma_{\text{error}B1} = 1$ for the number of errors whereas, with the mode C, the standard deviations are $\sigma_{\text{time}C1} = 1.93$ sec and $\sigma_{\text{error}C1} = 0.49$, which are smaller than with mode B.

Indeed, subjects dealing with mode B displayed two kinds of behaviors: in the first case, users tried to truly understand the frame of reference and its corresponding behavior for each position resulting in more accurate answers with more time to answer. In the second case, participants tried to give their answers quickly based on their intuition. The first case generally slowed the response time, while the second case tended to reduce the accuracy.

The average completion time using mode C was statistically significantly reduced by an average of 57% compared to mode B ($p = 2.48e^{-5} < 0.05$, Wilcoxon signed-rank one-tailed test). The answers' accuracy was also statistically significantly improved by 87% ($p = 8.64e^{-6} < 0.05$). Using the proposed control system, participants were thus able to give more precise answers much faster.

B. Experiment 2: Performing an orientation task

Many daily tasks require controlling the orientation of the assistive robot's hand. Such tasks may include picking up objects (a glass of water, a pencil on a table, remote control on the ground), pushing a button (elevator), paying with a bank card, etc. The task to be performed with the robot in this second experiment was defined based on the manipulation of a card in order to assess the performances of the rotation algorithm.

In order to simplify the trajectory and to focus on the orientation control, the card was already placed in the robot's palm so that the grasping task was not taken into consideration. The trajectory of the hand began at the initial position of the robot shown in Figure 11. The user then had to overlay in succession the three rectangles, shown in Figure 11, with the card. Each participant had to complete the following trajectory: (1)→(2)→(3)→(1).

The required orientation of the card at each position was shown on a sheet of A4 paper (cf. Figure 11). The position of the card had to be within the paper boundaries and its orientation had to be parallel to the rectangle printed on the paper. To avoid a collision between the fingers and the surfaces, a distance of 3 cm to 5 cm between the tip of the fingers and the paper was sufficient to validate one marker. The participants were evaluated based on the time taken and their accuracy when completing the task. Error points were compiled when the user performed a wrong joystick command to perform a given rotation. For example, rotating the robot hand to the right plane whereas the target was on the horizontal plane led to increasing the error counter. Errors made by the participant while using the robot in translation control were omitted.

Figure 12 shows the results of this experiment. The participants that had begun the first experiment with mode B also began with mode B for the second experiment and vice

(a) Position 1
Joystick input: Up
Mode B: face up
Mode C: face down

(b) Position 2
Joystick input: Up
Mode B: face front
Mode C: face down

(c) Position 3
Joystick input: Right
Mode B: face left
Mode C: face right

(d) Position 4
Joystick input: Right
Mode B: face front
Mode C: face right

(e) Position 5
Joystick input: Upward
Mode B: face down
Mode C: face down

Fig. 9: Position of the robot for the first experiment, input of the joystick and the response for the corresponding mode.

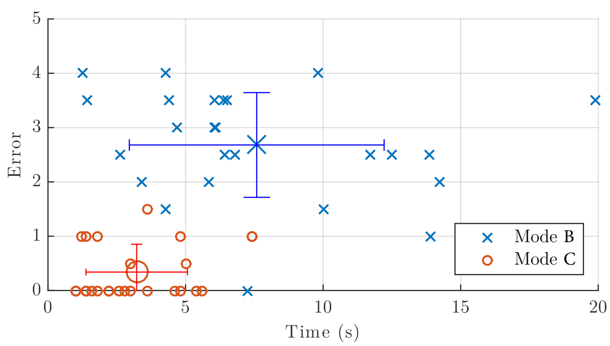


Fig. 10: Results of the first experiment with the number of errors and the average time taken to answer each position.

versa. The task completion time is shown in the horizontal coordinate whereas the number of errors is shown in the

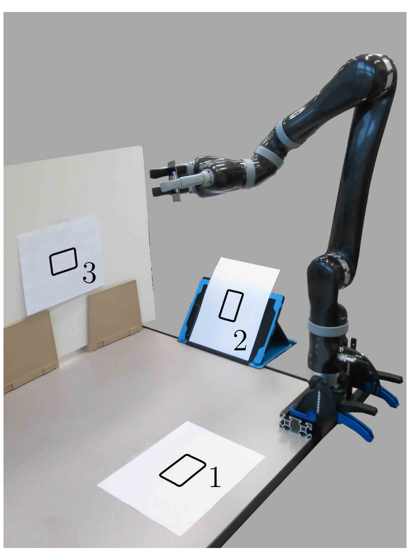


Fig. 11: Set up of the markers for the trajectories of the second experiment. The robot holds a card which has to face each of the surfaces indicated with one black rectangle.

