Virtual Reality Pre-Prosthetic Hand Training with Physics Simulation and Robotic Force Interaction

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***Abstract*—Virtual reality (VR) rehabilitation systems have been proposed to enable prosthetic hand users to perform training before receiving their prosthesis. Improving pre-prosthetic training to be more representative and better prepare the patient for prosthesis use is a crucial step forwards in rehabilitation. However, existing VR platforms lack realism and accuracy in terms of the virtual hand and the forces produced when interacting with the environment. To address these shortcomings, this work presents a VR training platform based on accurate simulation of an anthropomorphic prosthetic hand, utilising an external robot arm to render realistic forces that the user would feel at the attachment point of their prosthesis. Experimental results with non-disabled participants show that training with this platform leads to a significant improvement in Box and Block scores compared to training in VR alone and a control group with no prior training. Results performing pick-and-place tasks with a wider range of objects demonstrates that training in VR alone negatively impacts performance, whereas the proposed platform has no significant impact on performance. User perception results highlight that the platform is much closer to using a physical prosthesis in terms of physical demand and effort, however frustration is significantly higher during training.**

***Index Terms*—Prosthetics and Exoskeletons; Virtual Reality and Interfaces; Rehabilitation Robotics**

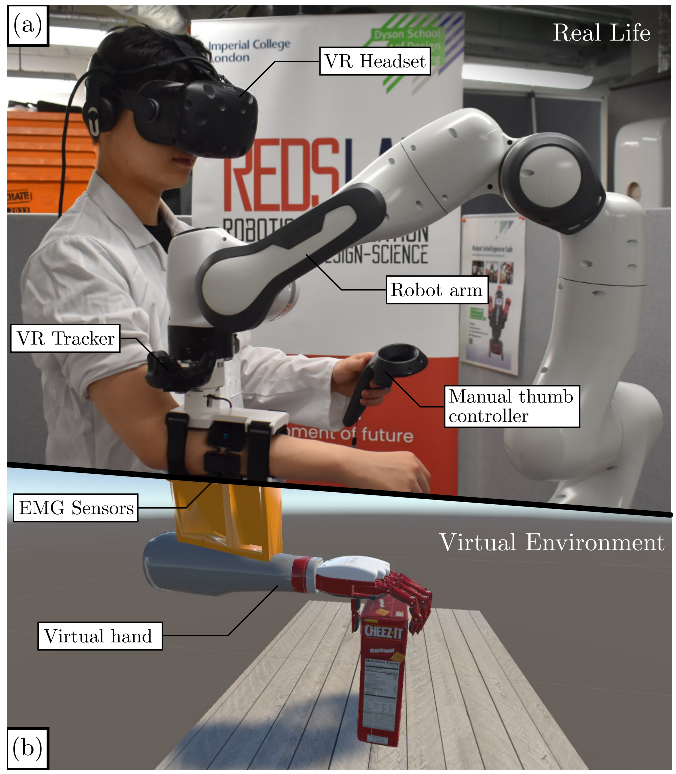

Fig. 1: The proposed robot-enhanced virtual reality training platform (a) in real life, (b) in virtual reality—the virtual hand is mounted below the forearm of the user.

I. Introduction

Simulation is an important tool in the vast majority of engineered systems, allowing developers to rapidly test and improve designs in a controlled, low-risk setting. Recently, virtual reality (VR) has gained popularity as not only a simulation tool, but also for user training [1]. Areas where user operation and interaction is critical stand to benefit significantly from VR, and this is particularly true for prosthetic hands.

Virtual reality has been utilised many times in amputee rehabilitation, with known benefits in alleviating phantom limb pain [2] and task-specific user training [3]. VR prosthetic systems can be used in combination with exercises and even in combination with a physical prosthetic hand to create targeted rehabilitation schedules that are personalised to the patient. Importantly, VR prosthetic systems can potentially enable patients to begin working towards full control of a prosthetic hand at an earlier stage after amputation, before the fitting of a prosthesis even takes place. Currently, prior to receiving their prosthetic hand, patients begin rehabilitation by using simplistic rehabilitation games [4] which may be limited in how well they prepare a user for actually using a prosthetic hand. For successful uptake of a prosthetic hand it is critical that this early-stage rehabilitation is high quality [4], [5].

Existing VR prosthetic systems typically focus on aesthetic qualities over functionality; the virtual hand is often just a visualisation [6], the myoelectric controller driving the virtual hand is not representative of a real prosthetic hand controller [3], and object interaction of the virtual hand is

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generally achieved by ‘attaching’ the hand to the object programmatically [7]. Furthermore, studies identify the need for object weight in virtual reality for more immersive training [6] and have found that force feedback can increase a user’s sense of embodiment of their virtual hand [8].

It therefore follows that a VR prosthetic hand system that accurately simulates the functionality and interaction of a real prosthetic hand is needed, and a force feedback system could improve the level of realism achieved by the simulation. A VR system such as this offers key benefits to both patients and developers; the simulation would offer patients a realistic simulation of their future prosthesis, allowing them to perform rehabilitation tasks usually only possible with a physical prosthesis in the weeks before their fitting, and the simulation would allow developers to rapidly test and evaluate new design and control features for prosthetic hands in an accurate setting with minimal risk. Furthermore, an accurate VR system can be used to create training scenarios specific to user needs, and can be combined with existing rehabilitation methods to provide a higher level of personalisation in rehabilitation.

