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Exploring the impact of myoelectric prosthesis controllers on visuomotor behavior

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Abstract

Background Prosthesis users often rely on vision to monitor the activity of their prosthesis, which can be cognitively demanding. This compensatory visual behaviour may be attributed to an absence of feedback from the prosthesis or the unreliability of myoelectric control. Unreliability can arise from the unpredictable control due to variations in electromyography signals that can occur when the arm moves through different limb positions during functional use. More robust position-aware control systems have been explored using deep learning methods, specifically ones that utilize data from different limb positions, that show promising improvements in control characteristics. However, it is unclear how these novel controllers will affect visuomotor behaviour. Specifically, the extent to which control interventions can influence gaze behaviours remain unknown, as previous studies have not yet demonstrated the sensitivity of eye metrics to these interventions. This study aims to explore how visuomotor behaviours change when individuals operate a simulated myoelectric prosthesis using a standard control strategy compared to a position-aware control strategy.

Methods Participants without limb difference tested two control strategies in a within-subject crossover study design. They controlled a simulated myoelectric prosthesis using a standard control strategy and an advanced position-aware control strategy designed to address the limb position effect. The order in which these control strategies were evaluated was randomized. Eye tracking and motion capture data were collected during functional task execution to assess if using the position-aware control strategy changed visuomotor behaviour compared to the standard controller.

Results There was less visual fixation on the prosthetic hand in the fully extended and cross-body arm position when using the position-aware controller compared to the standard controller. These changes were associated with shorter grasp phase duration and increased smoothness of prosthesis movements. These findings indicated that using the position-aware control strategy may have resulted in less reliance on vision to monitor the prosthesis actions in limb positions where they had better prosthesis control.

Conclusions This research suggests that visuomotor metrics may be sensitive to prosthesis control interventions, and therefore the use of eye tracking should be considered for performance assessment of prosthesis control.

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Keywords Eye tracking, Motion capture, Gaze behaviour, Visuomotor behaviour, Upper limb prosthesis, Myoelectric prosthesis, Electromyography, Limb position effect, Deep learning, Control strategy

Background

With amputation, the natural communication pathways between the brain and the hand responsible for motor control and feedback are lost. As a result, prosthesis users must rely heavily on vision to monitor the activity of their prosthesis, disrupting normal patterns of eye-hand coordination [1, 2]. In individuals with intact arm function, the eyes rarely fixate on the hand. Instead, the eyes guide the hand movements in a predictive, feedforward manner, using visual information to plan motor actions [3–6]. Haptic feedback from the intact hand is able to confirm successful grasp, allowing the eyes to disengage from current targets and shift towards future target areas [3, 5–7]. In contrast, prosthesis users typically rely on vision to monitor their prosthetic device, which can be characterized by increased visual fixations towards the prosthetic hand, reduced fixations towards target areas, and delays to disengage visual attention from objects when picked up or dropped off [1, 2, 8–10]. Together, these behaviours may reflect a lack of confidence in the prosthesis control, as well as a compensatory behaviour to overcome the lack of feedback.

Upper limb prosthesis users are therefore faced with high attentional demands when operating their prosthetic device. The need to visually attend to the hand is often regarded as being cognitively demanding and is one of the contributing factors to device dissatisfaction and rejection [11, 12]. In fact, visual fixations towards the hand have been shown to encompass multiple workload factors, such as mental demand, physical demand, visual demand, conscious processing, and frustration [13]. Therefore, new prosthetic interventions should aim to reduce the attentional demand associated with prosthesis use while also increasing movement functionality.

