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Learning to teleoperate an upper-limb assistive humanoid robot for bimanual daily-living tasks

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Abstract

Objective. Bimanual humanoid platforms for home assistance are nowadays available, both as academic prototypes and commercially. Although they are usually thought of as daily helpers for non-disabled users, their ability to move around, together with their dexterity, makes them ideal assistive devices for upper-limb disabled persons, too. Indeed, teleoperating a bimanual robotic platform via muscle activation could revolutionize the way stroke survivors, amputees and patients with spinal injuries solve their daily home chores. Moreover, with respect to direct prosthetic control, teleoperation has the advantage of freeing the user from the burden of the prosthesis itself, overpassing several limitations regarding size, weight, or integration, and thus enables a much higher level of functionality. *Approach.* In this study, nine participants, two of whom suffer from severe upper-limb disabilities, teleoperated a humanoid assistive platform, performing complex bimanual tasks requiring high precision and bilateral arm/hand coordination, simulating home/office chores. A wearable body posture tracker was used for position control of the robotic torso and arms, while interactive machine learning applied to electromyography of the forearms helped the robot to build an increasingly accurate model of the participant's intent over time. *Main results.* All participants, irrespective of their disability, were uniformly able to perform the demanded tasks. Completion times, subjective evaluation scores, as well as energy- and time- efficiency show improvement over time on short and long term. *Significance.* This is the first time a hybrid setup, involving myoeletric and inertial measurements, is used by disabled people to teleoperate a bimanual humanoid robot. The proposed setup, taking advantage of interactive machine learning, is simple, non-invasive, and offers a new assistive solution for disabled people in their home environment. Additionnally, it has the potential of being used in several other applications in which fine humanoid robot control is required.

Keywords: assistive robotics, bimanual tasks, daily-living activities, teleoperation, humanoid robotics, myocontrol, human-machine interaction

1. Introduction

The world around us is shaped to be operated by arms and hands [1]. The loss or impairment of the upper limb leads therefore to a dramatic degradation in the quality of living [2, 3]. A person with an upper-limb disability is prevented from swiftly acting in the world since state-of-the-art prosthetic or assistive solutions cannot usually operate more than one degree of freedom (DoF), or if they can, this happens, in most cases, sequentially, one motion at a time [3]. After an amputation, however, surprisingly rich residual muscle activity can still be detected from the surface of the residual limb using, e.g., surface electromyography (sEMG) [4]. In controlled conditions, amputees can produce several discernible signal patterns corresponding to the actions intended to be performed with the absent limb [5]. But so far, such techniques have shown little generalization power across participants and when used in practical environments. This is largely due to signal variability, for example when lifting weights or changing body posture [6], as the registered hand gesture patterns are no longer recognized by the machine learning algorithm in these cases. The problem becomes even more complex whenever the device is supposed to help the participant to operate in unstructured home environments while performing complex tasks such as daily-living chores.

So, whereas most research on using and decoding sEMG signals (myocontrol) for assisting impaired patients is naturally focused on controlling prosthetic devices [7, 8], in this work we tackle a new application, using myocontrol to teleoperate a humanoid robot performing bimanual manipulation tasks in a household environment. There are several reasons behind this idea:

i) Service humanoid robots are thought of as flexible and dexterous assistants for elderly or disabled people. Several dual-arm collaborative robots exist in this context [9]. Freed of the manufacturing constraints of prostheses (weight, size, space, etc.), they can be equipped with much more complex electronics, allowing better reaching and manipulation capabilities than current prosthetic arms.

ii) At the same time, the separation of the manipulation device from the participant avoids the hurdles posed by the typical prosthetic system: excessive weight [10] and heat, bad adherence to the skin, low biocompatibility, etc.

iii) To a large extent, teleoperation is irrespective of distances, meaning that the proposed approach could be used for remote maintenance or search-and-rescue tasks as well. Additionally it could provide disabled users with a possibility of teleworking [11].

iv) Lastly, such a setup allows direct comparison of non-disabled and disabled participants using exactly the same hardware, which has not been the case so far as non-disabled participants used bypass sockets [12], while impaired participants used their prosthesis shaft. Hence, the current setup allows to see how close the performance of impaired patients is to that of the non-impaired participants.

The reliability of myocontrol in unstructured environments can be greatly improved using incremental machine learning (iML) [13, 14], i.e., an algorithm that can accommodate for new knowledge on the fly. Degris et. al. [15] have explored the usage of reinforcement learning in the context of participant/prosthesis interaction. In such approaches, a “lazy” data-gathering strategy is enforced, actively recruiting the participant to update the intent-detection model whenever it becomes unstable and/or new patterns (i.e. actions) are required. In [16], the interaction between the participant and a simulated prosthetic system is studied from a psychological point of view in order to maximize the quality of the data produced by the participant. This methodology heavily relies on a carefully designed protocol to involve the participant in an *action / model building / action loop*. Whether this idea works in practice, however, is still controversial [1].

In order to verify the effectiveness of the proposed framework, we have designed an experiment in which participants teleoperated a dexterous assistive humanoid platform using two commercially available sEMG bracelets and a body posture detection device based upon inertial measurement units [17]. iML was employed to account for and correct instabilities of the intent detection system. The trained model was updated whenever the participant deemed the task to be unattainable. Simple verbal feedback with the experimenter was used to ascertain that an update was required. The tasks to be performed consisted of complex daily-living activities resembling kitchen and office chores involving bimanual coordination, such as unscrewing a bottle, dialing numbers on a phone and manipulating a pot and its lid.

As it is well known that, due to the plasticity of the human brain [18], the more a person repeats a task the more she/he learns and improves in performing it. This has already been shown in [19, 20], in which sEMG was used for teleoperating unimanual tasks. In [20], 8 subjects performed one task, with 4 repetitions and 2 sessions over 2 days. The learning, evaluated with TCTs and path efficiency, was visible over the repetitions and continued over the sessions. [19] shows that, even after a week of non-practicing, the learning regresses only slightly. In our case, we have wondered if disabled participants would achieve similar performance levels when compared to non-disabled participants after several repetitions of teleoperated tasks. We hypothesized that such a teleoperation setup and the associated protocol would enable participants to complete all tasks, and that a learning effect would be recognizable, leading, in the end, to uniform results across disabled and non-disabled participants. We also speculated that the performance of disabled participants would not differ statistically from that of non-disabled ones. The experimental results confirm that all participants were able to quickly and efficiently learn to teleoperate the platform and successfully complete all tasks, and that a learning effect was clearly visible, speeding up the execution of the tasks, increasing the efficiency and decreasing energy consumption over time. Learning was uniform across seven non-disabled participants and two upper-limb disabled persons. One disabled participant was born with right-hand trans-radial congenital deficiency and the second participant had bilateral trans-radial traumatic amputation. The learning effect was even stronger in the case of a single non-disabled participant who repeated the same full set of tasks for five consecutive days.

2. Materials and Methods

2.1. Participants

Seven able-bodied (all males, aged 28.4±7.1 years) and two disabled participants were involved in this experiment (cf. **Table S1**): one congenitally missing his right hand (D1) and the other one having been double-amputated (D2) following a trauma (more details about them are described in **Table S2**). All participants were evaluated over a single session and one of the non-disabled participants repeated the experiment over 5 days.

The experimental protocol was thoroughly explained to the participants before the experiment, and each of them signed a written informed consent form. The experiment was performed according to the WMA Declaration of Helsinki and was approved by the Work Ethical Committee of DLR.

2.2. Protocol of the experiment

The participants were asked to teleoperate the humanoid robot TORO [21] with the goal of performing complex bimanual tasks. In order to do so, the participants were equipped with an IMU-based body tracking device for controlling the arms and torso of the robot [17], and with two Myo-armbands from Thalmic Labs[1], recording the EMG data of the forearm muscles to control the robot's hands, and additionally the wrist(s) in the case of the disabled participants.

TABLE 1
DESCRIPTION OF THE TASKS

Task ID	Summary of the task	Detailed description of the task
1a	Take the lid off the pot and place it on the table.	Take the pot handle with the right hand. With the left hand, take the lid off the pot and place it on the table at place 2.
1b	Take an orange ball and put it in the pot.	With the left hand, take the foam ball from place 3 and place it in the pan. Take the pot's lid from place 2 and put it back on the pot in place 1.
2a	Unscrew the cap of the bottle	With the right hand, take the bottle from place 1, lift it, rotate it about 45° and with the left hand, unscrew the cap.
2b	Pour the bottle's contents into the open pot.	With the left hand, take the pot handle. With the right hand, simulate pouring the contents of the bottle into the pot by rotating the wrist. (The bottle is filled with pebbles blocked at the opening with a foam to avoid dangerous spreading in case of task failure) Place back the bottle at place 1.
3	Type numbers on a fixed phone.	With the left hand, with a pointing index, type on the buttons 9, 1, 1. With the right hand, with a pointing index, press on loud speaker.