This work aims to address shortfalls in current VR prosthetic hand systems via three main contributions. The first is an accurate VR simulation of the prosthetic device, which in the case of this work is the OLYMPIC hand [9]—a modular, tendon-driven prosthetic hand designed at Imperial College London, completed with two degree of freedom (DOF) myoelectric control. Second, an enhanced interaction between the user and the virtual prosthesis provided by an external robot arm rendering realistic forces that the user would feel at the attachment point of their prosthesis. Third, a participant group study targeting the scenario where virtual reality training is used prior to the fitting of the prosthetic hand, comparing the functionality and user perception after training A) using the enhanced system, B) using virtual reality alone, against the real-world OLYMPIC hand when performing the Box and Blocks dexterity assessment [10] pick-and-place tasks with objects from the YCB object and model set [11].

We find that enhancing virtual reality training with a robot arm improves Box and Block scores and does not significantly reduce pick-and-place performance, compared to training in virtual reality alone. Users perceive that training is closer to using a real prosthesis in terms physical demand and effort. However, limitations in simulation lead to a discrepancy between performance with the virtual hand and the real hand, and an increase in frustration when training with the robot-enhanced system.

II. Related Work

A. Upper Limb Prosthetic Rehabilitation

Early, specialised rehabilitation as well as managing realistic patient expectations of prosthetic technology are well known to be important factors in achieving high retention in upper limb prosthesis users [12], [13]. However, rehabilitation after upper-limb amputation is a complex process involving a cross-disciplinary team, and is rarely straight-forward due to the traumatic nature of most injuries that lead to amputation [5]. Rehabilitation technology is therefore a critical tool of the prosthetist in effectively targeting rehabilitation to both provide high quality training and manage expectations of the patient’s future life with a prosthetic hand.

Existing rehabilitation tools used prior to prosthetic fitting are generally game-based [4], and although serious games have found success in other rehabilitation settings, such as following a stroke [14], the games used in clinical prosthetic rehabilitation settings are relatively simplistic. For example, the rehabilitation game presented in [15] aims to train patients of recent amputation to activate individual muscles. Although this is useful for extremely early-stage rehabilitation, it is not suitable for preparing for a real prosthesis. Furthermore, any rehabilitation game used should be careful not to produce unrealistic expectations of prosthetic control, ability to grasp objects, or other functionality.

B. Virtual Reality Prosthetic Rehabilitation

In recent years, virtual rehabilitation for prosthetic hand users has become a popular idea [16], as a method of training users in an immersive way prior to prosthetic fitting. Virtual reality lends itself well to this style of rehabilitation; the appeal of operating a virtual version of either a human or prosthetic hand is clear, and has been shown to reduce phantom limb pain and other issues surrounding prosthetic hand use [2]. VR also enables the development of immersive rehabilitation scenarios, with some works producing attractive renderings of activities of daily living (ADLs) [6]–[8]. Similarly, [3] proposes an immersive rehabilitation game setup in which the user must complete three tasks designed to represent ADLs. However, in these recent works, although the task and environment may be designed to represent the real-world, the virtual hand is not. A common issue is that the virtual hand is not designed to replicate the function of its real-world counterpart; instead of accurately simulating the motion and interaction of a prosthetic hand, many works predefine a small number of interactions [3], [6], [7], [17] whereby grasped objects ‘attach’ themselves to the prosthetic hand. Naturally, this makes objects easier to grasp than in reality, and leads to prosthesis users performing better in assessment tasks in VR than in the real world [7]. It is clear that in order for VR prosthetic training to be effective the hand should be simulated, rather than animated, and it should interact with its environment with accurate physics. Another major shortcoming in recent work is the level of myoelectric control the user has over the virtual prosthesis. In order to form a realistic training environment, the myoelectric control system used to interpret muscle signals and convert them into desired hand movements should be as close to those used in clinical practice as possible. Yet, multiple works instead use EMG-based gesture recognition systems not designed for prosthetic hand control [3], [6].

In order to close the gap between virtual reality and the real world, force feedback should be considered. Previous works have highlighted the need for some form of rendering of the weight of the prosthesis in VR prosthetic systems [6]. [8] goes some way towards achieving this, using a robot arm to render forces from a simulated prosthetic hand, but its

