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An Objective Functional Evaluation of Myoelectrically-Controlled Hand Prostheses: A Pilot Study Using the Virtual Peg Insertion Test

Christoph M. Kanzler[1], Manuel Giuseppe Catalano[2], Cristina Piazza[3], Antonio Bicchi[2,3], Roger Gassert[1], Olivier Lambercy[1]

***Abstract*— Assessing upper limb prostheses and their influence when performing goal-directed activities is essential to compare the quality of different devices and optimize their control settings. Currently available assessments are often subjective, insensitive, and cannot provide a detailed evaluation of prostheses and their usage. The goal of this pilot study was to explore the feasibility of using the Virtual Peg Insertion Test (VPIT) to provide an in-depth assessment of a prosthesis and its functional performance. One transradial amputee performed the goal-directed manipulation task of the VPIT with the sound body side and four different myoelectrically-controlled prostheses. The subject was able to complete the VPIT protocol successfully with technically advanced prosthesis (two out of four devices). The kinematic- and kinetic-based objective evaluation measures extracted from the VPIT were able to capture clear differences between the sound and amputated body side and were able to identify varying movement patterns for different prostheses. Additionally, the outcome measures were sensitive to changes in prosthesis control settings and showed clear trends across measures of subjectively perceived prosthesis quality assessed through a questionnaire. This work demonstrates the general feasibility of objectively evaluating functional prosthesis usage with the VPIT.**

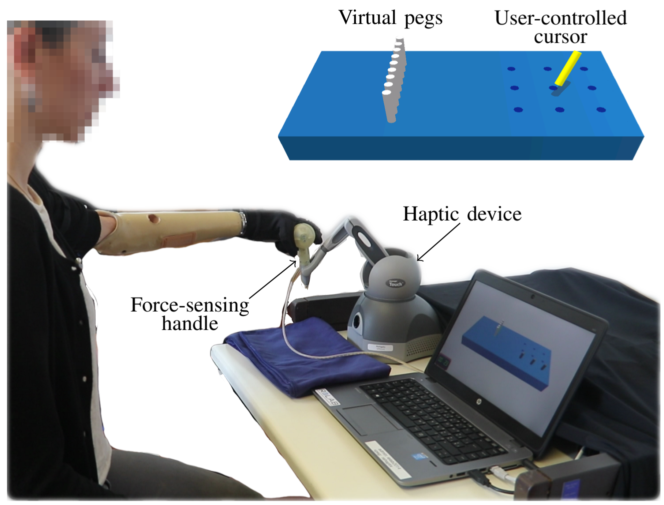


Fig. 1. Transradial amputee using a myoelectrically-controlled prosthetic device to perform the Virtual Peg Insertion Test (VPIT), an instrumented assessment of upper limb disability. The goal-directed task requires to insert nine virtual pegs into corresponding holes by precisely coordinating grasping forces as well as arm and hand movements.

I. Introduction

In 2005, 541,000 persons lived with an upper limb amputation in the United States of America, with the number of amputees being expected to double until 2050 [1]. Prostheses, and especially myoelectrically-controlled devices, have been developed to provide active assistance during goal-directed activities [2] and have the potential to increase quality of life of amputees [3]. The complexity of such activities, which often require the coordination of arm movements, precise manipulations, and a stable grip to transport objects, create a challenge even for state of the art prostheses [4]. In particular, there is a need to optimize the technical specifications of prostheses (e.g., weight, opening and closure resolution) and aspects related to electromyographic (EMG) control (e.g., pattern recognition [2]) to ensure intuitive use and functional benefits. However, the impact of these technical specification on the capacity to perform goal-directed activities remains unknown and rarely studied.

In research settings, upper limb prosthesis users are often evaluated with a time-consuming battery of standardized assessments, such as the Southampton Hand Assessment Procedure [5], the Orthotics and Prosthetics User Survey [6], and the Box and Block Test (BBT) [7]. These assessments fail to quantify underlying movement patterns, are often subjective, mostly use ordinal scales with low resolution limiting their sensitivity, and suffer from ceiling effects [6, 8].