[1] previously available at www.thalmic.com

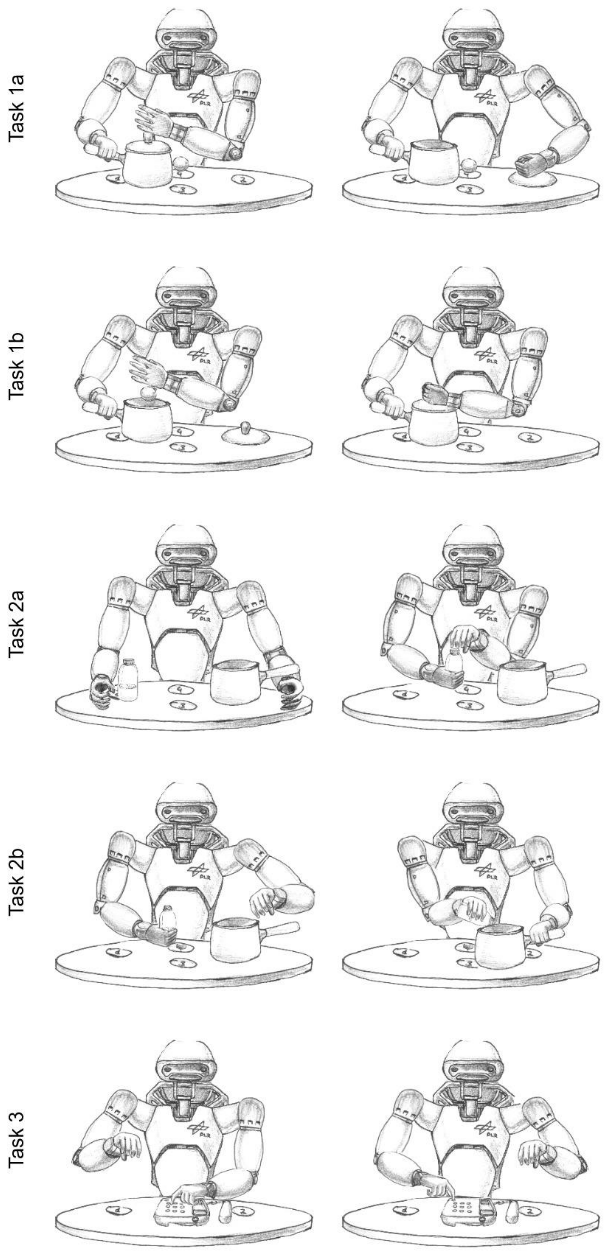

Figure 1. Illustration of the tasks to execute with the assistive robot.

Seven participants performed the experiment, each one in a single session. Additionally, to further investigate the learning effect, one participant was randomly selected from the pool of single-session participants to perform the experiment on 4 additional days for a total of 5 sessions.

The experiment consisted of three tasks, the first two tasks being divided each in two subtasks. These tasks are inspired by those found in assessment protocol for prosthetics users such as the Assessment of Capacity for Myoelectric Control

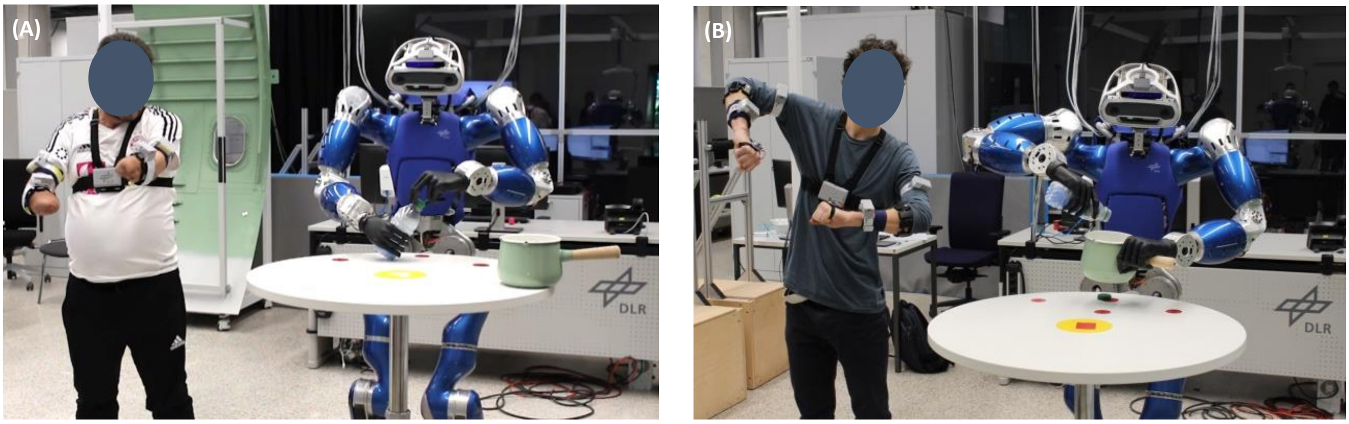

Figure 2. Bird-eye view of the experiment. (A) The double-sided amputee opening a bottle's cap (Task 2A). **(B)** One of the non-disabled participants pouring a bottle's content into a pot (Task 2B).

(ACMC) [22] and from the Chedoke Arm and Hand Activity Inventory (CAHAI) [23, 24], a validated upper-arm functional assessment for stroke recovery, already used in teleoperation experiments [25, 26]. The tasks are explained in detail in **Table 1** and illustrated in **Figure 1**. For the single-session participants, each task had to be repeated four times: the subtasks had to be completed separately before starting a new repetition. As we considered the very first repetition as a familiarization phase, the long-term participant had to perform only three repetitions of the tasks on the remaining days of the experiment after his first session. The familiarization phase was however still kept in the analysis, as it is considered an important phase for the learning effect.

During the experiment, the participants were placed on the right side of the robot at a proper distance from it for safety reasons but so that the table setup was clearly visible to them in order to accomplish the tasks. A bird-eye view of the experiment is shown in **Figures 2A** and **2B**.

Before the first execution of each subtask, the participant was instructed by the experimenter on how to perform that specific subtask. A task was considered as failed by the experimenters if one of the objects fell from the table, if the participant could not retrieve an object, or if it was estimated by the experimenter that the participant could not regain a correct setting of the objects to complete the task. If such a case happened, the teleoperation mode was suspended and the objects would be set back to the initial task setting by the experimenters before the participant could start a new attempt. The participants were not restricted in the number of attempts per repetition. A repetition was considered as completed once the participant achieved the task. Subtasks were achievable separately, meaning, for example, that the participant did not need to restart from task 1a if task 1b failed. A participant could decide to pause or stop the experiment at any moment. If there was a failure from a device, this was also considered as a failed attempt, as the longer the participant took to complete a task, the higher the risk was that a system failure happened. Additionally, if the prediction of the hand action was judged too unstable to perform a task, this was also considered as a failed attempt and the experimenter could decide to collect more samples to train the hand action predictor.

The tasks were performed in the order presented in **Table 1**, except for D2, where, due to a time limitation, and to make sure as many tasks as possible would be completed in this limited time, the experimenters had the participant perform Task 3 before Task 2 as it was considered a shorter task. At the end of the session, the participants were asked to complete a subjective assessment form. Participant D2 was unfortunately not able to complete this form due to a time limitation. The questionnaire was based on the NASA TLX test [27] and different factors were evaluated by the participants on a scale from 0 to 20: mental demand, physical demand, temporal demand, performance, effort and frustration (cf. Supplementary Materials for definitions). When averaging over all criteria, it was decided to transform the only positive criteria 'performance' into a negative one by subtracting the evaluated score to the maximum value of 20 in order to get a global negative index.

As a side note, since the tasks were very different and not designed to be achieved in the same amount of time, we did not compare the TCTs task-wise.

For this experiment, we evaluate the Task Completion Times (TCTs) for each task, the subjective evaluation concordance, the travelled path and the speed of motion for all participants.