Sensory feedback interventions have demonstrated the potential to alleviate this reliance on vision for prosthesis users. By restoring the natural feedback channels and providing users with touch and kinesthetic feedback, visual fixations towards the hand have been shown to be reduced [14]. Such evidence lends support to the hypothesis that a lack of sensory feedback contributes to the high visual demand associated with prosthesis use. However, no studies have investigated whether prosthesis control interventions have similar beneficial effects on gaze behaviour [15]. Chadwell et al. [16] revealed that a higher frequency of undesired activations (e.g. hand opening/closing when unintended, incorrect prosthesis response, or no prosthesis response) was linked to altered visuomotor behaviours, including increased fixations towards the hand, decreased fixations towards the target and an increased number of gaze switches, as well as decreased functionality. This evidence suggests that vision is continually drawn towards the prosthesis to ensure that the hand performs as intended. Therefore, addressing the unpredictability of myoelectric prosthesis control could potentially reduce the reliance on vision and thereby improve the usability of these devices.

One major factor affecting the accuracy and reliability of myoelectric control is the alteration of electromyography (EMG) signal patterns caused by limb positioning [17–19]. These variations in EMG signals can degrade prosthesis control and may cause unwanted prosthetic hand and wrist movements to occur [17]. Recent work has explored the use of deep learning methods, specifically transfer learning, as a possible solution for improving movement predictions and providing more consistent control [20–22]. This work demonstrated that task performance metrics (such as success rate, task duration, and hand kinematic measures) were insufficient to identify instances of limb position effect. However, control characteristics (such as wrist rotation and grip aperture across specific movements) did identify significant differences when using a position-aware control strategy meant to address the limb position effect. This control strategy combines user-specific training data with a model pre-trained on a large dataset of defined hand gestures in multiple limb positions. The benefit of such a model is the potential to accurately predict movement intent across different limb positions, while also shortening the time required to train the control system. Theoretically, this advanced position-aware controller should reduce the cognitive burden of the user; a theory that may be explored by recording and measuring changes in user's visual behaviour while performing tasks with their prosthesis.

In this work, we therefore extend the previous study by Williams et al. [22] to explore whether visuomotor behaviours differed when individuals used two different myoelectric control strategies with a simulated myoelectric prosthesis. Importantly, no studies to date have explored the impact of different prosthesis controllers on gaze behaviour [15]. As such, this study is the first of its kind to investigate the sensitivity of eye metrics in response to various prosthesis controllers. It was hypothesized that the control strategy that was shown to have more reliable myoelectric control should show a corresponding change in visual attention– specifically, less visual fixations to the prosthetic hand and quicker disengagement of visual fixation after grasping or releasing objects. To test this hypothesis, we examined eye gaze and hand movement data collected during an experimental task that challenged the user in various planes of movement, while using the novel position-aware control strategy that was designed to address the limb position effect compared to a standard controller. We were specifically interested in changes in visual attention that would correspond to the movements and positions that were identified by Williams et al. [22] to represent control difficulties related to the limb positioning.

Methods

Participants

Nine participants (7 male, 2 female) with no upper limb pathology or history of neurological or musculoskeletal impairment were recruited for this study. The data from one participant was incomplete due to technical issues. The eye data from another participant was considered to be poor quality based on a predetermined set of rules that checked eye data loss and spatial accuracy (described in the data processing section). Therefore, two participants were removed from this study and the data of the remaining 7 participants were included for analyses. Of the remining 7 participants, 5 were male and 2 were female. All participants had little to no experience with controlling a prosthetic hand using EMG pattern recognition. Four had normal or corrected-to-normal vision, the remaining three participants that required eyeglasses were asked to remove them when wearing the eye tracking headset. These participants self-reported that their uncorrected vision was sufficient to perform the tasks in this study. The mean age was 23.4 ± 4.3 years, and the mean height was 178.8 ± 6.4 cm. One individual reported to be left-handed and the remaining 6 participants reported to be right-handed. All participants provided written informed consent. This study was approved by the University of Alberta Health Research Ethics Board (Pro00086557).