Technology-based assessments might help to address these caveats by providing quantitative movement data and fine-grained assessment metrics [9]. However, these approaches have, in amputees, predominantly been applied in an exploratory manner without taking their applicability for research studies and clinical practice into account. For example, adaptations of the musculoskeletal and central nervous system (CNS) were studied by analyzing movement strategies [10] including compensatory trunk movements [11, 12] based on data acquired with optical motion capture systems. Even though more readily applicable, instrumented assessments have been performed using the InMotion2 robot [13] or the Virtual Egg Test [14, 15], there is still the need for rapid, standardized, and detailed kinematic and kinetic-based assessments. These might allow to quantitatively capture the quality of different behavioral patterns of arm and hand in the context of a goal-directed activity. This is important, because it might help to evaluate and improve prosthesis design and better compare the quality of different prosthetic hands. Additionally, this might help to tailor prosthesis control settings to a specific subject and to better evaluate novel sensory restitution approaches [15].

[1]Rehabilitation Engineering Laboratory, Institute of Robotics and Intelligent Systems, Department of Health Sciences and Technology, ETH Zurich, Switzerland.
[2]Soft Robotics for Human Cooperation and Rehabilitation, Istituto Italiano di Tecnologia, Genova, Italy.
[3]Research Center "Enrico Piaggio", University of Pisa, Pisa, Italy.
Corresponding author: christoph.kanzler@hest.ethz.ch.

The goal of this pilot study was to explore the feasibility of using the Virtual Peg Insertion Test (VPIT) as a technology-based assessment for upper limb prostheses. The VPIT provides a rapid, standardized, kinematic- and kinetic-based evaluation of arm- and hand-control during a goal-directed manipulation task and was developed to assess sensorimotor profiles of upper limb disability in neurological patients [16, 17]. We hypothesized that amputees using technically advanced (i.e., allowing precise grasping force control) prostheses could successfully complete the VPIT protocol. We additionally expected that some of the sensor-based metrics of the VPIT, originally aimed to describe sensorimotor disability in neurological patients, could also be used to inform on the technical specifications of prostheses and their impact on the capacity to perform goal-directed activities. In particular, we expected that the metrics (1) reveal different movement patterns between the sound and prosthetic side as well as between different prostheses, (2) are sensitive to changes in prosthesis control settings, and (3) are related to subjective indicators of prosthesis quality.

II. Methods

A. Virtual Peg Insertion Test (VPIT)

The VPIT (Fig. 1) consists of a virtual reality (VR) environment that can be controlled through a commercial haptic end-effector (Phantom Omni or Touch, 3D Systems, CA, USA) with a rapid-prototyped force sensing handle that contains three flexible parallel structures equipped with piezoresistive sensors (CentoNewton40, EPFL, Switzerland). The test was described in detail in previous work [16, 17]. In short, the VPIT requires the coordination of arm movements, precise manipulations, and a stable grip to transport nine virtual pegs into nine holes, thereby mimicking a goal-directed manipulation activity. To perform the task, a cursor representing the end-effector of the haptic device has to be spatially aligned with a peg, a grip force above a threshold of 2N has to be applied and maintained, and the peg has to be transported and finally released into a hole. The virtual pegboard is physically rendered through the haptic device, which helps to perceive depth in the 3D VR space.

B. Procedure

One transradial left arm amputee (female, age 37 yrs, affected by limb agenesis, no concomitant diseases), who uses a cosmetic prosthesis in daily life but has extensive prior experience with myoelectric prostheses, was recruited at the University of Pisa. The subject gave informed consent prior to the study. Measurements were split into two separate testing days and were recorded on video. On the first day, the subject was familiarized with the VPIT setup and could explore different myoelectric prostheses while interacting with the haptic device. Based on this initial experience, the prostheses were judged to be suitable or inadequate for the standardized assessment with the VPIT that was performed on the second day. Additionally, the possibility to optimize the control settings of a prosthesis was evaluated on day two by performing the VPIT while using a prosthesis with standard control settings and the same device with subjectively optimized control parameters. Finally, the subject also performed the task with the sound arm on day two to provide baseline information. For each condition, the VPIT was performed once for familiarization followed by five repetitions (i.e., inserting all nine pegs five times). In between repetitions, the subject could rest up to five minutes, while pauses of up to 20 minutes were allowed between experimental conditions to minimize fatigue. The subject started in seated position with approximately 45° shoulder abduction, 90° elbow flexion, and 10° shoulder flexion and was initially advised to use a power grip to complete the VPIT. However, the subject was allowed to adjust the grip type if another configuration was more suitable with a specific prosthesis. In case the subject dropped the handle of the haptic device during the task or needed to readjust the grip configuration due to slippage of the handle, the experimenter helped the subject grasp the handle again by holding it in an upright position. After each experimental session, a questionnaire with three usability-related items was performed: "how difficult was the task in general", "how difficult were the parts of the task related to arm movements?", and "how difficult were the parts of the task related to hand movements?". The questions were rated on a visual analog scale from "not at all" to "very", were transformed to the interval [0%,100%], and interpreted as subjective measures of prosthesis performance quality.