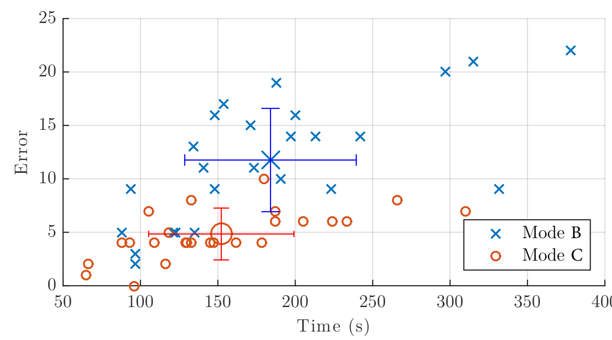


Fig. 12: Results of the second experiment with the number of errors while orienting the robot and the time taken to complete the task.

vertical coordinate (lower and to the left is better). The average time taken in order to perform the trajectories with mode B is 184 sec with an average number of errors of 11.7 errors while mode C shows a better performance with an average completion time of 152 sec and an average of 4.8 errors. The standard deviations with mode B are $\sigma_{\text{time}B2} = 78.1$ sec for the time and $\sigma_{\text{error}B2} = 5.74$ for the number of errors whereas, with mode C, the standard deviations are $\sigma_{\text{time}C2} = 61.41$ sec and $\sigma_{\text{error}C2} = 2.3$.

The completion time was significantly reduced by 17% with mode C compared to mode B ($\text{p} = 0.003 < 0.05$), Wilcoxon signed-rank one-tailed test). The number of errors was also significantly reduced from mode B to mode C by 59% ($\text{p} = 1.23\text{e}^{-5} < 0.05$). The results of the two experiments corroborate the assessment of the orientation control being more efficient and intuitive with mode C (proposed adaptive orientation control) rather than with mode B (classical tool frame orientation control).

C. Qualitative assessment of the system's intuitiveness

The main purpose of the proposed orientation control system is to enhance users' experience by enabling them to control the robot with more performance and intuitiveness. Apart

TABLE II: Results from the QUEAD questionnaire. The 'Value' column represents the average answers on a 7-point Likert scale (4 being neutral) and the p value represents the statistical significance.

Question	Value	p
I accomplished the given task more rapidly with adapt. mode	5.4	0.05
I completed the task more efficiently with adapt. mode	5.7	0.02
I performed more precise motions with adapt. mode	5.7	0.02
The adapt. mode was more intuitive	6.2	0.004
It was easy to learn to use this control mode	5.9	0.01
Globally, I prefer the adapt. mode	5.7	0.03

from quantitative data obtained in the preceding experiments, an important metric is the participant preference. Following this, the most important rubric must be which system the participants qualitatively preferred. To that effect, at the end of the experiments, participants were asked questions about their experience with the orientation control. These questions were based on the QUEAD (Questionnaire for the Evaluation of Physical Assistive Devices) [41] and were answered by 9 of the participants. The QUEAD is based on a 7 points Likert scale with the following options: (1) Entirely disagree, (2) Mostly disagree, (3) Somewhat disagree, (4) Neither agree nor disagree, (5) Somewhat agree, (6) Mostly agree, (7) Entirely agree. In order to eliminate any bias, the question referred to the first mode they used and they did not know if this mode was the classical or the newly proposed mode. The results of the evaluation are shown in Table II.

The results from the QUEAD questionnaire are statistically significant ($p \leq 0.05$) (Wilcoxon signed-rank one-tailed test). In addition to the QUEAD, comments from the participants were collected. In all but one case, the subjects preferred using the new proposed mode over the classical mode. Additionally, many participants commented that they could easily understand the control of the proposed adaptive mode whereas they had to control classical mode mostly through trial and error. Participants instinctively concluded that they could not accurately and efficiently predict the behavior of the robot under classical tool-frame mode. This is corroborated by average values of 6.2 and 5.9 to the questions "The adaptive mode was more intuitive" and "It was easy to learn to use this control mode".

These qualitative results along with the participants' comments corroborate the conclusions from the previous experiments, that is, the adaptive tool-frame orientation control system presented in this paper is significantly more intuitive than the classic tool-frame system.