Experimental setup

Simulated prosthesis

A simulated prosthesis was modified to be used in this study [23]. The device was designed to simulate a myoelectric prosthesis that is worn by an individual with a transradial amputation. The simulated prosthesis consisted of 3D printed parts that were secured to the right forearm of the participant by a brace that restricted hand and wrist movements. A terminal device with two degrees of freedom (hand open/close and wrist rotation) [24] was attached to the palmar side at the approximate location of the participant's anatomical hand, as shown in Fig. 1a. A Myo armband (Thalmic Labs, Kitchener, Canada– discontinued) was placed around the participant's right forearm, an average of 7.1 ± 1.2 cm distal to the medial epicondyle of the humerus (Fig. 1b). The Myo armband collected EMG data from 8 surface electrodes sampled at 200 Hz and positional data from one inertial measurement unit (IMU) sampled at 50 Hz. EMG data and accelerometer data from the IMU were collected and used to control the terminal device. Patterns of EMG activity recorded during wrist extension and wrist flexion were mapped to prosthetic hand open and close, respectively. Patterns of EMG activity recorded during wrist supination and wrist pronation were mapped to rotate the prosthetic wrist clockwise and counterclockwise, respectively.

Pasta box task

A standardized Pasta Box Task, developed by Valevicius et al. [25], involved moving a pasta box from shelves at different heights to mimic a kitchen scenario. The task required participants to manipulate objects in different planes of movement. There were three movements: Movement 1 involved moving a pasta box from a lower table on the right side of the body to a shelf directly in front of the participant; Movement 2 involved moving the pasta box across the midline around a barrier to

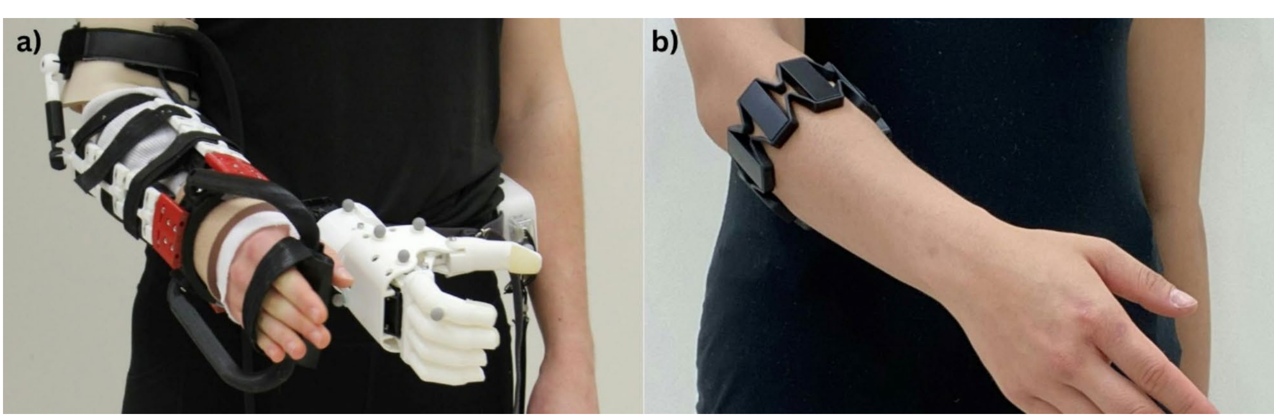

Fig. 1 **a**) Simulated prosthesis worn by an individual with an intact arm and **b**) Myo armband worn around the forearm underneath the simulated prosthesis

a second higher shelf; and Movement 3 consisted of a cross-body movement to return the pasta box to the initial starting position. Each movement began and ended when the hand was moved to a neutral 'Home' position, which allowed for the motion capture and eye tracking data to be segmented into discrete movements. Each movement consisted of 4 phases: 'Reach', 'Grasp', 'Transport' and 'Release'. Task description and details were published in Valevicius et al. [25].