C. Description of prosthetic devices

Four myoelectrically-controlled prostheses, both commercially available and research prototypes, were evaluated in this study. In particular, the SensorHand Speed (weight 460g, 1 degree of freedom (DoF), 1 actuator, power grip force unknown; Otto Bock, Duderstadt, DE), i-limb ultra (464g, 6 DoFs, 5 actuators, power grip force 100 N; Touch Bionics, Livingston, UK), SoftHand Pro (SHP) Mk.I (weight 620g; 19 DoFs, 1 actuator, power grip force 76 N [18]), and SHP Mk.II (340g; 19 DoFs, 1 actuator, power grip force 45 N) were used by the subject. The SHP Mk.II was further tested with different control settings (SHP Mk.II* having reduced closure velocity and increased gain of the EMG amplifier compared to the SHP Mk.II). The same commercial glove, socket, and surface electromyographic sensor system (13E200=60, Otto Bock) were used when testing the prostheses.

D. Data analysis

The number of repetitions the VPIT could be successfully completed (i.e., insertion of all nine pegs) with a prosthesis was measured. The objective assessment with the VPIT was based on a previously defined computational framework, which relies on kinematic, kinetic, and haptic data that is processed into 12 mostly independent metrics describing sensorimotor impairments and their influence when performing coordinated, goal-directed arm and hand movements [17]. The metrics were selectively calculated during the *transport* (i.e., after picking up a peg until approaching a hole), *return* (i.e., after inserting a peg until approaching the next peg), *peg* *approach* (i.e., from targeting a peg until picking it up), *hole approach* (i.e., from targeting a hole until peg insertion), and *force release* (i.e., maximal release of force) phases. In more detail, *log jerk transport* and *number of velocity peaks transport/return* represent the smoothness of movements, *path length ratio transport/return* the efficiency of movements, *force rate mean hole approach* the scaling of grip forces, *force rate spectral arc length transport/return/peg approach*, *force release spectral arc length*, and *force release duration* the coordination of grip forces, *velocity max. transport* the speed, and *task completion time* the overall disability level.

All measures were averaged across pegs as well as repetitions and subsequently normalized with respect to the median and variability of a *reference population* (i.e., data from 120 neurologically intact subjects) [17]. Subsequently, each metric was further normalized with respect to the neurologically impaired subject that indicated maximal disability for this metric, chosen from a representative cohort of 80 neurological subjects. This led to values in the interval $]-\text{inf}, \text{inf}[$ with the median of the reference population being at 0% and the worst observed subject at 100%. Lastly, the influence of confounding factors such as age, gender, handedness, and tested body side was removed [17].

Herein, we additionally provided the outcome measures *dropped handle* (i.e., number of virtual pegs during which the device handle was dropped) and *grip readjustments* (i.e., number of times the hand grip configuration had to be readjusted with assistance from the experimenter), which were commonly observed events during this experiment and manually extracted from video data. Pegs where the handle was dropped or the grip configuration readjusted were excluded for further quantitative analysis.

The outcome measures were visualized and compared between body sides and prostheses. Abnormal behaviour was defined if a value exceeds the 95th-percentile of the *reference population* [17]. Additionally, the relationship between the questionnaire responses and specific metrics was analyzed. In particular, *task completion time*, *log jerk go*, *handle drops/grip readjustments* were chosen as potential indicators of overall disability, arm, and hand control, respectively.