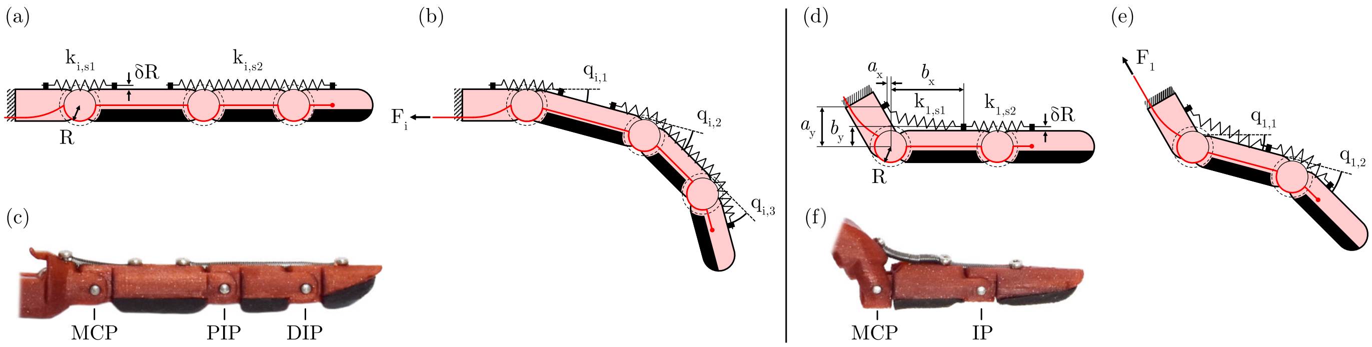


Fig. 2: Left: lateral view of finger i of the OLYMPIC prosthetic hand, (a) relaxed (b) flexed (c) real finger. Right: lateral view of the thumb of the OLYMPIC prosthetic hand, (d) relaxed, (e) flexed, (f) real finger.

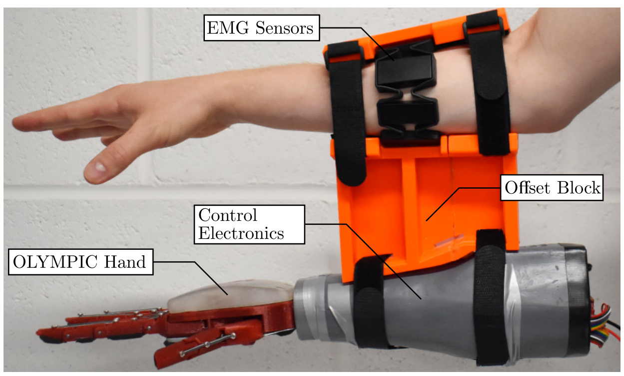


Fig. 3: The OLYMPIC hand attached to the forearm of a user. Annotated: EMG Sensors, Offset Block, Control Electronics, and the OLYMPIC Hand. To be as close as possible to existing direct control prosthetic control methods, only two of the eight EMG electrodes on the Myo Armband are monitored. No other Myo Armband features were used.

workspace is small, and the work only preliminary. The effect of missing haptic feedback is particularly evident in [18], who present a simulated human hand controlled through motion capture of non-disabled users' real hands. Although accurate hand simulation is achieved and high quality control, the functionality of the VR hand is still significantly lower than its real counterpart, with the authors citing haptic feedback as the biggest factor at play.

III. Methods

A. Physical Prosthetic Hand Setup

The OLYMPIC hand is a modular prosthetic hand that offers independent control of the flexion/extension of each finger, and an additional degree of freedom in thumb abduction/adduction, which is manually set by the user [9]. A single tendon controls finger flexion, and extension springs mounted on the dorsal side of each finger are able to open the finger in the absence of tendon force. In this study, the hand is mounted to non-disabled users using a 3D printed offset block, shown in Fig. 3, which holds the hand and accompanying socket below the participants real arm at a distance of ~100 mm. The prosthetic hand and participant arm are attached to the mounting block using velcro straps, where space is left between the straps on the participant to allow for the EMG sensors to be positioned. The OLYMPIC hand was modified to include encoders on each motor to allow for position control of the fingers, which in turn required a redesign of the modular wrist to support the increased number of electrical signals. Low level control of the hand is performed using a Nvidia Jetson Nano microcontroller, located in the forearm of the prosthesis. The forearm also houses electronics used for sensing motor torque and position.

B. Virtual Reality Setup

This subsection describes the process of simulating the virtual prosthetic hand and rendering forces at the user's forearm.

1) Virtual Prosthetic Hand: To accurately simulate the OLYMPIC hand, a mathematical model of the tendon-driven flexion motion and spring-driven extension motion is presented. As seen in Fig. 2, each finger consists of a single tendon actuating three joints, and two springs; one driving the extension of the metacarpophalangeal (MCP) joint, and one driving the extension of the proximal interphalangeal (PIP) and distal interphalangeal (DIP) joints together.

The extension springs of the finger are on the surface of the dorsal side, with the centre-line of the springs at a radial distance of $R + \delta R$ from each joint, so the force in each of these, $F_{i,s1}$ and $F_{i,s2}$ is simply:

$$F_{i,s1} = k_{i,s1}(R + \delta R)(q_{i,1} - \bar{q}_{i,s1}), \tag{1}$$

$$F_{i,s2} = k_{i,s2}(R + \delta R)(q_{i,2} + q_{i,3} - \bar{q}_{i,s2}), \tag{2}$$

where $\bar{q}_{i,s1}$ and $\bar{q}_{i,s2}$ are the zero-force angles of the first and second extension springs, respectively. Assuming the tendon is light and inextensible, the flexion torque applied to each joint in the finger is equal to $F_i R$. Neglecting dynamics, the torque, $\tau_{i,j}$, on each joint of finger i, taking flexion as the positive direction, is equal to

$$\tau_{i,1} = F_i R - F_{i,s1}(R + \delta R), \tag{3}$$

$$\tau_{i,2} = F_i R - F_{i,s2}(R + \delta R), \tag{4}$$

$$\tau_{i,3} = F_i R - F_{i,s2}(R + \delta R). \tag{5}$$

Note that the torques in the PIP and DIP joints of the finger are identical.