Motion capture and eye tracking setup

The Gaze and Movement Assessment (GaMA) was performed to quantify hand kinematics and gaze behaviour during object interaction [25–28]. An 8-camera Optitrack Flex 13 motion capture system (Natural Point, OR, USA) was used to measure the 3-dimensional movements of the hand sampled at 120 Hz. Eight individual motion capture markers were attached to the prosthetic device— one on the thumb, one on the index finger, and six on a rigid surface of the hand (Fig. 1a). Additional individual markers were placed on task-relevant areas of the workspace (pasta box, shelving unit, and side table), as outlined in the supplementary materials of Valevicius et al. [25]. A head-mounted binocular eye tracker (Pupil Labs GmbH, Berlin, Germany) with 4 affixed motion capture markers was placed on the participant to record pupil movements sampled at 120 Hz. The cameras were optimally positioned, such that the pupils remained in frame when the eyes moved around the task space.

Experimental procedure

On two separate days, participants performed functional tasks using the simulated prosthesis with either a standard control strategy or an advanced position-aware control strategy. Testing sessions were separated by an average washout period of 27 ± 9 days to avoid any learning effects. Additionally, the order in which controllers were tested was randomized to counterbalance any potential learning effects. Four participants used the standard strategy first, while the other three participants used the position-aware control strategy first.

Controller training

On the same day of testing and before controlling the simulated prosthesis, a controller training routine and calibration was performed to learn the muscle signals of the participant. EMG and IMU data were collected and streamed into Matlab using Myo SDK. Custom Matlab scripts captured the data to learn an individual's intended movements from muscle patterns that were later used to send control signals to the prosthesis. Participants were instructed to perform moderate forearm muscle contractions while following onscreen instructions for specified wrist movements (rest, flexion, extension, pronation, supination).

The standard control strategy used a statistical machine learning model (linear discriminant analysis) that was trained in one limb position. This training routine involved wrist at rest, flexion, extension, pronation, and supination with the elbow bent at 90°, holding each muscle contraction for 5 s. This series of wrist movements were repeated twice. The EMG data resulting from this routine, along with the corresponding labels of wrist positions, were used to train the standard control model.

The position-aware control strategy used a recurrent convolutional neural network (RCNN) model with transfer learning, developed by Williams et al. [21, 22]. This model was originally trained with data from a large group of 19 individuals without upper limb loss. These individuals performed a training routine similar to those used in the literature to address the limb position effect [18, 29, 30]. It included performing each of the wrist movements in 4 arm positions (arm at side, elbow bent at 90°, arm out in front at 90°, and arm at 45° above shoulder height). The EMG and accelerometer data from all 19 participants, along with the corresponding labels of wrist positions, were used to pre-train the control model. This data, the control models, and the experimental procedure were described in full details in Williams et al. [29].

Prosthesis usage training

Each participant took part in a device usage training block to learn how to control the prosthetic hand using forearm muscle activity. This training was completed for each session once the controller was trained. Participants progressed through a structured training protocol and were given the opportunity to practice functional tasks (including the Pasta Box Task) before the first data collection trial. There were 3 stages of training: participants practiced controlling (1) only the hand open and close degree of freedom (DOF), (2) only the wrist rotation DOF, and (3) both DOFs together. A variety of picking up and placing objects, and object rotation tasks were presented to participants in each stage. As they carried out these tasks, verbal cues were given to help improve control of their device. Breaks were provided after each stage of training or as required. To ensure that participants had sufficient training and a reasonable level of competency in controlling the prosthesis to proceed with the data collection, participants needed to demonstrate that they could successfully pick up a cup containing a ball and pour the ball into another cup with more than 75% success rate after at least 10 trials within a 10-minute time period [31, 32].

Data collection

Each participant performed 10 trials of the Pasta Box Task. If an error was made, the data from that trial was discarded. Errors included dropping the box, incorrect grasp, incorrect box placement, missing the drop off target, incorrect task sequence, hitting the task cart frame, movement hesitation, or unintentional movements, such as a sneeze. Prior to the first trial and immediately after the last trial of the Pasta Box Task, two gaze calibrations were collected to construct a gaze vector that represented the location of the participant's gaze in the task space [33]. In these gaze calibrations, participants were instructed to fixate on a motion capture marker attached to the tip of a calibration wand as the experimenter moved the wand through the task space.