Lastly, the possibility to automatize the detection of phases where the handle was dropped or the grip configuration readjusted was explored using a supervised machine learning approach (i.e., two binary classification problems with video-annotated ground truth). Therefore, nine metrics (range, standard deviation, and maximum per axis) were extracted per peg from the 3D angular velocity trajectories of the handle to capture abrupt changes in orientation during *handle drops*. Similarly, a sliding-window (duration of 0.5 s without overlap) and energy-based (i.e., sum of squared values within each window) approach [19] was used to calculate eight metrics (0th, 5th, 10th, and 15th percentile of energy across windows per trajectory) from the grip force and cursor velocity trajectories to capture *grip readjustments* (i.e., cursor temporarily remaining static without any force applied to handle). The binary classification problems were evaluated in a 10-fold cross-validation using a Random Forest [20]. Class balance was restored during training using the Synthetic Minority Over-Sampling Technique [21]. Classifier performance was evaluated using sensitivity (i.e., true positives over condition positive), specificity (i.e., true negatives over condition negative), and their average (i.e., balanced accuracy).

III. Results

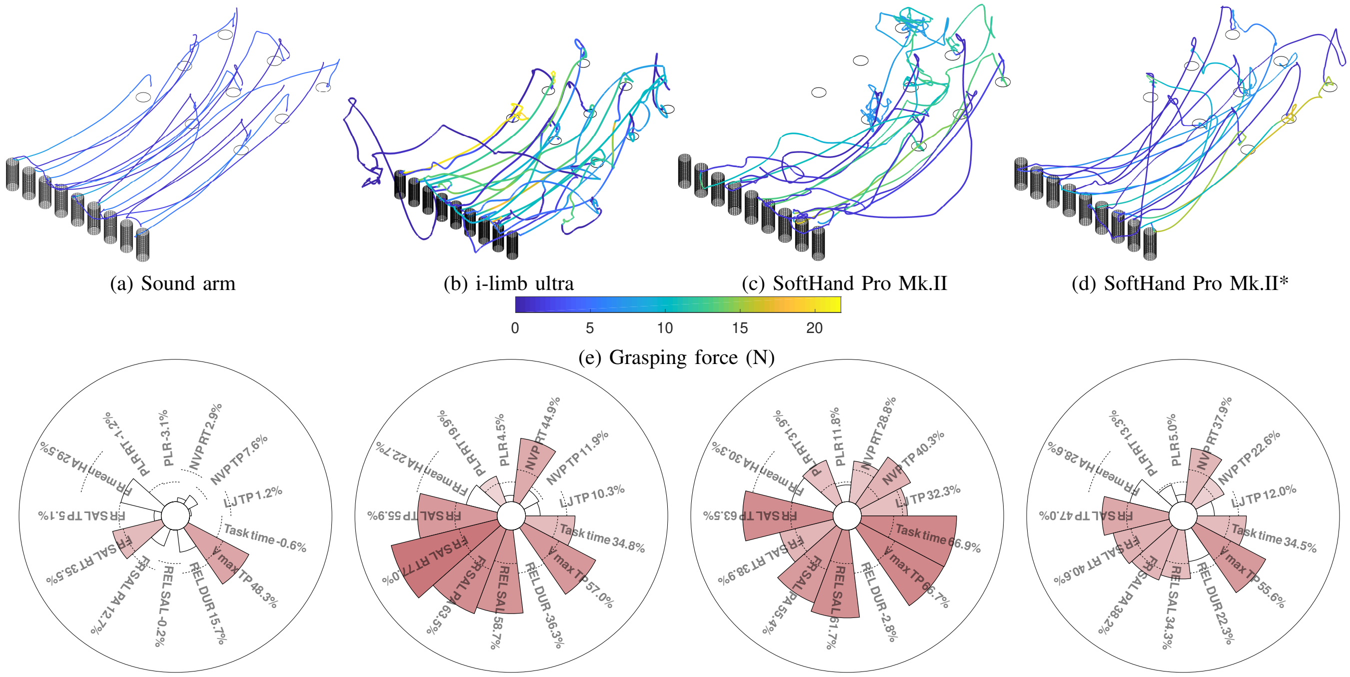
A. Feasibility and objective prostheses evaluation