The thumb has two joints that move in the flexion/extension direction, the metacarpophalangeal (MCP) joint $q_{1,1}$ and the

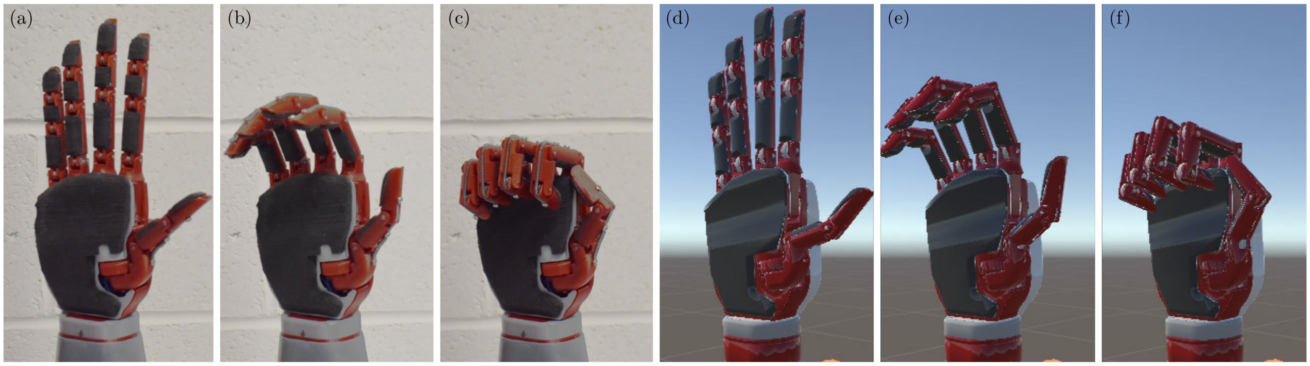


Fig. 4: The real OLYMPIC hand (a) open, (b) partially closed, (c) fully closed. The virtual OLYMPIC hand (d) open, (e) partially closed, (f) closed.

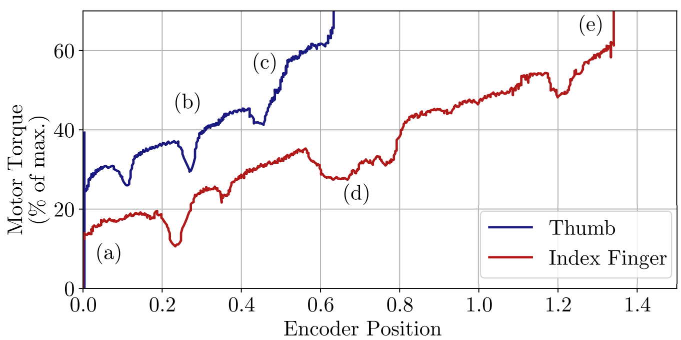


Fig. 5: The motor torque required to drive to encoder position for the thumb and index finger of the OLYMPIC hand. (a) torque required to overcome pre-tensioned springs. (b) friction pattern in the gear driving the thumb. (c) non-linearity caused by the offset spring mounting. (d) static friction overcome as joint begins to move. (e) finger contacts palm.

interphalangeal (IP) joint $q_{1,2}$. The spring force of the thumb is complicated by the offset attachment of the first extension spring, shown in Fig. 2. The length, $L_{1.s1}$ of the spring can be calculated as a function of the joint angle $q_{1,1}$:

$$L_{1,s1}(q_{1,1}) = \sqrt{(a_x + b_x \cos\alpha)^2 + (a_y - b_y \sin\alpha)^2}, \quad (6)$$

where $\alpha = q_{1,1} - \arctan(b_y, b_x)$. The force in each of the extension springs of the thumb is then equal to

$$F_{1,s1} = k_{1,s1}(L_{1,s1}(q_{1,1}) - L_{1,s1}(\bar{q}_{1,s1})), \quad (7)$$
$$F_{1,s2} = k_{1,s2}(R + \delta R)(q_{1,2} - \bar{q}_{1,s2}). \quad (8)$$

The perpendicular distance, $d_{1,s1}$, of the first extension spring to the centre of the first joint is:

$$d_{1,s1}(q_{1,1}) = \frac{(a_x + b_x \cos\alpha)a_y + (a_y - b_y \sin\alpha)a_x}{L_{1,s1}(q_{1,1})}. \quad (9)$$

The torque on each joint of the thumb is then equal to

$$\tau_{1,1} = F_1 R - F_{1,s1} d_{1,s1}(q_{1,1}), \quad (10)$$
$$\tau_{1,2} = F_1 R - F_{1,s2}(R + \delta R). \quad (11)$$

As seen in Fig. 5, the thumb and index finger of the OLYMPIC hand approximately follow the force-position relationships described in (1) - (11). As expected, the finger exhibits a linear relationship between motor torque and encoder position, deviating due to periodic gear friction and at points where a new joint overcomes its own static friction and begins to move. The thumb shows similar characteristics, but due to the offset mounting of the extension spring on the first joint of the thumb described in (6)-(10), the relationship is nonlinear.