2.3. Setup of the teleoperation equipment

The IMU-based upper body tracker system, also called BodyRig [17], was used for transmitting the position and orientation of the participant's hands. It uses the absolute orientation in space of the participant's body segments, gathered via IMUs, to compute the forward kinematics of the participant's body up to the level of the hand using a set of pre-defined link lengths. The difference between these lengths and the link lengths of the participant's actual skeletal frame causes a divergence between the actual absolute position of the participant's hands and the ones measured by the BodyRig. This factor does not influence the measured orientation of the body segments. A problem, which occurred because of this, is, e.g., the user trying to join the robot's hands, but not being able to, due to their own limbs colliding with each other, while the robot's hands are still separated. This was fixed by introducing translational offsets, which could be adjusted on the fly, that were applied to the commanded pose as transmitted from the BodyRig.

The desired hand pose was computed by a hand movement intention predictor. The predictor utilizes EMG as input, as measured by the two Thalmic Lab's Myo sensors. The setup is depicted in **Figure S1A** of the Supplementary Materials (SM) and uses computers to process the data between the BodyRig and the humanoid robot. The sEMG sensors were sampled at a frequency of 200Hz and filtered through a low-pass 1st order Butterworth filter with 2Hz cut-off frequency, while the BodyRig was sampled at 500Hz and filtered through a low-pass 2nd order Butterworth filter with 5Hz cut-off frequency. The main reason for the relatively low cut-off frequencies is that the participants were directed to perform slow and steady movements, which should allow considering any signal with components of higher frequencies as noise, both on the sEMG and on the BodyRig measurements. In the case of non-disabled participants, IMUs were fitted on chest, humeri, forearms and hands (cf. **Figure S1B** in SM), which allows for direct transmission of the participant's hands' pose and orientation. In the case of amputated participants, it was not possible to fit an IMU directly on the hand, and therefore no direct measurement of the wrist angles was possible. In these cases, the hand movement predictor, trained accordingly, transmitted the desired wrist flexion. For the wrist pronation/supination, the desired angle was measured based on the orientation of the corresponding humerus and forearm IMUs. The relevant vectors are shown in **Figure S1C** in SM. The measured pronation/supination angle θ_{radial} was then multiplied by a magnifying factor and an offset was added so as to guarantee reachability of all operationally necessary hand poses by the participant. These factors were set during a calibration procedure at the beginning of the session and at later points, if the need arose.

2.4. Hand movement intention predictor training protocol

The hand movement intention was predicted by a ridge regressor with a Random Fourier Feature-based Kernel [28, 29]. This characteristic typically guarantees better accuracy, but makes the prediction non-linear with respect to the sEMG samples. Due to this, any hand pose given by the combination of two or more actions had to be separately sampled. For example, if a power grasp with flexed wrist was required to complete a task, it was necessary to create a new target vector (for example power flexed in addition to a normal power grasp) and train the predictor with samples corresponding to this specific position. Using a simple ridge regressor, on the other hand, it is sometimes possible to combine target vectors such as wrist movement and a hand grasp to obtain the combination of the two, provided that a high enough number of sensors is available [30], which was not the case here. It has to be noted that commercially available systems (COAPT and Ottobock) also use machine learning allowing multi-DoF control of upper-limb prostheses.

In the case of non-disabled participants, the hand movement intention predictor was trained on samples for all required hand poses (namely rest, power grasp and pointing), while the desired pose wrist was measured directly based on an IMU coupled to the user's hand.

In the case of amputees, the hand movement intention predictor was required to estimate the desired wrist pose as well, as it was not possible to monitor the desired wrist angles by coupling an IMU to the participant's hand. Therefore, the total number of required hand poses was larger, and accordingly the protocol for the disabled participants was to train the predictor on samples corresponding to only the hand poses specifically needed for the current task. These were defined as shown in **Table S3**.

For the case of the unilateral amputee (D1), the predictor was trained only for the missing right hand, while the wrist pose for the healthy limb was transmitted based on the data of the IMU coupled to the hand, like in the case of non-disabled participants. For D1, as a congenital amputee, a non-intuitive control mapping was applied, which consists in using the signals generated by a group of muscles initially not targeted to produce a specific hand action, to actually control the robotic hand's equivalent pose. For D2, the same mapping was used for the pointing gesture in different wrist positions, as the intuitive signal patterns that D2 was able to produce were too similar to each other.

In all cases, the experimenter could add new samples if the prediction was too unstable, with particular focus on samples acquired with the participant in the specific body poses in which the prediction seemed most unstable. These new samples were acquired in 1 to 2 minutes and this time was not considered in the overall completion times, which were based on the cumulative TCTs for successful and unsuccessful trials. The participants were actively requested to indicate if they thought an update was required. At the beginning of each session, EMG was sampled in two body poses, in order to generalize the prediction over the limb position effect. Typically, each hand pose was sampled twice at session start, with the user holding their arms bent at about 90 degrees, respectively with the elbows in contact with the trunk, and with the elbows held outwards from the body.

2.5. Setup of the humanoid robot

In order to perform the teleoperated bimanual tasks, the test participant controlled the humanoid robot TORO. This robot was developed by the German Aerospace Center (DLR) for conducting research on walking and multi-contact balancing. A detailed description of the system architecture can be found in [31, 32, 21]. TORO has a height of 1.74 m, and a weight of 76.4 kg. It features 39 DoFs in total. The legs, arms, and hip contain 25 joints that are based on the technology of the DLR-KUKA LBR (Lightweight robot arm), and can be operated both in position and torque-controlled mode [33]. The neck comprises two DoFs, which are locked at all times during the session, as they are not used for conducting the presented experiments. The robot is also equipped with two prosthetic hands from Touch Bionics (i-Limb Ultra Revolution), each hand providing six DoFs, five for individually flexing each finger and one for rotating the thumb. In terms of sensing, the robot features a position and torque sensor in each of the 25 joints based on the LBR. Besides, the ankles are equipped with force-torque sensors to measure the contact forces and torques at the feet. The chest carries an IMU for obtaining the orientation and angular velocity of the torso.

The participant's intention and motion were captured using the equipment above described. The commands of the participant were summarized as desired poses for each hand's frame of reference. Those poses were transmitted via Wi-Fi to the control system of the robot. The architecture of the control framework [34] for the robot (**Figure S1D** in SM) can be summarized as follows: i) In order to maintain balance, the location of the Center of Mass (CoM) and the orientation of the hip are stabilized via a Cartesian compliance in a predefined configuration. ii) The hands are also governed by Cartesian compliance, and their set points (desired poses) are commanded by the operator. iii) The resulting forces required at the CoM (to keep the balance) and at the hands (to perform the desired task) are used as input to compute the required forces at the feet to fulfill both goals (keeping the balance and performing the task). This is achieved via a constrained quadratic optimization problem [34]. iv) As a last step, the computed forces are mapped to the joint torques, which are then commanded to the robot.

To perform the experiments, the humanoid robot TORO was autonomously keeping the balance using suitable forces at the feet, while the hands were free to perform the commanded manipulation tasks. The balance of the robot was ensured via a passivity-based, whole-body control framework [34]. One of the advantages of this control framework is that it enables a compliant and robust behavior, which is crucial for operating the humanoid robot in environments with uncertainties, such as the presented teleoperation scenario. Furthermore, it allows the operator to safely stand close to the robot to get a better view on the manipulation task at hand.

2.6. Statistical methods

We performed a linear mixed effect regression (LMER) analysis over all tasks, using the R package lme4 [35], with log(*var*), to normalize the data, with *var* being respectively the TCT, speed or travelled distance (sumdist), as the dependent variable, the repetition and the amputation condition as independent variables, and participants and tasks as random effects to adapt to the different initial skill level of each participant and the different difficulties of the tasks. The distributions of the residuals were not statistically different from the normal distribution according to Shapiro-Wilk and Jarque-Bera tests. One-way analysis of variance and Tukey's multiple-comparison test were used to analyze the data ($P<.05$). Notice that a slightly different protocol is used for the disabled participants to consider their amputation. For the long-term subject, we only analyzed the data on a descriptive level as the data were not independent due to the learning effect.