The SensorHand speed prosthesis was judged to be not suitable for the VPIT, as the low resolution of hand opening and closure control prohibited precise manipulations. Additionally, the SHP Mk.I was excluded from further testing as the relatively high weight of the device led to fatigue in the arm of the subject, which prohibited the completion of the protocol. All five repetitions of the VPIT could be successfully completed with the sound side, i-limb ultra, SHP Mk.II, and SHP Mk.II*, even though four pegs had to be inserted by the experimenter when using the SHP Mk.II. The handle of the haptic device was dropped zero times with the sound side, four times with the i-limb ultra, nine times with the SHP Mk.II, and seven times with the SHP Mk.II*. The grip configuration had to be readjusted zero times for the sound side, three times for the i-limb ultra, 10 times for the SHP Mk.II, and five times for the SHP Mk.II*. The observed movements (Fig. 2 a-d) were smooth and efficient for the sound body side. As expected, less smooth and efficient movements were seen when using a prosthesis, especially when transporting and inserting the pegs. The quantitative VPIT profiles (Fig. 2 f-i) revealed a *task completion time* of -0.6% (increasing values indicates decreasing task performance) for the sound side with the three components *path length ratio transport* (-3.1%), *path length ratio return* (-1.2%), and *actual total time* (-0.6%) having the lowest scores and the three components *force rate spectral arc length return* (35.5%), *velocity max transport* (48.3%), and *force rate mean approach hole* (78.4%) receiving the highest scores.

The *task completion time* across prostheses was 45.4%±18.6%. Lowest scores across prostheses were found in *force release duration* (-5.6%±29.4%), *path length ratio transport* (7.1%±4.1%), and *log jerk transport* (18.2%±12.2%). Highest scores across prostheses were seen in *force rate spectral arc length transport* (55.4%±8.2%), *velocity max transport* (59.8%±6%), and *force rate mean approach hole* (86.9%±16.7%).

B. Influence of prosthesis control settings

The SHP Mk.II was the only prosthesis that was used with regular and subjectively-optimized control settings (SHP Mk.II*), as the configurations could not be adapted for the tested commercial devices. The SHP Mk.II* showed better task performance (d: SHP Mk.II* minus SHP Mk.II; large negative values indicating better task performance with the SHP Mk.II*) according to the *task completion time* (d: -32.4%). Additionally, the SHP Mk.II* received better scores according to *force release spectral arc length* (d: -27.5%), *log jerk transport* (d: -20.3%), and *path length ratio return* (d:



(a) Sound arm (b) i-limb ultra (c) SoftHand Pro Mk.II (d) SoftHand Pro Mk.II*

(e) Grasping force (N)

(f) Sound arm: VPIT 30.4s (g) i-limb ultra: VPIT 80.2s (h) SoftHand Pro Mk.II: VPIT 180.4s (i) SoftHand Pro Mk.II*: VPIT 83.1s

Fig. 2. Movement trajectories (grip force color coded; e) of one representative VPIT repetition for the sound body side and two different prostheses (i-limb ultra, SoftHand Pro Mk.II; a-c). The SoftHand Pro Mk.II was additionally tested with subjectively optimized control settings (SoftHand Pro Mk.II*; d). Movements during which the handle was dropped or the grip readjusted were not visualized. Further, objective VPIT profiles using kinematic and kinetic metrics were constructed (f-i). The inner solid circle represents the median of the reference population (0%) and the outer circle the performance of the worst neurologically impaired subject for that metric (100%). The end of each pie segment indicates the average across five test repetitions. The dashed lines marks the 95th-percentile of the reference population (i.e., abnormal behaviour threshold). Metrics were colored red if their value exceeds the threshold. TP: transport. RT: return. AP: approach peg. AH: approach hole. REL: force release. LJ: log jerk. NVP: number velocity peaks. PLR: path length ratio. FR: force rate. SAL: spectral arc length. DUR: duration. V: velocity.

-18.6%), whereas the SHP MK.II scored better according to *force release duration* (d: 25.0%). Other metrics describing grasping force coordination were either not considerably influenced (d<10%) or the SHP Mk.II* was consistently superior (e.g., *grip readjustments* -5, *handle drops* -2, and *force rate spectral arc length approach peg* -17.2%).

C. Relation between VPIT metrics and questionnaire

Scatter plots (Fig. 3) showed monotonically increasing task performance scores in *log jerk transport*, *handle drops*, and *grip readjustments* with an increase in the subjective difficulty of arm-related and hand-related movements. The *task completion time* did not follow the trends of increasing subjective task difficulty when using the SHP Mk.II and SHP Mk.II*.