The motors that drive the tendon forces have a high gear ratio of 300 : 1, meaning they are not back-driveable. This effect is modelled by adding a barrier term to commanded tendon force $\bar{F}_i$ that is active if the tendon length L_i extends beyond its taut value $\hat{L}_i$ without the motor allowing:

$$F_i = \begin{cases} \bar{F}_i + K_b \max(\hat{L}_i - L_j, 0), & \bar{F}_i \geq 0 \\ 0, & \bar{F}_i < 0 \end{cases}, \quad (12)$$

where K_b is a proportional constant set at a suitably high value to prevent backdriving. Position control of each finger is achieved by adding a proportional-integral control loop to the taut tendon length, with desired length $\bar{L}_i$:

$$\bar{F}_i = K_{p,t}(\bar{L}_i - \hat{L}_i) + K_{i,t}\int_0^t (\bar{L}_i - \hat{L}_i) d\tau. \quad (13)$$

The OLYMPIC hand is simulated (as shown in Fig. 1) in Unity3D [19] as an articulated kinematic tree built on the NVIDIA PhysX engine. At each time step, the torques defined in (3)-(5) and (10)-(11) are applied to the joints of the hand. The manually operated thumb abduction and adduction of the simulated hand is controlled via a separate user input from a virtual reality in-hand controller, held in the free hand of the user. Fig. 4 shows a visual comparison between the real and virtual OLYMPIC hand while closing the hand. As seen, the hands follow similar trajectories, and reach nearly identical closed positions.

The pose of the base link of the hand is controlled as part of the entire articulation using an extra 6 joints, with the position, $\boldsymbol{x}$, and orientation of the base of the prosthetic hand driven to a reference tracker pose using a proportional-derivative controller:

$$\boldsymbol{F} = K_{p,x}(\boldsymbol{x} - \boldsymbol{x}_{ref}) - K_{d,x}\dot{\boldsymbol{x}}, \quad (14)$$
$$\boldsymbol{\mathcal{T}} = K_{p,r}\hat{\boldsymbol{n}}\theta - K_{d,r}\boldsymbol{\omega} \quad (15)$$

where $\hat{\boldsymbol{n}}\theta$ is the relative angle-axis rotation between the reference tracker and the base of the OLYMPIC hand projected into the world frame, and $\boldsymbol{\omega}$ is the angular velocity of the base.

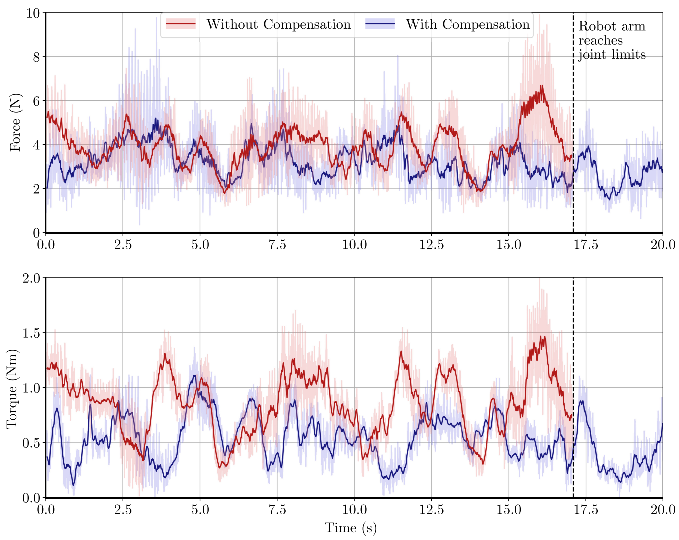


Fig. 6: The magnitude of the force (top) and torque (bottom) applied by the user to trace a circle at constant speed while attached to the robot arm. Blue - with compensation, red - without compensation. Without compensation the robot arm reaches joint limits and the user is unable to complete the trajectory.

This relative rotation represents the rotation from the hand, R_h, to the tracker, R_t:

$$^{h}R_t = R_h^T R_t. \tag{16}$$

The angle-axis representation of this relative rotation is extracted by solving:

$$1 + 2\cos\theta = \text{trace}(^{h}R_t), \tag{17}$$

$$(^{h}R_t - I)\boldsymbol{n} = \boldsymbol{0}. \tag{18}$$

Then, projecting $\boldsymbol{n}$ to the world reference frame:

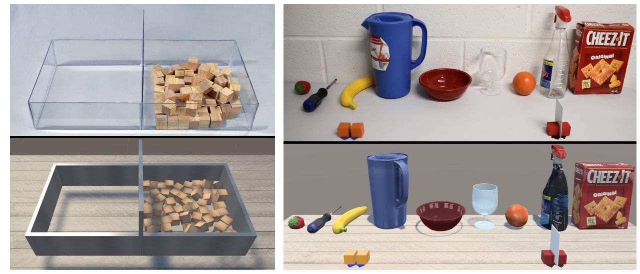
$$\hat{\boldsymbol{n}} = R_t\boldsymbol{n}. \tag{19}$$

2) Force Feedback Setup: In order to produce the most realistic VR prosthetic hand possible, a robot arm is used to render the forces that the user would experience from a physical prosthesis attached to their forearm. The physics solver governing the motion of the simulated prosthetic hand makes use of one of Featherstone's algorithms [20] to solve forward and inverse dynamics at each time step. The force and torque transmitted to the attachment point of the prosthetic hand to the user is applied by the end effector of a Franka Emika robot arm [21] attached to the forearm of the user, as shown in Fig. 1.