Data processing

Motion capture and eye tracking data were first cleaned to fill any gaps. Second-order, low-pass Butterworth filters with a cut-off frequency of 6 Hz for motion capture [25] and 10 Hz for eye tracking [27] were applied to remove any noise that may have been introduced during data collection. The motion capture and eye tracking data were then synchronized to the motion capture frame rate using the common timestamps in the Lab Streaming Layer data stream files, as described in Stone et al., [33]. The combined data were imported into our custom software platform for integrated analysis of eye and motion capture data [28]. The movements were segmented and divided in 'Reach', 'Grasp', 'Transport', and 'Release' phases for analysis using hand velocities and distances as described by Lavoie et al. and Valevicius et al. Where relevant, comparison to normative data was referenced from the "repeated study" (Optitrack set up) condition from Williams et al., [28].

For hand kinematic measures, reach and grasp phases were combined into a reach-grasp segment, and transport and release phases were combined into a transport-release segment. Eye latency measures were defined relative to two key events: 'Pickup', which referred to the transition between grasp and transport as the object began moving and 'Drop off', which referred to the transition from transport to release as the object stopped moving. Using these object-related 'Pickup' and 'Drop off' events afforded the ability to reveal the temporal dynamics between the location of visual fixations and the location of the hand and object.

To ensure the accuracy and validity of the eye data, a set of rules were followed describing the quality of the best gaze vector based on whether fixations were towards relevant areas of interest (AOIs) at specific time points, similar to descriptions in [27, 33]. After the best gaze vector was identified, we then evaluated the quality of each trial to remove trials with poor eye data. Firstly, a trial was removed if more than 15% of the best gaze vector data was missing or if the average distance to relevant AOIs for the best gaze vector was greater than 50 mm. Secondly, a trial was removed if the total percent fixation (sum of percent fixation to current, hand and future) for any phase, except Reach in Movement 1 was less than 50%. In addition, a trial was removed if the total percent fixation in Reach of Movement 1 was less than 30%, as it is known that objects outside the field of view are fixated less [27]. Lastly, if more than 50% of a participant's trials from one testing session were removed, data from that participant was removed altogether. Following this process, one participant was removed due to poor quality of eye data. A total of 25 trials out of 148 collected trials were removed (17% data removed). An average of 9 trials were retained for each participant for both control strategies. Figure 2 illustrates the steps taken to remove trials with poor eye data.

Outcome metrics

Gaze behaviour

Number of fixations referred to the number of continuous fixations (duration > 100ms) to either the current target or the hand. Percent fixation was the amount of time spent fixating either the hand or the current target in reach and transport phases as a percentage of the duration of that phase. During the reach phase, the current target referred to the pasta box and its starting location. During the transport phase, the current target referred to the next drop off location. A detailed description of the areas of interest for each phase of the pasta box task can be found in the supplementary materials of Lavoie et al. [27]. Normative reference data indicate that the majority of time during a movement (around 75%) is spent fixating on the next target of action, with a less time focused on the hand (around 10%). In contrast, prosthesis users tend to have much higher fixations to the prosthetic hand [10]. It was hypothesized that with a more reliable control strategy, there will be less fixation to the hand and more fixations to the current target when transferring the pasta box. This effect should be most apparent when the arm moves in an elevated cross-body position (drop off of movement 2 and pick up of movement 3) where the position-aware controller showed an improvement over the standard controller [22].