D. Detection of handle drops and grip readjustments

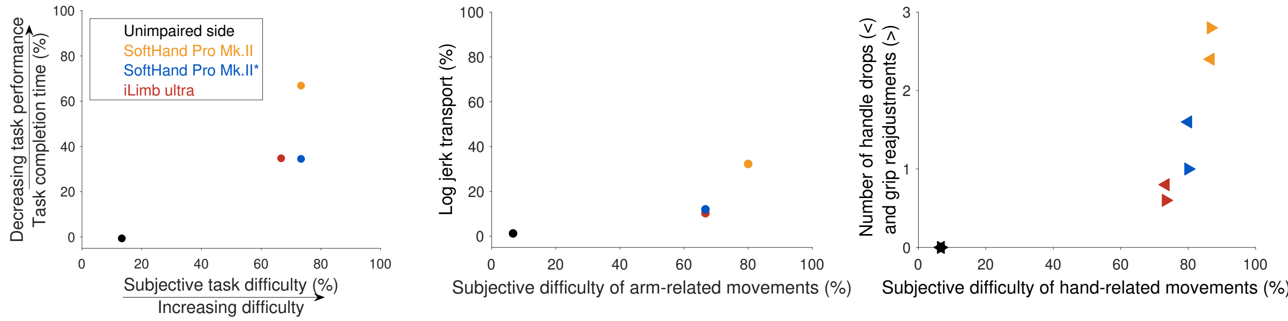
In total, data from 17.2% of all pegs were removed due to *handle drops* and *grip readjustments* using video data. The sensitivity, specificity, and balanced accuracy were 98.5%, 90.9%, and 94.7% for automatically detecting *handle drops* and 93.8%, 69.6%, and 81.7% for *grip readjustments*, respectively.

IV. Discussion

In this work, we presented a pilot study to evaluate the feasibility of objectively assessing upper limb prostheses and their influence when performing goal-directed activities using the VPIT, a technology-based assessment initially designed for applications in neurological disorders. One transradial amputee used four state of the art myoelectrically-controlled prosthetic devices to perform the VPIT protocol, which assesses arm movements, grasping force coordination, and grip stability.

A. Feasibility of using the VPIT in prosthesis users

The task could be successfully performed with technically advanced myoelectric prostheses (i.e., two out of four devices). Especially a high hand closure resolution, as provided by the i-limb ultra and the SHP Mk.II/Mk.II*, was important to allow a precise adjustment of the grasping forces that are required to successfully lift, transport, and release the virtual pegs. Reduced hand closure resolution was also the main factor preventing the use of the VPIT with the SensorHand Speed. Additionally, the implemented control strategy of the prosthesis influences the possibility to perform precise manipulations [22]. Advanced control strategies, such as the synergy-based control as implemented in the SHP [18], may provide advantages when performing the task, although further comparisons for the tested prostheses are prohibited by the limited documentation available for the commercial devices. As suboptimal grasping force control can lead to *handle drops* and *grip readjustments* that negatively affect the quality of the movement data, a machine learning approach was successfully applied to automatically detect and remove



(a) (b) (c)

Fig. 3. Relation between task difficulty (questionnaire) and objective VPIT measures describing overall (a), arm-related (b) and hand-related (c) task performance. For the VPIT metrics, 0% represents the median of a healthy *reference population* and 100% the worst performance of previously recorded neurologically impaired subjects.

phases where such events occurred. This strengthens the data processing framework of the VPIT and eases its application in prosthesis users, as it makes the time-consuming, manual annotation of video data obsolete. Additionally, the generated information about *handle drops* and *grip readjustments* can even be used as further promising assessment metrics.

Factors that challenged the feasibility were the prosthesis weight leading to fatigue when lifting the arm against gravity, which prohibited the subject from performing the protocol with the SHP Mk.I. Lastly, deviations from the power grip that is normally used with the VPIT and collisions between the joints of the haptic device and prosthesis fingers were observed during the task and might influence comparisons between prostheses.

The objective detailed kinematic- and kinetic-based evaluation with the VPIT revealed clear differences between the sound and the amputated body side for arm as well as hand control. More interestingly, the VPIT allowed to identify varying movement patterns for different prostheses, likely resulting from their heterogeneous hardware specifications and control algorithms. This would likely not be captured by clinical assessments that mostly focus on task efficacy (e.g., number of transferred blocks for BBT) and can not quantify the underlying behaviour due to the absence of data related to movement quality.