The robot arm applies the wrench defined in (14), and (15), along with compensation for the robot's own gravity, inertia, joint friction, and a safety term to allow the robot to avoid joint limits:

$$\boldsymbol{\tau} = J^T \begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{\mathcal{T}} \end{bmatrix} + \boldsymbol{\tau_g} + K_1 H\ddot{\boldsymbol{q}} + K_2\Delta\boldsymbol{\tau} + K_3 N(\boldsymbol{q}_0 - \boldsymbol{q}), \tag{20}$$

where J is the Jacobian of the end-effector of the robot arm, $\boldsymbol{\tau_g}$ is the torque required to compensate for gravity, H is the joint-space inertia matrix of the arm, and $\ddot{\boldsymbol{q}}$ is its joint



(a) Box and block test. (b) YCB objects.

Fig. 7: The real (top) and simulated (bottom) experimental setups used in this work.

accelerations. $\Delta\boldsymbol{\tau}$ is the difference between the compensated joint torques and the measured joint torques at the previous time step, which captures the excess torque that the user must apply to move the robot arm. The null-space projector N is used to apply safety torques in order to keep the robot arm close to a zero configuration $\boldsymbol{q}_0$ (and therefore away from joint limits) without impacting the wrench applied to the user. K_1, K_2, and K_3 are diagonal weighting matrices used to tune the level of compensation at each joint. K_1 and K_2 are tuned to target joints that require a large user force to move, and are carefully set to low values since both apply positive feedback to the user. After tuning K_3, the robot arm is able to avoid joint limits as the user moves, and maintain this even in the presence of external disturbances. As seen in Fig. 6, a user can trace a circle at constant speed by applying a force and torque of their own at the end effector. Without compensation, these forces and torques are slightly increased and the robot arm is unable to avoid joint limits, meaning the user fails to complete the desired trajectory.

For safety, the robot arm is limited in maximum force that it can apply, and the robot-user connection is held by an electromagnet that has a holding force of 30 N, which detaches the user from the robot when an e-stop is pressed.

C. Myoelectric Control

A direct control myoelectric control method is used in this study. To simulate existing direct control prosthetic control methods, only two of the eight EMG electrodes on the Myo Armband are monitored. The first electrode is positioned in the inner forearm to detect muscle activity during wrist flexion while the second electrode is positioned on the antagonistic muscle group on the outer forearm to detect wrist extension. These signals are interpreted as part of a binary control system; if the signal on the wrist flexion electrode passes a threshold then the hand closes, if the signal on the wrist extension electrode passes a separate threshold then the hand opens:

$$\bar{L}_i = \begin{cases} L_{min}, & e_1 \geq E_1 \\ L_{max}, & e_2 \geq E_2 \end{cases}, \tag{21}$$

where e_1 and e_2 are the post-processed values read from the two electrodes, and E_1 and E_2 are tuned thresholds that are personal to each user. This method of control was chosen because direct control methods are common in prosthetic hands available to patients, and offer a robust baseline to test the virtual reality platform with.

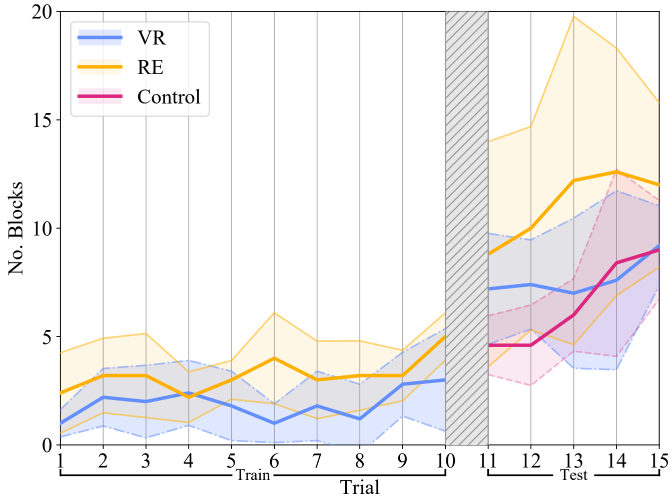


Fig. 8: Average Box and Block scores of user groups across 10 training trials and 5 test trials. Shaded regions represent ± 1 standard deviation. VR - virtual reality group, RE - robot-enhanced group, C - control group.

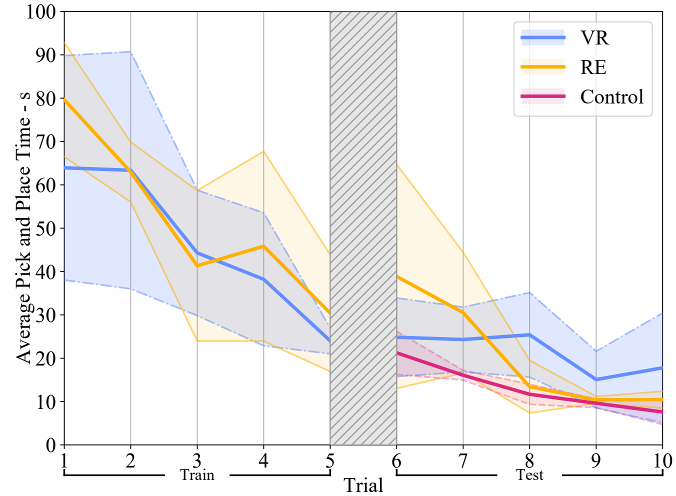


Fig. 9: Average pick-and-place times of YCB objects of user groups across 5 training trials and 5 test trials. Shaded regions represent ± 1 standard deviation. VR - virtual reality group, RE - robot-enhanced group, C - control group.