Eye arrival latency (EAL) was calculated as the difference between the time of eye arrival to the target location relative to the start of transport time for pickup and relative to the end of transport time for drop off. Normative EAL values are typically under 1 s for the pasta task. The EAL was positive if the eyes began fixating the target before the object was picked up or dropped off and negative if the eyes began fixating the target after the object was picked up or dropped off. EAL at pick-up was related

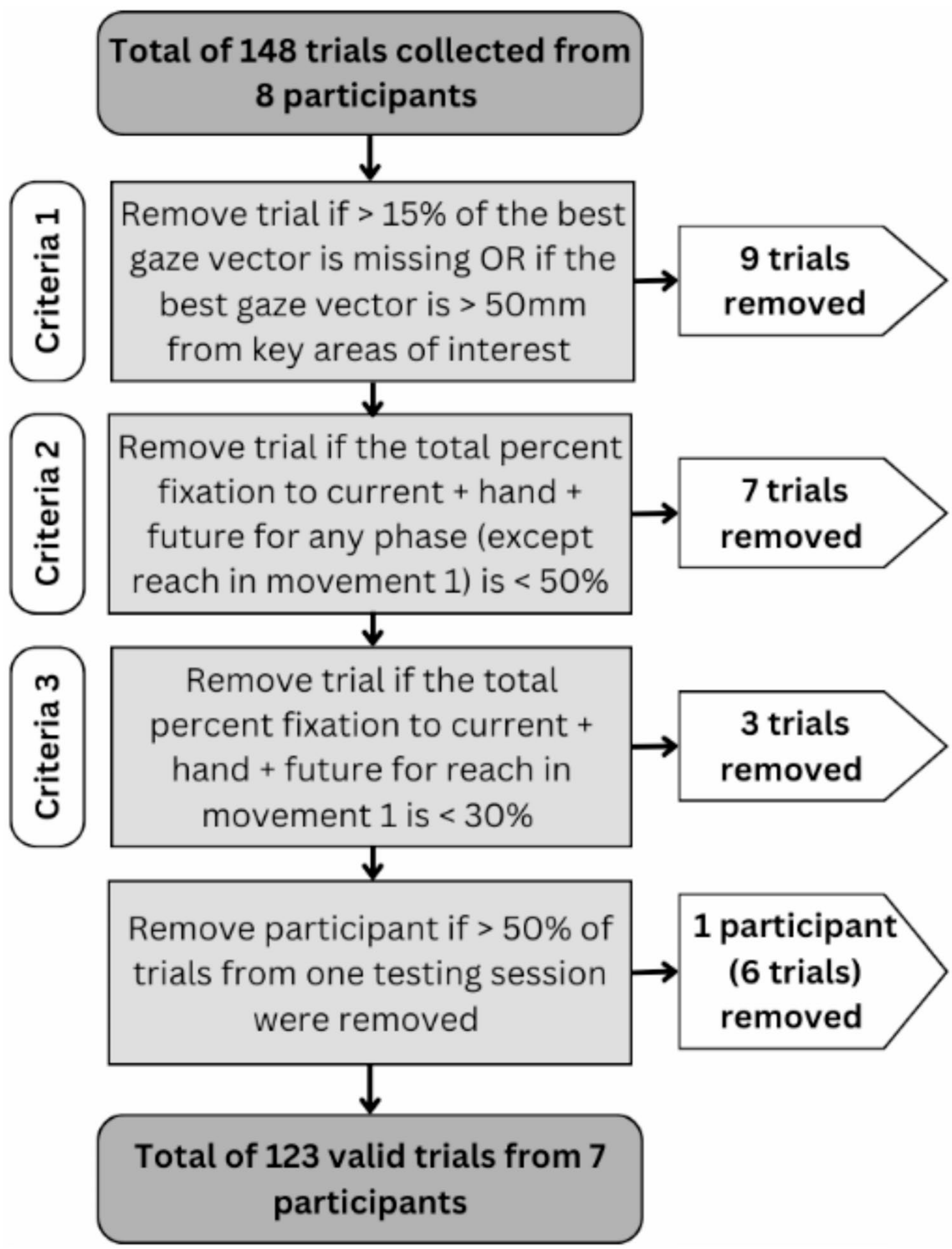

Fig. 2 Flowchart outlining the steps taken to check the quality of the eye data. These criteria verified the amount of data loss and spatial accuracy of the best gaze vector that was constructed for each trial

to the reach-grasp segment. EAL at drop off was related to the transport-release segment.