3. Results

The participants had five daily-living tasks to accomplish by teleoperating a humanoid platform while their movements and TCTs were registered. The five tasks, which are described more in detail in **Figure 1** and **Table 1**, can be summarized as follows: opening a pot, placing a ball inside the pot and closing

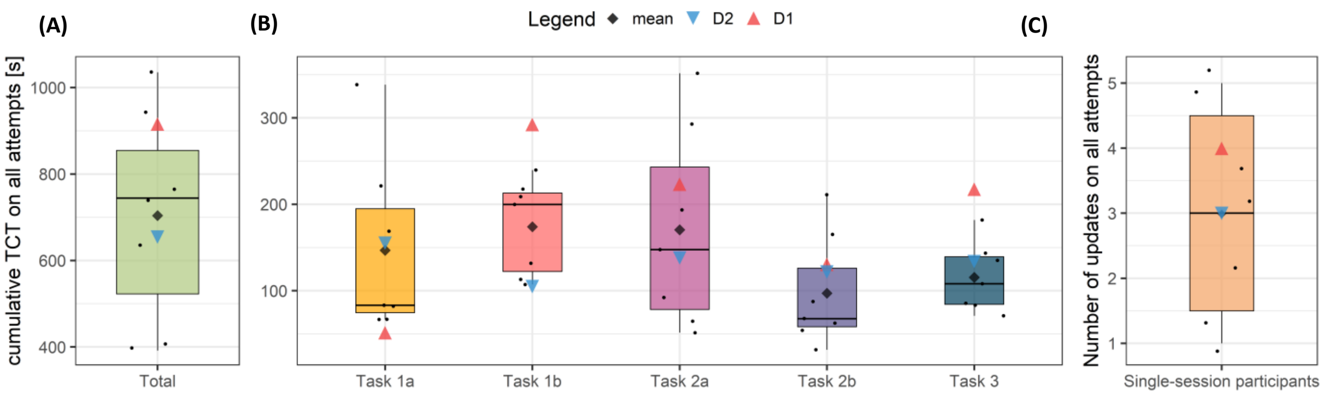

Figure 3. Results of the study on all attempts averaged over the four repetitions. Points indicate the values for each participant. The box limits represent the interquartile range. Error bars indicate 25th and 75th percentile. The bold line represents the median. **(A)** The total task completion time (TCT) on all attempts of all tasks with an average over the 4 repetitions is shown. **(B)** The averaged TCT over the 4 repetitions is shown for each task. **(C)** Number of updates of the iML model during the session, in addition to the initial training.

it, opening a bottle, pouring the content of the bottle, pressing a sequence of buttons on a phone. All details about the design and protocol including the tasks, metrics, setup, and statistical analysis of this experiment can be found in the Materials and Methods section. In the following subsections, we evaluate the TCTs for each task, the subjective evaluation concordance, and the path efficiency for the single-session participants, including disabled participants, and for the long-term participant. In order to better describe the experimental protocol, a video clip in the Supplementary Materials shows exemplary runs of the study with non-disabled participants, as well as with D1 and D2.

3.1. Quantitative evaluation: uniform Task Completion Times

All participants successfully completed all tasks (**Figure 3B**), albeit in some cases the successful attempt (defined in the protocol part of the Materials and Methods section) was preceded by a few failed ones. On average, 1.6 attempts were required to successfully complete each task for the non-disabled participants, 1.95 for D1 and 1.32 for D2 (**Figure 3C**). Total TCTs for all tasks averaged over the 4 repetitions ranged from 392s to 1035s (**Figure 3A**) and the total TCTs of the disabled participants, namely 916s and 655s for D1 and D2 respectively, are comparable to the ones of the non-disabled participants, which averages at 704s. Although in some cases a disabled participant needed more time than the others, e.g., D1 in Task 3, the opposite case also appears, e.g., Task 1a, which D1 accomplished with the shortest TCT of all. D2 also achieved results comparable to the others, with an average TCT for all tasks (131s) slightly better than the mean TCT of non-disabled participants (141s). D1, who has an overall average TCT of 183s, is still comparable to the non-disabled participants. Notice that D1 and D2 obviously used a slightly different setup and protocol to control the robotic wrist (see Materials and Methods for more details). All participants were actively requested to update the intent-detection model whenever it became instable or new patterns were required. The number of updates required per session is visible in **Figure 3C**. On average, during the session, 3 updates were required, ranging from 1 to 5 across the

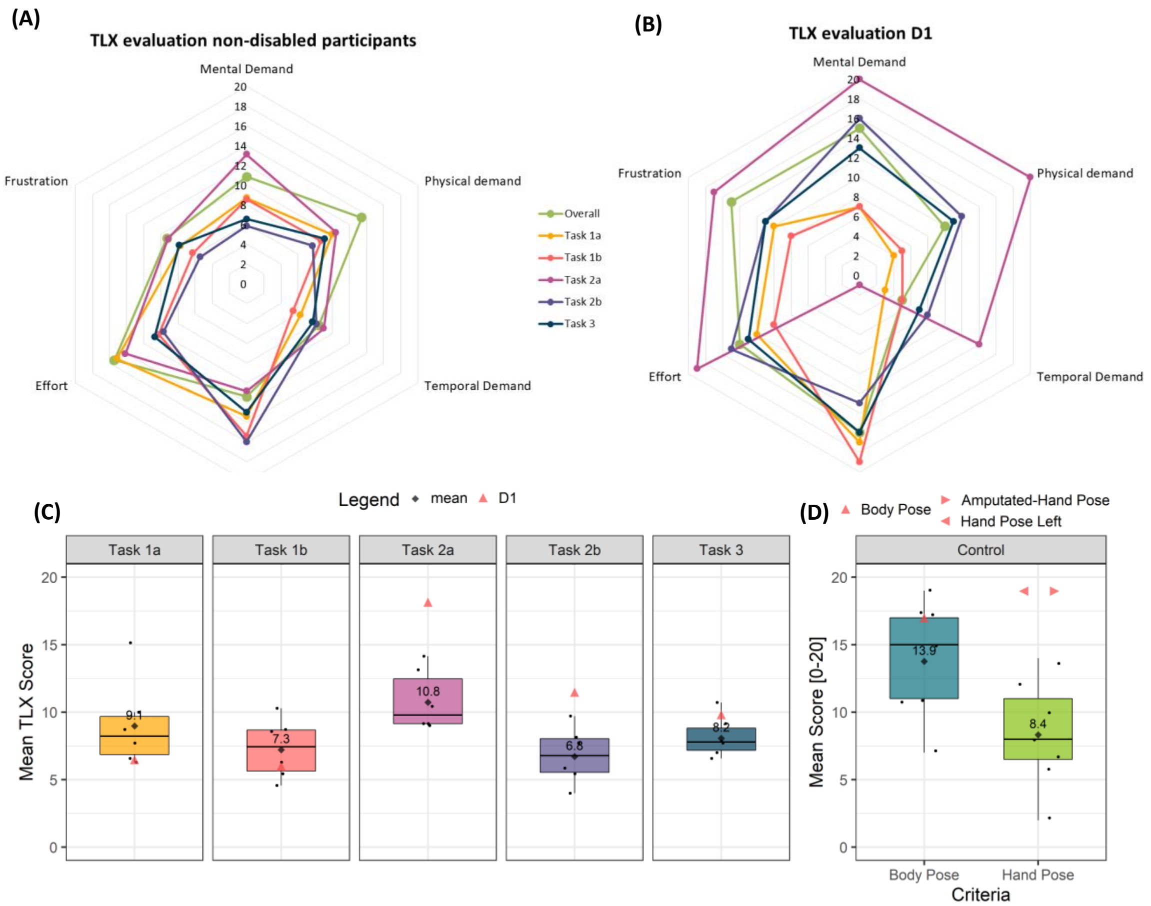

Figure 4. Subjective assessments (based on the NASA TLX evaluation test) for the single-session participants. Subjective scores are between 0 and 20 (the lower the better, except for evaluation of Performance and Control). All criteria are based on self-assessment, including 'performance' and 'control'. D2 did not fill the TLX evaluation due to a time limitation. **(A)** Spider plot of the average TLX evaluation on all non-disabled participants for each criterion. **(B)** Spider plot of the TLX evaluation for the disabled participant D1 for each criterion. **(C)** Task-wise average evaluation criteria. For this average, the positive criteria 'performance' was transformed into a negative one by subtracting the evaluated score to the maximum possible (20) in order to get a global negative index. (the lower the better) **(D)** Evaluation of the quality of the body pose control and the hand pose control. (the higher the better)

participants. D1 and D2 respectively needed 4 and 3 updates, including the necessary update for Task 3 as described in Table S3 in the Supplementary Materials.

3.2. Subjective evaluation

Figure 4A shows the outcome of the subjective evaluation based on the NASA TLX questionnaire [27]. Task 2a (unscrewing a bottle) was judged the most complicated one, having the highest scores in terms of mental, physical and temporal demand as well as frustration, the second-highest in terms of effort and the lowest in terms of estimated performance with a total average score of 11.1 out of 20. Task 1a was graded with the highest effort score. The temporal demand of each task of this subjective evaluation qualitatively matches the TCTs found in **Figure 3B** with the exception of Task 2a, which was considered as more time consuming than Task 1b, whereas the mean TCT of the latter is actually slightly higher than the one of the former. As can be seen in **Figure 4C**, both Tasks 1a and 2a were considered more complicated than the tasks which followed them with the same table setup, respectively Tasks 1b and 2b. Quality of control perceived by the participants is shown in **Figure 4C**: out of 20, the body pose control was graded on average at 13.9 while the hand pose control was estimated at 8.4.