D. Assessing Task Performance

To assess how well the VR prosthetic system is able to train users for physical prosthesis use, two control group experiments were performed. In each experiment, participants completed a number of sets of timed pick-and-place exercises (each set is henceforth referred to as a trial) in training before transitioning to use the physical prosthetic hand for a number of test trials. Participants were placed into three groups: a VR group, who performed training trials in virtual reality, a Robot-Enhanced (RE) group, who performed training trials in virtual reality with the robot arm providing force feedback, and a Control group, who performed no training trials. Non-disabled participants were recruited for each group, and are particularly useful for this work because they have no prior experience controlling prosthetic hands, and can therefore be considered naive users. The use of human participants in this work was granted ethical approval by the Imperial College London Research Governance and Integrity Team (RGIT), Science Engineering and Technology Research Ethics Committee (SETREC) number 21IC6716. Written consent was obtained from participants prior to taking part in the study.

The Box and Blocks dexterity assessment [10] was used for the first experiment, in which 10 training trials were performed, then 5 test trials with the physical prosthetic hand. In each trial, participants were given 60 seconds to transfer as many individual blocks from one box to another, with a higher number of blocks representing a higher level of dexterity. 5 participants were recruited to each group, giving a total of 15 participants.

For the second experiment, 10 objects from the YCB object and model set [11] were used to explore user dexterity across a wider range of objects that are representative of objects used in ADLs. 5 training trials were performed, followed by 5 test trials in order to provide a direct comparison between the virtual and physical setups. In each trial, each of the 10 objects were grasped, lifted, then transferred 500 mm, before being placed, as in [9]. In this work, the pick and place action is timed to offer a more detailed measure of functionality, similar to other dexterity assessments such as the Southampton Hand Assessment Procedure [22] or the Box and Block Test [10]; a quicker time to complete the pick and place task is thought to correspond to better hand functionality. Average pick and place time over a trial is recorded. 3 participants were recruited to each group, giving a total of 9 participants in this experiment.

E. Assessing User Perception

User perception is an important aspect of prosthesis use that is often neglected. To assess user perception of the system, each participant completed a supplementary questionnaire and a copy of the NASA Task Load Index, also known as the NASA-TLX [23], first after completing the training trials, then after the test trials of the YCB pick-and-place experiment (it should be noted that the Box and Blocks experiment contains more training trials than testing trials, so cannot be compared). The NASA-TLX contains questions assessing mental and physical demand, temporal demand, task performance, effort, and frustration. The questionnaire was completed by each participant after training and again after testing. In this work, we report the 'raw' TLX scores scaled between 0 and 100, as they allow for direct comparison between each aspect of task load [24].

IV. Results & Discussion

Average Box and Block scores of each group for the 10 training trials and 5 test trials are shown in Fig. 8. As seen, neither group perform as well in training as with the physical prosthetic hand. Both groups show a statistically significant difference in performance compared to the control group with an uneven t-test across the 10 training trials against the 5 control test trials ($p < 0.01$). However, the RE group perform consistently better in training than the VR group ($p < 0.01$).

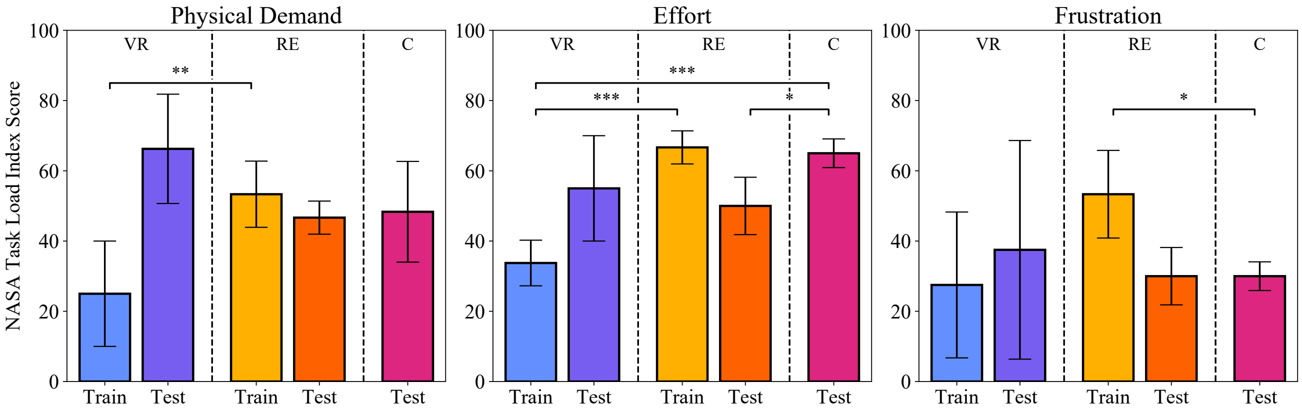


Fig. 10: Average NASA-TLX responses for physical demand, effort, and frustration for user groups. VR - virtual reality group, RE - robot-enhanced group, C - control group. Statistical significance of: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

After transitioning onto using the physical prosthetic hand, the RE group outperforms both the VR group and the Control group across the 5 test trials, showing statistical significance with p-values of below 0.05 and 0.01, respectively. No statistical significance was observed between the VR and Control group in testing.