V. Experimental validation with UR5

In order to evaluate the intuitiveness and the performance of the proposed orientation control system for industrial robots, two experiments were also conducted on a UR5 industrial robot from Universal Robot. The first experiment assesses how easy it is to predict the behavior of modes A, B and C while the second experiment evaluates the control modes with more practical tests. 12 participants aged between 24 and 38 participated in the experiments. The control mode testing sequence was modified for each participant (e.g.: A-B-C, B-C-A, C-A-B, etc.). Instructions about how to operate the corresponding modes were given to the participant while she/he was getting accustomed to the controller pad for two minutes for each mode.

A. Experiment 1: understanding the orientation system

The first experiment aims to evaluate if participants understand the rotation systems well while using the joystick with mode A (fixed-frame, which is the default orientation control mode for the UR robot), mode B (classic tool-frame) and mode C (proposed adaptive tool-frame). Then, the robot was set to five different positions as shown in Figure 13. For each position, and for each control mode (A, B and C) the participant was asked which command he/she should perform to rotate the end-effector towards a given direction.

The user was evaluated on the time to give an answer and on the validity of his/her answers. One point was granted if the given orientation was correct, half a point if the opposite direction was given (i.e. correct joystick axis, but wrong direction) and no point otherwise. Therefore, the maximum number of errors (incorrect answers) is five.

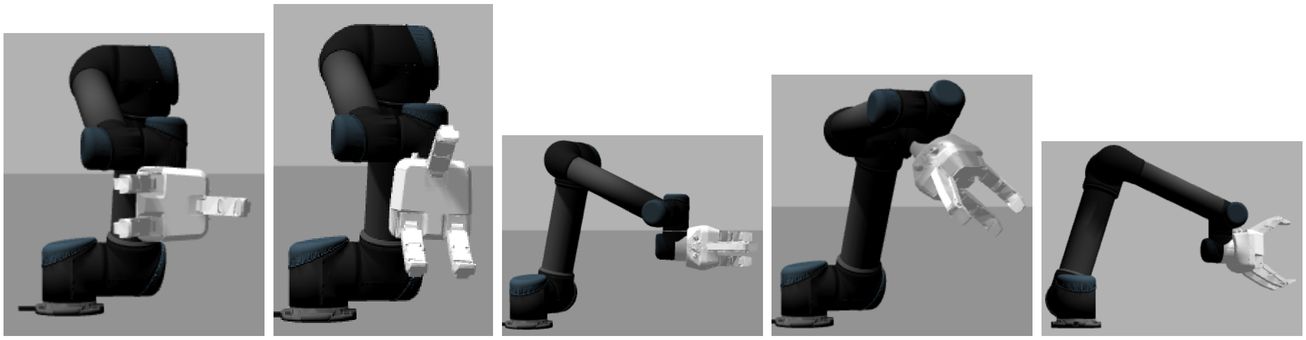
Figure 14 shows the results of the experiment. For each participant, the number of errors is depicted in the vertical coordinate whereas the average time taken to answer is depicted in the horizontal coordinate. The ideal zone would thus be the lower left corner. When mode A is used (fixed-frame), the average number of errors is 2.9 with an average time of 8.3 sec. to answer. When mode B is used (classic tool-frame), the average number of errors is 1.5 and the average time to answer is 5.9 sec. When mode C is used (proposed adaptive tool frame), the average number of errors is 0.6 and the average time to answer is 2.9 sec. The standard deviations with mode A are $\sigma_{\text{time}A1} = 2.3$ sec. for the time and $\sigma_{\text{error}A1} = 0.8$ for the number of errors, with the mode B, the standard deviations are $\sigma_{\text{time}B1} = 1.7$ sec. and $\sigma_{\text{error}B1} = 0.7$, and with the mode C, the standard deviations are $\sigma_{\text{time}C1} = 1.0$ sec. and $\sigma_{\text{error}C1} = 0.6$.

Compared to mode A, mode C led to an average completion time reduction of 65% which was considered statistically significant by using a Wilcoxon signed-rank one-tailed test which led to $\text{p} = 4.9\text{e}^{-4} < 0.05$. The average number of errors was reduced by 79% ($\text{p} = 4.9\text{e}^{-4}$). Compared to mode B, mode C led to an average completion time reduction of 51% which was also considered statistically significant by using a Wilcoxon signed-rank one-tailed test which led to $\text{p} = 4.9\text{e}^{-4} < 0.05$. The average number of errors was reduced by 60% ($\text{p} = 0.014$).