Figure 4B shows D1's subjective evaluation. His ratings are comparable to those of all other participants, with the remarkable exception of Task 2a which he rated very difficult on all criteria. Considering the other tasks, overall the mental demand was higher; the temporal demand was judged slightly lower for all tasks compared to the pool of intact participants in **Figure 4A**; the frustration was overall superior, whereas the performance was overall rated similarly higher. When analyzing the mean TLX score of **Figure 4C**, a lower averaged score compared to the pool of intact participants emerges for Tasks 1a and 1b, while the opposite appears for Tasks 2a, 2b and 3. On the other hand, D1 rated control

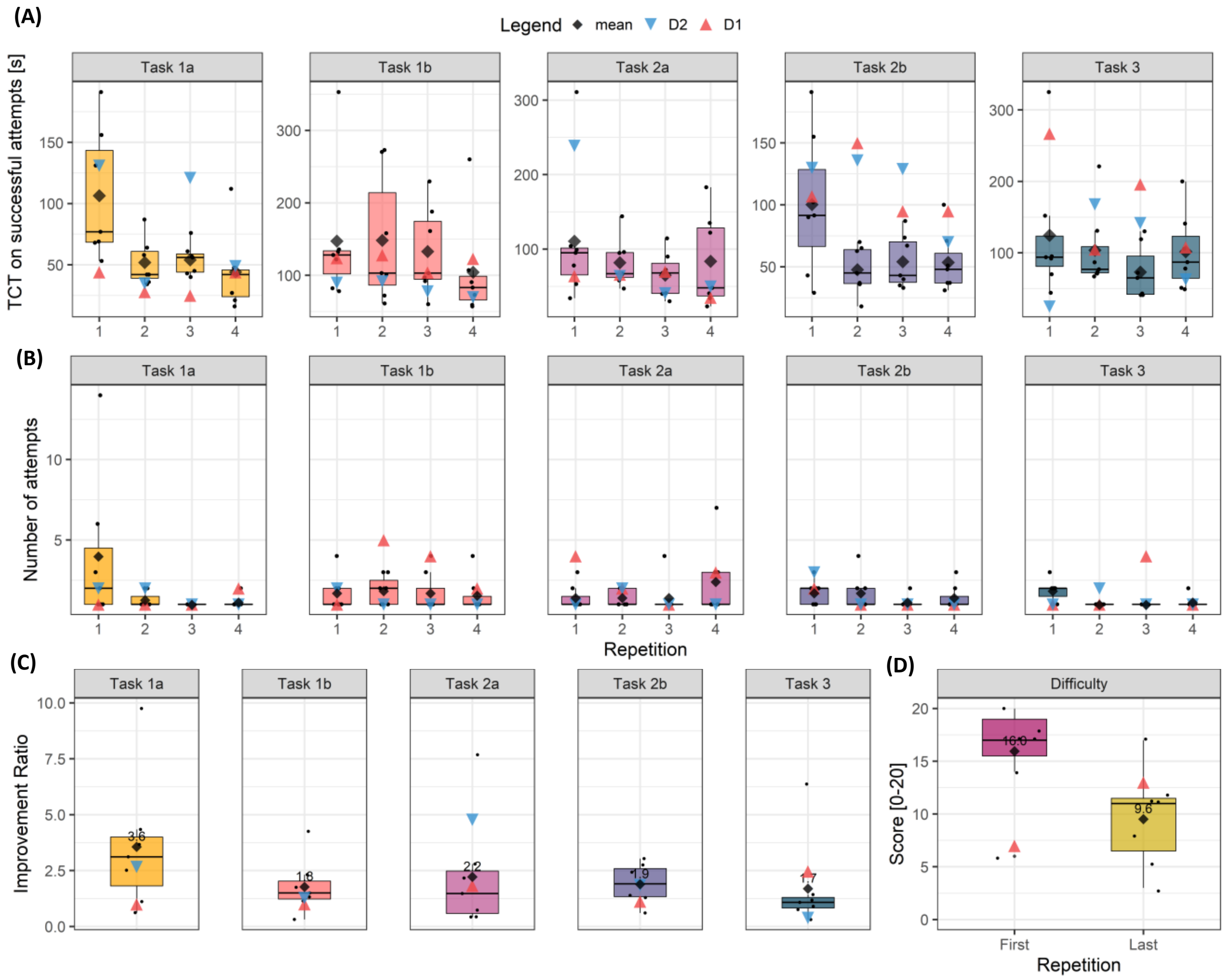

Figure 5. Results of the study on successful attempts for the single-session participants. All criteria are based on self-assessment, including 'performance' and 'control'. D2 did not fill the TLX evaluation due to a time limitation. **(A)** Task-wise TCTs on the successful attempts across repetitions performed by the single-session users (including the disabled ones). **(B)** Task-wise number of attempts per repetition performed by the single-session users. **(C)** Task-wise improvement ratios on the TCTs of the successful attempts between the first and the last repetition for the single-session users (including the disabled ones). (the higher the better) **(D)** Evaluated difficulty on the first and last repetitions for the single-session users and D1 (the lower the better). D2 did not fill the subjective assessment.

(**Figure 4D**) quite in the opposite way with respect to other participants, with a higher rating on the hand pose and a slightly lower one for the body pose. Remarkably, D1 rated similarly control of the left and the right hand. All in all, control scores by D1 are higher (therefore better) than those by non-disabled participants.

3.3. TCTs and number of attempts during single-session experiments

Figure 5 shows the TCTs obtained during single-session experiments, split across single tasks and task repetitions, considering the successful attempts only, and the number of attempts per task and repetition. A decrease in the TCTs while considering each task and the related repetitions is apparent. In all cases, the first repetition has the longest TCTs. While participant D1 had a higher average regarding cumulative TCT on all attempts (293s) for Task 1b, as shown in **Figure 3B**, the averaged TCT for this specific task when considering only the successful attempt (120s) is lower than the average TCT of the pool of participants (133s) as it can be seen in **Figure 5A**. Additionally, D1's TCTs are in line with the non-disabled participants' TCTs, despite being graded with the lowest scores in the TLX evaluation. Considering the data of all single-session participants (with both intact and disabled participants), we performed an LMER analysis, with log(TCT), to normalize the data, as the dependent variable, the repetition and the amputation condition as independent variables, and participants and tasks as random effects to adapt to the different initial skill level of each participant and the different difficulties of the tasks. The analysis showed a significant difference between repetitions 1 and 2 ($p=0.040$), between repetitions 1 and 3 ($p=0.007$), and between repetitions 1 and 4 ($p<0.001$), and no significant difference deriving from the amputation condition.

The number of attempts shown in **Figure 5B**, while also showing a decreasing trend for Task 1a and Task 3, does not follow the same trend for the other tasks. **Figure 5C**, showing the improvement ratio between repetitions 1 and 4 of each task, confirms this statement. The improvement ranged from 3.6 times (Task 1a) to 1.7 times (Task 3), with an average of 2.2 times. A clear improvement is also visible in **Figure 5D** showing that the subjective assessment of difficulty dropped from the first repetition to the last one from 16.0 to 9.6 out of 20.

D1 achieved a very low TCT in Task 1a, therefore his improvement is relatively low in this task. D2 had a higher improvement rate for Task 2a than most of the participants. In the other tasks, both D1 and D2 are in line with the pool of intact participants with the exception of Task 3, in which their improvement rate is higher. The perceived difficulty evaluated in **Figure 5D** by D1 shows an opposite trend compared to the pool, with a higher difficulty during the last repetition than during the first one.