Average YCB pick-and-place time of each group for the 5 training trials and 5 test trials are shown in Fig. 9. Again, both the VR and RE group perform significantly worse in training than the control group ($p < 0.01$), however in this experiment the RE group also performed comparably to the VR group in training. When transitioning to the physical prosthesis, the VR group were unable to adapt within the 5 test trials, performing significantly worse than the Control group ($p < 0.01$). The RE group, on the other hand, show no statistical significance for average pick-and-place time across testing trials compared to the Control group.

It is clear that there is a gap between the virtual and physical prostheses that prevents users from attaining real-world performance on the chosen pick-and-place tasks. One major source of this that is common to both the VR and RE groups is that the simulation relies on rigid-body collisions; the actual prosthesis is equipped with soft silicone pads that deform on contact to provide a better grip. This is particularly important when grasping small objects such as the blocks present in the Box and Blocks test, or objects of irregular shape such as the screwdriver in the YCB object set, and is not possible to simulation with current physics simulators. Furthermore, the collision geometry used in the simulation is an approximation of the collision geometry of the physical hand. Small features and irregularities on the surfaces of the physical hand can also improve grasping ability, but are not present in the virtual prosthesis. Despite this gap, Robot-Enhanced training results in better physical hand results compared to VR training alone. Furthermore, results with the YCB objects indicate that VR training alone could even be detrimental to performance when using the real prosthesis, although a larger participant group would be required to validate this fully. A result that is perhaps surprising is that RE training has a significant impact on Box and Block performance, whereas VR training does not. The force feedback from the robot arm may allow users to identify with greater certainty whether the virtual hand is in contact with its surroundings when attempting to grasp a block, which can prevent the hand from closing successfully.

Group NASA-TLX responses for the virtual reality, robot-enhanced, and control groups are shown in Fig. 10. As seen, the physical demand and effort to complete the pick-and-place tasks in VR training are lower than the control group, and significantly lower than RE training ($p < 0.05$), due to the lack of force feedback to the user. Similarly, the effort required to complete the training trials for the VR group is significantly lower than both the RE and Control groups ($p < 0.01$). However, frustration is significantly higher for RE training than the control group, although to a lesser degree ($p < 0.1$).

TLX results highlight an important shortcoming in VR training alone; training without realistic force feedback may lead to an unrealistic expectation of the physical demand and effort required by the user. Frustration before and after VR training is not significantly higher than the control group, but a high variance can be seen in responses. This could be detrimental to rehabilitation, as it is difficult to predict how someone will respond to VR training. This issue is not present in the RE group, however the RE group found training significantly more frustrating than the control group found using the real prosthetic hand. This could be caused by the aforementioned discrepancies between simulation and reality, making grasping objects more difficult than expected, coupled with the weight of the prosthetic hand amplifying user frustration. After the RE group transition to using the physical prosthesis this frustration is alleviated, returning to control levels, indicating that training with the Robot-Enhanced system is not detrimental to user frustration in the long term. In fact, RE group results for effort were significantly lower than control results after testing trials, giving hope that RE training may be beneficial for user perception when transitioning to using a real prosthesis.

V. Conclusions & Future Work

In this work we have presented a virtual reality platform for pre-prosthetic hand training, enhanced by utilising a robot arm to render the forces the user would experience when using a real prosthetic hand. This platform addresses significant shortcomings in other comparable systems by using an accurate physics simulation of the prosthetic hand, standard myoelectric control technology, and force feedback.

Experimental results with non-disabled participants show that training with the robot-enhanced platform improved user performance on the Box and Blocks dexterity assessment significantly compared to both participants who had trained in virtual reality alone, and the control group who had received no prior training. On more complex pick-and-place tasks with YCB objects, the final performance of the robot-enhanced training group were comparable to the control group, whereas training in purely virtual reality resulted in a significant reduction in performance.

Results of the NASA-TLX questionnaire show that training with the robot-enhanced system is comparable in terms of physical demand and effort to directly using the real prosthesis, a considerable improvement over training in VR alone. However, limitations of rigid-body simulation create discrepancies between the simulated and real hand that lead to an increase in frustration during robot-enhanced training, which is exacerbated by force feedback applied to the user. This is alleviated when transitioning to the real prosthesis.

This work has shown that this platform can be an effective tool to prepare users for prosthetic hand use, without producing negative side-effects such as non-representative control and interaction, and unrealistic user expectations. It is anticipated that robot-enhanced training can be used as part of a scheduled rehabilitation process, where the level of force feedback can be graduated as the patient progresses. Furthermore, the platform can allow users to practice specific scenarios in a controlled manner, leading to personalised rehabilitation environments, in combination with ongoing rehabilitation with a physical prosthetic hand. This work also offers benefits for future prosthetic hand development, as new designs and control algorithms can be tested with a higher degree of realism than just virtual reality.

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