The Virtual Egg Test has previously been proposed as an instrumented version of the BBT for prostheses and provides two metrics focusing on gross movements (number of transferred blocks) and prosthesis control (number of broken blocks), which were successfully used to evaluate sensory restitution approaches [14, 15]. The assessment with the VPIT could provide additional information through an in-depth evaluation with 14 heterogeneous outcome measures, which have the potential to inform on prostheses quality and its influence on goal-directed activities with high resolution and without ceiling effects, thereby further improving upon the limitations of clinical scales. These metrics complement the information from the Virtual Egg Test by quantifying kinematics and haptic collisions, which can be used to better characterize different upper limb movement patterns and potentially also adaptations of the musculoskeletal and central nervous system, as done in neurological patients [17]. This additional knowledge could also help to better evaluate the potential benefits of approaches providing haptic feedback of grasping forces to prosthesis users [23, 24].

B. Interpretation of the VPIT profiles

The VPIT profiles cannot be directly related to their initial application in neurological disorders [17] and should instead be interpreted considering the design requirements of prostheses. For example, designing devices that enable dynamic and precise adaptations of grasping forces is essential to ensure the applicability of prostheses in daily life activities. Abnormal behaviour (i.e., different than the *reference population*) in the adaptations of grip forces was observed for all prostheses according to the *force rate spectral arc length* metric for the *transport*, *return*, *peg approach*, and *release* phases (Fig. 2 f-i). While these metrics are expected to describe the quality of grasping force coordination, *handle drops* and *grip readjustments* should instead describe the influence of prosthesis quality on the efficacy of object manipulations. It is therefore intuitive that the unraveled reduction in grip force coordination was accompanied by an increase in *handle drops* and *grip readjustments* for all prostheses. Further evidence that the latter two metrics can be used to describe the efficacy of object manipulations is provided by the clear trends between these measures and the subjectively-rated difficulty of hand movements (Fig. 3 c). Interestingly, the metric *force release duration* instead indicated faster release of force than the *reference population* with two prostheses (Fig 2 g-h). This might be related to the specific implementation of the prosthesis controller, but seemed to not directly influence the efficacy of object manipulations during goal-directed movements.

Lastly, the assessment metrics were sensitive to changes in prosthesis control settings, which could help to better tailor a prosthetic device to the user. For example, the reduced closure velocity of the SHP Mk.II* compared to the SHP Mk.II led to an increased *force release duration*. However, these adaptations, in conjunction with the changes to EMG control, seemed to actually be beneficial for the quality of grip force coordination (according to improvements in e.g. *force rate spectral arc length transport*) and the efficacy of object manipulations (according to improvements in e.g. *grip readjustments* and *handle drops*).

C. Exploring adaptations of the musculoskeletal and central nervous system

Assessing adaptations of the musculoskeletal and central nervous system could be relevant to quantify compensatory movements during prosthesis usage [11, 12] or neuronal processes underlying the familiarization to novel prostheses and environmental dynamics [13]. For example, the observed abnormal movement efficiency according to the *path length ratio return* (Fig. 2 g-h) when using the prostheses might result from compensatory trunk movements due to the missing DoF at the wrist of the devices [11, 12]. Additionally, the internal model of the CNS, which translates intended movements using physiological and environmental system states into neural activation patterns, might not be able to quickly adapt to the dynamics of different prostheses that were unfamiliar to the subject [25]. This could also influence the feedforward control of movement and might be reflected by abnormal movement smoothness according to the *number of velocity peaks transport/return*. The proposed approach might therefore allow to inform on learning and adaptation mechanisms of the musculoskeletal and central nervous system, which should be further investigated in follow-up studies.

D. Limitations

This work is a preliminary investigation and additional subjects would be required to analyze the applicability of the assessment in-depth. Also, the recruited subject had considerable prior experience with myoelectrically-controlled prostheses. The generalization of the approach to users that are naive to such devices will therefore be evaluated in a follow-up.

V. Conclusions

This pilot study demonstrates the feasibility of using the VPIT as a technology-based assessment in experienced upper limb prosthesis users and highlights its potential to objectively and quantitatively evaluate the performance of advanced myoelectrically-controlled prostheses. Future work will moreover focus on unraveling the correlates of the VPIT profiles through comparisons with clinical assessments.

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