By using the proposed control system, participants were thus able to give faster and more precise answers.

B. Experiment 2: Performing an orientation task

In the first experiment, the participants had to tell which joystick command they would perform to reach a given desired



(a) Position 1
Des. orient.: Downward
A: Joyst.1 Left
B: Joyst.1 Down
C: Joyst.1 Down

(b) Position 2
Des. orient.: Left
A: Joyst.2 Left
B: Joyst.1 Up
C: Joyst.1 Left

(c) Position 3
Des. orient.: Upward
A: Joyst.1 Up
B: Joyst.1 Down
C: Joyst.1 Up

(d) Position 4
Des. orient.: Downward
A: Joyst.1 Left-Down
B: Joyst.1 Up
C: Joyst.1 Down

(e) Position 5
Des. orient.: in paper
A: Joyst.2 Right
B: Joyst.1 Down
C: Joyst.1 Right

Fig. 13: Position of the robot for the first experiment, input of the joystick and the response for the corresponding mode.

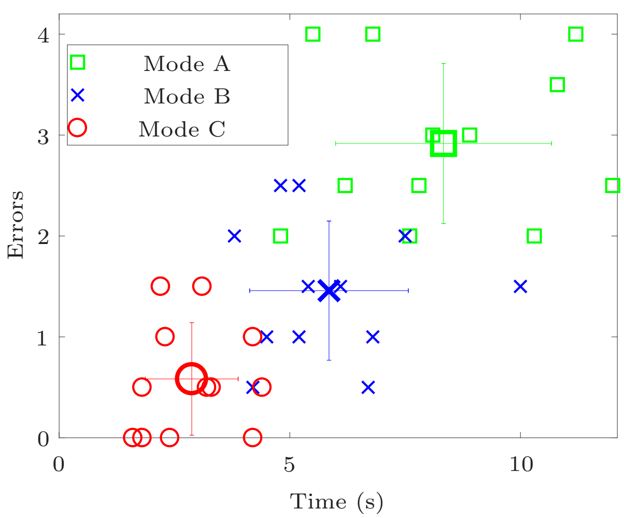


Fig. 14: Results of the first experiment with the number of errors and the average time taken to answer each position.

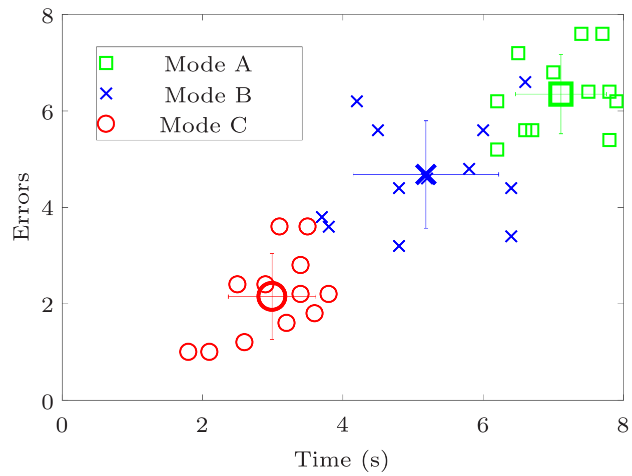


Fig. 15: Results of the second experiment with the number of errors while orienting the robot and the time taken to complete the task.

orientation, without actually touching the controller. In this second experiment, the participants were asked to use the control pad to actually reach the target orientation with the UR5 robot. The objective of the first experiment was to assess if the orientation control mode is intuitive by measuring the time to answer and the exactitude of the answers. In this second experiment, the objective is also to assess the practical impact of employing a given rotation mode while performing a task. The motivation behind this experiment was that even if a given control mode is more intuitive, the actual impact on the time to achieve the task is might not be significant as the user could rapidly find the correct command by trial and error.

The experimental procedure was the same as in experiment 1 but with different desired orientations (right, upward, out of the paper, out of the paper, downward) than in experiment 1 to avoid any learning effect. Also, here, the participants had to physically move the robot to the required orientation.

The participants were first evaluated based on the time to complete the task. Error points were also compiled when the user performed a wrong joystick command to perform a given rotation. For example, rotating the robot hand to the right whereas the target was upward incremented the error counter.