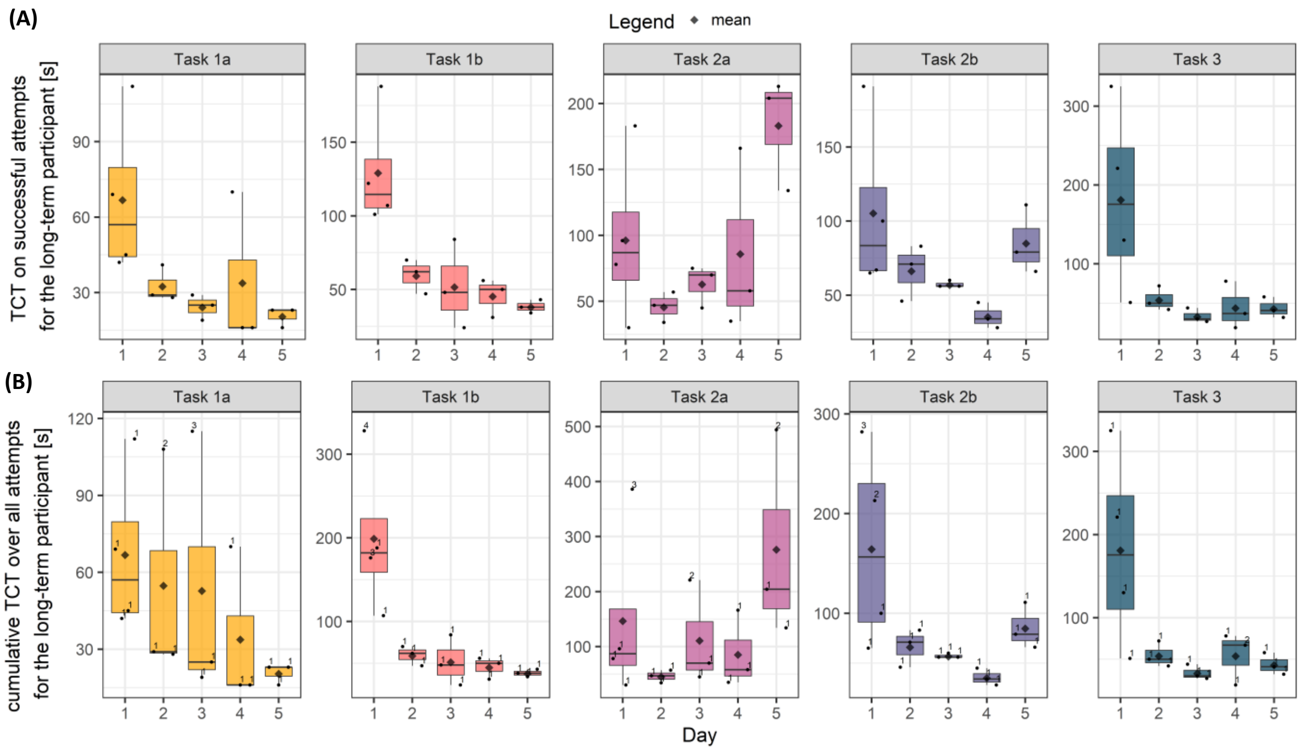

Figure 6. Results of the study for the long-term participant. (A) Task-wise TCTs on the successful attempts performed by the long-term participant across the days. All tasks except Task 2a present a decreasing trend. The points represented in each box plot are placed in the order of the repetition number. **(B)** Task-wise cumulative TCTs over all attempts performed by the long-term participant across the days. All tasks except Task 2a present a decreasing trend. The points represented in each box plot are placed in the order of the repetition number and the number above it indicates the number of attempts.

3.4. TCTs and attempts number during the multi-session experiment

A day-by-day learning effect (decrease in the TCTs on successful attempts), similar to the one previously observed in the single-session users, is apparent in **Figure 6A**, especially for Tasks 1a, 1b and 3. For Task 2b, this decrease is visible over the first 4 days; and on the fifth day, a slight increase can be noted. The tendency over the days for Task 2a is not completely clear. A similar effect is apparent from **Figure 6B**, showing the cumulative TCTs over all attempts. Task 1a shows the highest variance; additionally, the number of attempts between Day 1 and Day 5 is also decreasing with an average of 1.5 attempts on the first day, already decreased to 1.1 on Day 2 maintained until Day 5 with the exception of 1.2 attempts on Day 3. When considering the difference between the TCTs of Day 1 and the other days for all tasks, we notice a strong decrease between Days 1 and 2, Days 1 and 3 and Days 1 and 4 but when considering Day 5, the decrease is not visible for Tasks 2a (being considered as the most difficult task) and 2b.

Figure 7. Results of the NASA TLX test and improvement ratios of the long-term participant. (A) Evaluation of the different TLX criteria over the days for each task and overall. **(B)** Evaluation of the difficulty for the first and last repetitions over the session with a box plot gathering the results over all days. (the lower the easier) **(C)** Evaluation of the quality of the body pose control and the hand pose control over the session with a box plot gathering the results over all days. (the lower the better) **(D)** Task-wise improvement ratios on the TCTs of the successful attempts between the first and the last repetition. One data-point represents the improvement ratio for one day. (the higher the better) **(E)** Improvement ratios averaged over the tasks on the TCTs of the successful attempts between, respectively, Day 1 and Day 2 (RatioD12), Day 1 and Day 5 (RatioD15), and Day 2 and Day 5 (RatioD25). (the higher the better)

Figure 7A, showing the results of the NASA TLX test of the long-term participant, furthermore confirms the effect. While the participant estimated his overall performance at 8/20 on the first session, it rises to 19/20 on the last one. Individual tasks also show a relatively regular growth on this criterion with the exception of Task 2a, which, after a significant increase from 8 to 13 on the second session, seems to decline during the following sessions until finally reaching 12 on the last one. The subjective effort evaluation follows a similar trend with an important increase between the first and second session followed by stabilization. Task 2a's mental demand is relatively high compared to the other tasks and the temporal demand increases over the sessions. Nonetheless, a clear learning curve is visible for all the other tasks as well as for the overall evaluation.

The long-term participant also presents an overall decreasing trend in terms of evaluated difficulty as shown in **Figure 7B**. While the participant evaluated the tasks as being less difficult on the last repetition than on the first one on the first day, it arrives at an equal level for both repetitions on Day 5, indicating a learning effect by the stabilization of the difficulty. Regarding the evaluation of the control (**Figure 7C**), as previously shown in the single-session pool, the body pose control obtains better grades than the hand pose control. Additionally, while the body pose control grading stays relatively stable over the 5 sessions, the hand pose control is increasing over the sessions with a considerably higher increase between Day 1 and Day 2. The improvement ratio of the long-term participant over the sessions shows a similar learning to most tasks as shown in **Figure 7D**. Additionally, as indicated by the improvement ratios over the days (**Figure 7E**), the main part of the learning happened between Day 1 and Day 2 with an improvement ratio of 2.2, while the improvement ratio between Day 2 and 5 was of 1.1. The overall improvement ratio between the first and the last session reached 2.5.

On the first day, 5 updates of the interactive machine learning model were necessary for the long-term participant. This number decreased to 1 for all following days.

3.5. Average speed and travelled path

Both the single-session participants and the long-term participant show an increased hand speed over the repetitions of the different tasks (**Figure 8**). For the single-session participants, all tasks display an increasing trend, except Task 3 (**Figure 8A**). The disabled participants have an average speed (0.071m/s) higher than the non-disabled ones (0.044m/s). Considering the data of all single-session participants (disabled and non-disabled), we performed an LMER analysis, with log(speed), to normalize the data, as the dependent variable, the repetition and the amputation condition as independent variables, and participants and tasks