When mode A is employed (fixed-frame), the average number of errors is 6.3 with an average time of 7.1 sec. to answer. When mode B is employed (classic tool-frame), the average number of errors is 4.7 and the average time to answer is 5.2 sec. When mode C is employed (proposed adaptive tool frame), the average number of errors is 2.15 and the average time to answer is 3.0 sec. The standard deviations with mode A are $\sigma_{\text{time}A1} = 0.65$ sec. for the time and $\sigma_{\text{error}A1} = 0.8$ for the number of errors, with mode B, the standard deviations are $\sigma_{\text{time}B1} = 1.0$ sec. and $\sigma_{\text{error}B1} = 1.1$, and with mode C, the standard deviations are $\sigma_{\text{time}C1} = 0.62$ sec. and $\sigma_{\text{error}C1} = 0.9$.

Compared to mode A, mode C led to an average completion time reduction of 58% which was considered statistically significant by using a Wilcoxon signed-rank one-tailed test which led to $\mathrm{p} = 4.9\mathrm{e}^{-4} < 0.05$. The average number of errors was reduced by 66% ($\mathrm{p} = 4.9\mathrm{e}^{-4}$). Compared to mode B, mode C led to an average completion time reduction of 42% which was also considered statistically significant by using a Wilcoxon signed-rank one-tailed test which led to $\mathrm{p} = 4.9\mathrm{e}^{-4} < 0.05$. The average number of errors was reduced by 54% ($\mathrm{p} = 9.8\mathrm{e}^{-4}$).

When utilizing mode A and B, the participants were able to to bring the robot approximately to the right orientation by trying different joystick inputs to infer which command they should choose. However, even if the participants were able to bring the robot approximately to the desired orientation, their trial and error movements led the end-effector to be misaligned in other directions. In order to correct the final orientation, they had to find out again the correct joystick command. However, because mode A and B orientation directions depend on the actual end-effector position or orientation respectively, the orientation direction for a given joystick input changed between the initial position and final position which is even less intuitive. Control modes A and B led to significant increase both in task completion time and efforts compared to the proposed adaptive orientation system (mode C) which allowed participants to reach the desired orientation much faster and with less manipulations of the joystick. The results of the two experiments corroborate the assessment of the orientation control being more efficient and intuitive with mode C (proposed adaptive orientation control) rather than with mode B (classical tool-frame) and mode A (fixed-frame).

C. *Qualitative assessment of the system's intuitiveness*

The main purpose of the proposed orientation control system is to enhance users' experience by enabling them to control the robot with more performance and intuitiveness. Apart from quantitative data obtained in the preceding experiments, an important metric is the participant preference. To that effect, at the end of the experiments, participants were asked to discuss about their orientation control mode preferences. In order to eliminate any bias, the question referred to the first, second and third mode they used and they did not refer specifically to the fixed-frame, tool-frame or adaptive tool-frame. In all cases, mode A (fixed-frame) was revealed to be very difficult and unintuitive. While mode B (classic tool-frame) was easier to use than mode A (fixed-frame), all participants preferred mode C (adaptive tool-frame).

VI. Discussion

Every experiment conducted in this work confirmed that the novel orientation algorithm is significantly more intuitive and efficient to operate. Furthermore, all participants preferred the proposed orientation control method. An important limitation however is that the algorithm was validated with naive users and not yet with the target population (people living with upper body disabilities and operators in industry). Using the opinion of naive users helped us to have access to the opinion of an important number of participants in order to draw statistically valid conclusions. We hypothesize that the participants' opinion will be close to the opinion of target users. Then, based on this version of the algorithm, future work will focus on improving the algorithm for the specific needs of these populations and on assessing the algorithm in real-life tasks. Furthermore, as pointed out by an anonymous reviewer, it would be interesting to include in a study concepts about the mental representation of rotations [42, 43]. Finally, it would be interesting to apply the proposed orientation algorithm to other fields of robotics such as humanoid robots.

VII. Conclusion

In this work, a novel intuitive adaptive orientation control algorithm for human-robot interaction was proposed. The system was implemented on the JACO robot from Kinova and on the UR5 from Universal Robot. Every experiments conducted in this work confirmed that the novel orientation algorithm is significantly more intuitive and efficient to operate. Furthermore, all participants preferred the proposed orientation control method. By making the control more intuitive, the proposed algorithm could also potentially improve the performance in collaborative or cooperative tasks or even controlling humanoid robots.

Future work will focus on clinical validation with motor impaired end-users utilizing different control modalities and on validation with operators in industry. These tests will be employed to assess the algorithm's performance in real-life scenarios and for the improvement of the algorithm.

ACKNOWLEDGMENT

The authors would like to acknowledge the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC).

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