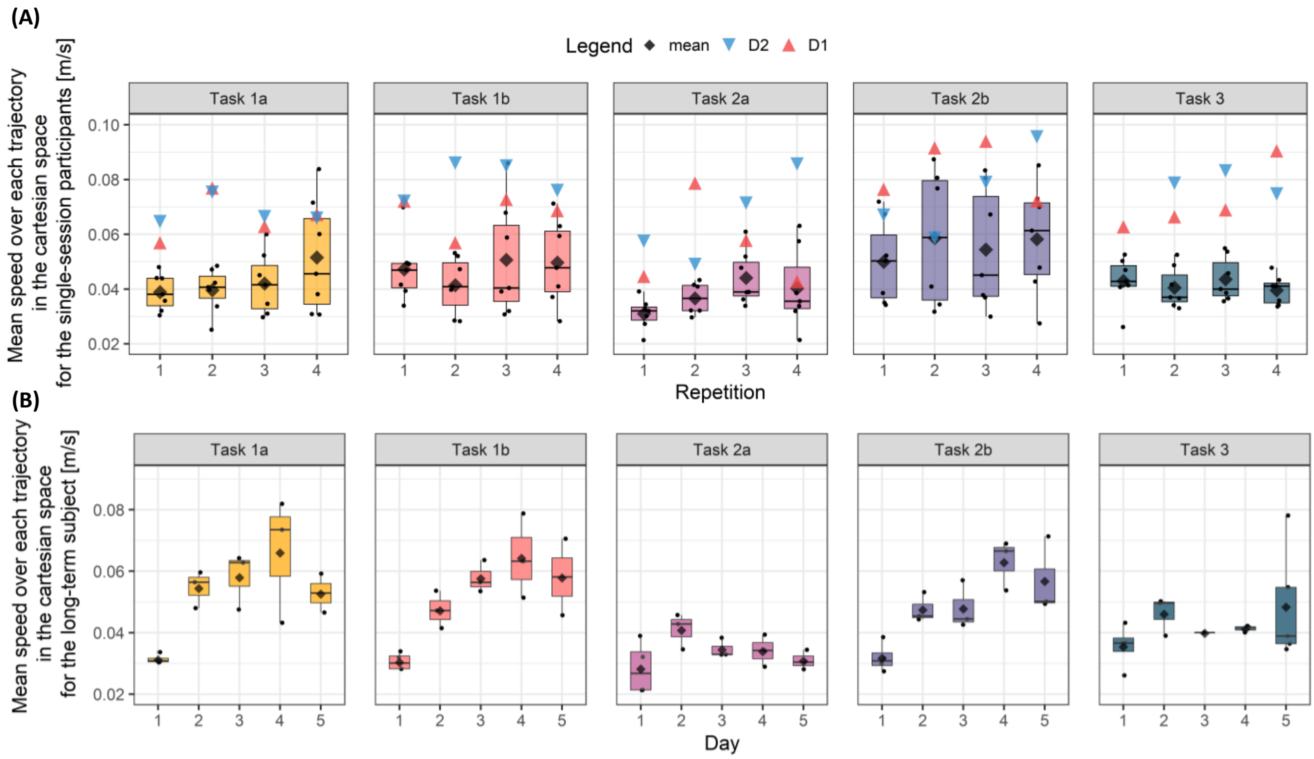

Figure 8. Averaged speed for all participants. The average speed over the trajectories is calculated for the hands of the participants and summed for both hands. **(A)** Task-wise average speed over the trajectories for each repetition for the single-session participants (including the disabled ones) with a generally increasing trend. Outliers of S2, S5 and D2 on respectively, rep. 2 of Task 2b, rep. 2 of Task 2a, and rep.1 of Task 3 were removed due to logging errors. **(B)** Task-wise average speed over the trajectories for each day for the long-term participant with a generally increasing trend. Outliers of the long-term participant on the third repetition of Tasks 1a and 1b of Day 5 were removed due to logging errors.

as random effects. The analysis showed a significant difference between repetitions 1 and 3 (p=0.017) and between repetitions 1 and 4 (p=0.015).

The speed over days (**Figure 8B**) also display a generally increasing trend for all tasks. The trend for Task 2a (evaluated as more difficult) over days is flatter than for the other tasks. On the last day, the long-term participant reached an average speed of 0.053m/s for Tasks 1a, 1b and 2b (compared to the mean of 0.043m/s for intact single-session participants, 0.066m/s for D1, 0.068m/s for D2), and 0.031m/s for the Tasks 2a and 3 (0.042m/s for intact single-session participants, 0.072m/s for D1, 0.079m/s for D2), which require less arm movements.

Additionally, not only the participants gained in speed, but their total travelled path was also reduced over the repetitions and days as shown in **Figure S2** in SM. The cumulated distances over the trajectory of each successful repetition was calculated for each hand and summed together. The total travelled distance of both hands follows a generally decreasing trend over the repetitions for each task.

Considering the data of all single-session participants, we performed an LMER analysis, with log(sumdist), as the dependent variable, the repetition and the amputation condition as independent variables, and participants and tasks as random effects. The analysis showed a significant difference between repetitions 1 and 3 (p=0.035) and between repetitions 1 and 4 (p=0.002).

The hands of the disabled participants travelled distances comparable (albeit higher) to the ones of the non-disabled participants with an average of 6.56m travelled for all tasks over all repetitions for D1 and 7.54m for D2. In comparison, non-disabled participants travelled on average 3.62m. The total distances travelled by the hands of the long-term participant also followed a decreasing trend over the days, except for Tasks 2a and 2b in which the hands travelled longer distances on the last day.

4. Discussion

4.1. Feasibility, TCTs and improvement ratios

The first general remark is that *all participants (disabled or not) were able to complete the 5 tasks*, requesting on average 3 updates of the iML per session; moreover, the disabled participants had overall TCTs comparable to those of non-disabled ones. The tasks were complex bimanual ones requiring fine arm / hand coordination, and involved daily-living non-instrumented objects.

Secondly, *a uniform decreasing trend* in the TCTs was found, with substantially shorter times during the last repetition of each task, in spite of a slight increase in the very last repetition when compared to the previous one, which could be explained by fatigue. From the statistical analysis. A significant difference appeared between repetition 1 and all the other repetitions with no significant effect from the amputation condition. The decreasing trend is consistent across disabled and non-disabled participants and in both the single- and multi-session experiments, and is confirmed by the improvement ratios (2.3 for non-disabled, 1.49 for D1, 2.2 for D2, and 1.54 for multi-session participants). Regarding the multi-session participant, there is a strong decrease of the TCTs between the first and second day but less important between the second and the last days, implying possibly that a large part of the learning happened between Day 1 and Day 2. This is confirmed by the improvement ratios between Day 1 and Day 2 being at 2.2 and the improvement ratios between Day 1 and 5 and Day 2 and 5 being 2.5 and 1.1, respectively.

4.2. Subjective evaluation

4.2.1. TLX Score

This learning effect is further confirmed by the subjective evaluation, with a substantial decrease in the perceived difficulty of 32% between the first and the last repetition for the non-disabled participants. D1 however perceived a higher difficulty for the last repetition, which might be due to the fatigue that could have been increased by two factors in the case of disabled participants, namely the non-intuitive mapping of control patterns inducing a high mental demand (confirmed by the higher scores given overall to the mental demand criterion when compared to non-disabled participants) and the stimulation of usually unused muscle groups causing physical fatigue. This would additionally explain the increasing TCTs of the disabled participants for the last two tasks. This tiredness of the participant could have been further increased by Task 2a, which was considered as the most demanding task, and was the one requiring the highest number of hand-wrist poses to be predicted in the case of disabled subjects. The fatigue induced by such tasks involving precise manipulations would also explain the performance deterioration in the following tasks [36]. The task-wise averaged TLX score would also confirm this hypothesis with a lower (and therefore better) score compared to the non-disabled participants on the first two tasks and a higher one on the last three tasks. Unfortunately, as D2 did not fill the post-experiment subjective form, we could not corroborate this hypothesis with his results.

4.2.2. Hand and body-pose control score

The overall lower grades of the hand pose control when compared to the body pose control are reflecting the fact that the hands were controlled by the prediction of a machine learning algorithm trained on previously registered EMG data while the body pose had a more direct control via the IMUs. Additionally, when looking at the multiple-days experiment, the body-pose control rating remains almost stable over the days while the hand-pose control increases. This could indicate that most of the learning had to be done on the hand-pattern control. *De facto,* this reflects what the experimenters noticed, namely that the participants, being confronted with a humanoid robot, tended to imitate the hand gesture that they wanted the robotic hand to mimic rather than the ones trained in the initial phase of the experiment. For instance, they actively opened their hand to grasp the ball rather than relaxing their muscles, or made a half-open grasp rather than a closed fist to grasp objects.

On the other hand, D1 rated the control in the opposite way with respect to the non-disabled participants, with a higher rating on the hand pose control and a slightly lower one for the body pose control, which could be determined by the daily use of a 1-DoF prosthesis by the disabled participant as opposed to a 6-DOF one in this experiment. The equally-rated control of the left and right hands by D1 highlights the successful control scheme established for the amputated side with respect to the intact side; this control scheme is further detailed in the Material and Methods section. Finally, the overall higher control scores by D1 compared to non-disabled participants indicates successful usage of the device.

The long-term participant presents the highest improvement ratio in Task 3. The fact that this specific task involved more hand gesture control skills (the pointing gesture being more difficult to reproduce with relation to the trained one) would furthermore confirm that an important part of the learning had to be realized on the hand gesture control.

4.2.3. Particularly challenging task: Task 2a

Task 2a was considered very demanding according to the subjective evaluation of the single-session participants. Its difficulty is confirmed by the evaluation of the long-term participant, the mental demand being considerably higher than the other tasks and the temporal demand even increasing over the sessions. The difficulty of this task can be explained by the high precision required to remove the cap and the vision angle of the subject, which limited the depth perception. The extension of the wrist while maintaining the power grasp did not seem to be a problem for the non-disabled participants but was more complicated for the disabled ones due to the fact that the combined movements depended solely on the prediction of the machine learning algorithm.

4.3. Travelled path and speed of motion

Lastly, given a few exceptions, we found *a uniform decreasing trend in the path travelled by the hands of the participants, together with a similar increasing trend in the speed of motion.* This denotes increased time- and energy-efficiency as the experiments progressed, learning to follow shorter paths with higher speed, thus better controlling the robot. In particular, it indicates that arm movements became more precise over time, and that the subjects became progressively able to avoid most mistakes. Some exceptions can be noticed: the travelled path of Task 3 for the single session participants and Task 2a for the long-term one follows a relatively flat trend compared to the other tasks, which could partially be explained by the fewer hand movements needed in these specific tasks where good hand gesture control and more precise body pose control were required. This could also justify the slower speed that the long-term participant showed for the same two tasks. Additionally, we suppose that the constraints for the pouring of the bottle in Task 2b were not defined strictly enough. This action was performed by shaking the bottle by only some subjects, and this could explain the larger interquartile range shown by the single-session subjects on Task 2b. Additionally, while the specific prediction control of the hands in the case of the disabled participants may have had an influence on their longer travelled path and higher speed, the latter might also be due to the daily experience of using a prosthesis.

4.4. Comparison with the state of the art

The experiment presented in this study is, to the best of our knowledge, unique so far; therefore, the study presents a number of limitations. Firstly, despite the use of standardized performance metrics [37], a proper comparison with any baseline whatsoever is difficult, due to the very peculiar experimental conditions and setup we used. Nonetheless, Herlant et al. [25] have performed similar tasks, also inspired from the CAHAI in a teleoperation setup, involving one robotic arm controlled via a joystick and mode switching. The six participants performed the tasks of unscrewing a jar, pouring water and dialing 911 in an average time of 400s, 460s and 180s respectively, while the average cumulative TCTs for the similar tasks in our study were of 171s, 97s and 115s. Although different objects and instructions were obviously used, the bimanual capability and the intuitive control of our setup would, in all likelihood, be the reason behind the shorter times obtained in our experiment. Although bimanual teleoperation has been widely studied [38, 39, 40, 41, 42, 43], our work was mainly evaluating home tasks, while other bimanual teleoperation experiments focused on field tasks where TCTs, difficulty were also evaluated as well as success rates [44]. The tracking method used is often wired or dependent on external tracking [45, 46], including also the previously published video[2] [47], which has initiated this study (of which initial results were presented in [48]). In this work, we use a wearable, wireless and independent device both for hand movement recognition and upper-body tracking.

4.5. Limitations and future work

Our work is the first one evaluating teleoperation of a bimanual assistive platform by disabled persons. In this case, amputees with two different kinds of amputations were participating in the study. However, we believe that this setup, or a similar one, could eventually be adapted for other kinds of disabilities, such as Parkinson’s disease. For people suffering from muscular atrophy, the IMUs in this setup would

[2] https://www.youtube.com/watch?v=M6mQWcLAiko

likely have to be replaced by additional thoughtfully placed sEMG sensors. For instance, in [49], two persons suffering from spinal muscular atrophy (SMA) and equipped with an sEMG-based interface could perform autonomously functional reach and grasp tasks in activities of daily living.

A further limitation of this teleoperation experiment was the viewpoint of the participants with relation to the objects to manipulate: their vision was sometimes occluded by the arm of the robot, thus forcing the participants to take a step forward or backward (as long as the torso stayed aligned, this step was possible without causing an unintended robot motion). This visibility problem is all the more pertinent in a real-world scenario, where it would be common to have the robot placed at a remote location from the user. Valiton et al. [50] have studied this problem in more detail by evaluating camera selection and placement strategies with relation to the time to complete the tasks and the cognitive load. The results are however highly user-dependent, and further studies on the topic are necessary with possible decision support from learned models of camera preference to help the operators. An additional option is to integrate depth perception, which has shown to improve the execution of certain tasks [51], within the visual feedback, which would be feasible in our case by using the 3D cloud of points generated by the robot's cameras and having the user wear a virtual reality headset.

Although embodiment is generally solicited for enhanced teleoperation [52], the higher level of embodiment induced by the headset could also have a counter effect by increasing the problem of mimicking untrained hand gestures that the participants had while performing the tasks. This could be solved in the case of non-disabled users by replacing the prediction-based hand gesture control by a direct mapping of subject-to-robot finger motions using for instance a data-glove[2] [53, 54, 55]. Such data-gloves could be a better alternative to sEMG for non-disabled people to teleoperate such a platform. The complementarity with IMUs if the glove only covers the hand would however remain useful [53] and a comparison study would be interesting with a full data-suit.

At the expense of embodiment, shared control would be another option to evaluate in such a context and it has already been successfully implemented in bimanual humanoid robot manipulation in [56] for non-disabled participants as well as adapted for SMA patients in [57], in which non-disabled participants are involved in a teleoperation experiment of a robotic arm attached to a wheelchair. Additionally, participants could benefit not only from a visual feedback but also from a haptic one, leading towards telepresence rather than teleoperation [58, 59]. For example, a bimanual haptic feedback device has been implemented for teleoperation with non-wireless setups in [60, 44], as well as by the *Shadow Robot Company*[3]. For application to amputees however, a special feedback device should be thought of, e.g. a vibrotactile one [61, 62] or intraneural stimulation [63, 64]. As it is well known in the prosthetic community, feedback is one of the numerous problems still unsolved [2, 5], partly due the lack of space for sensor electronics in the dexterous prostheses currently on the market. These hands have numerous regulations to follow and the size, weight, robustness and electronics integration are problems invariably faced by the manufacturers. There are some notable exceptions involving sometimes targeted muscle reinnervation [65], allowing for instance feedback, multi-DoF wrist (such as in the RIC arm [66] or the Modular Prosthetic Limb [59], only available for trans-humeral amputees so far) or finger abduction/adduction. Yet another problem is the current lack of a 2-DoF active wrist integrated in the multi-dexterous trans-radial prostheses [5]. The presented setup allows the control of these 2 DoFs: flexion/extension by machine learning prediction, and pronation/supination, that no prosthetic companies provides simultaneously to the best of our knowledge. This pronation/supination is added very intuitively as it is simply controlled by the worn IMUs and the user has only to move the arms for the robot to reproduce it. The same is valid for all the additional DoFs of the humanoid platform: as they are controlled from the end-effector position, there is no additional burden to the user and they can possibly allow positions that available prostheses would not. While it needs to be noted that, in most cases, amputees would be able to tackle the task with their own prosthesis as most of our everyday tasks are egocentric, such a setup could come as a complementary help for them when a prosthesis does not bring the required amount of dexterity and complexity, such as with the number of DoFs mentioned above. Of course, the cost of such a platform would need to be taken into consideration as it can vary widely and a dual-arm system could be a viable alternative to a humanoid robot. Moreover, as discussed beforehand, this setup could be adapted to other kind of disabilities in which a prosthesis would not be of help. Notwithstanding the fact that the wearable multimodal sensors presented in this paper could be used when such advanced prostheses, i.e. including a 2-DoF active wrists, will be available (also for trans-radial amputees), the access to teleoperation platforms by disabled persons could open new possibilities of autonomy not available to them as of now, including telework [11].

5. Conclusion

In this study we validated the feasibility of using interactive myocontrol to teleoperate a humanoid robot performing highly complex bimanual tasks, inspired by daily-living activities. Clear learning curves were apparent from the results, demonstrating a decrease in the completion times, an increase in speed, but also a reduction of travelled distance underlining the gain in energy-efficiency for all participants, irrespective of their disability. This setup could potentially be used to teleoperate any other bimanual system in a home

[3] https://www.youtube.com/watch?v=3rZYn62OId8

environment as an assistive platform, and also theoretically in extreme environments in which an operator could teleoperate the robot at very distant locations in order to perform critical tasks.

Appendix

All appendices are attached as supplementary material (stacks.iop.org/BPEX/8/015022/mmedia):

Text. Definition of Task Demand Factors

Figure S1. Setup of the experiment.

Figure S2. Distance travelled by both hands for all participants

Table S1. Participant characteristics.

Table S2. Disability characteristics of the disabled participants.

Table S3. List of task-specific hand poses on which the predictor has to be trained in the case of amputation.

Movie S1. Telemanipulation experiment on a humanoid platform by disabled and non-disabled participants.

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Data and materials availability: All data needed to evaluate the conclusions in the paper are present in the manuscript or the Supplementary Materials. Data files are available upon reasonable request.

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