Eye leaving latency (ELL) was calculated as the difference between the time of the eye leaving the target location relative to the start of transport time for pick-up and relative to the end of transport time for drop off. ELL values were positive if the gaze departed the target before the object was picked up or dropped off and negative if the gaze departed the target after the object was picked up or dropped off. ELL at pick-up was related to the transition point from grasp to transport and ELL at drop off was related to the transport-release segment. ELL normative values are typically close to zero to negative 250ms, indicating individuals very quickly [27, 28] or instantaneously disengage their eye fixation after picking up or dropping off an object. In contrast, prosthesis users tend to have prolonged ELL times of up to 1 s [10]. The hypothesis was that with more secure pickup and drop off of the box, the eyes will disengage quicker and so demonstrate shorter ELLs closer to normative range.

Duration

Total task duration consisted of the total time in seconds to complete an entire trial. Phase duration was the time in seconds for each phase of reach, grasp, transport and release. Relative phase duration was the length of each phase represented as a percentage of the total movement time. Prosthesis user generally have overall longer task durations than persons with normal arm function, but they also spend a disproportionate amount of time grasping and releasing objects (compared to transporting) [10]. Therefore, both absolute and relative phase durations provide different but valuable information on how the task is being performed, and how visual fixation might be altered depending on the time spent grasping and releasing.

Hand kinematics

Visual behaviour can only be interpreted in relation to hand movement, as hand-eye coordination is inextricably linked. Therefore, hand kinematic measures were included to provide context for the eye metrics, and were analyzed per movement rather than averaged across movements as in Williams et al., [22]. Peak hand velocity was defined as the maximum speed of the end effector (in any direction), given in mm/s. Number of movement units referred to the number of times that the hand acceleration profile crossed zero to produce a local velocity peak, and indicate the smoothness of the movement. Hand trajectory variability was calculated as the maximum of the mean three-dimensional standard deviation at each time-normalized point in millimetres. Grip aperture plateau was defined as the time in seconds between the end of hand opening and the start of hand closing. This was defined when the grip aperture was $<90\%$ of maximum and when the hand opening or closing velocity was $<20\%$ of maximum [8].

Statistical analysis

For each participant, the outcome metrics were averaged across trials for each control condition. To investigate the within-subject differences between standard and position-aware control, a series of repeated measures analyses of variance (RMANOVA) were conducted for each outcome metric. Significant interaction effects or main effects were followed up with additional RMANOVAs or pairwise comparisons. Only significant effects involving the control strategy used were further investigated, as the primary focus was to determine whether different control strategies had an effect on visuomotor performance. If the assumption of sphericity was violated, the Greenhouse-Geisser correction was used for the interpretation of results. Interaction effects or main effects were considered to be significant if the p value was less than 0.05 or if the Greenhouse-Geisser corrected p value was less than 0.05. Pairwise comparisons were considered to be significant if the Bonferroni corrected p value was less than 0.05.

Results

Eye gaze metrics

Percent fixation

With the position-aware control strategy, there was a significant decrease in percent fixation to hand in movement 3 compared to the standard controller (standard $26.2 \pm 4.4\%$; position-aware $20.7 \pm 3.1\%$, $p = 0.037$). A 3-way RMANOVA revealed no significant three-way interaction between strategy, movement and phase ($F(2, 12) = 1.367$, $p = 0.29$). Further analysis revealed a statistically significant difference in two-way strategy x movement interaction ($F(2, 12) = 5.23$, $p = 0.023$) (Additional File 1). Figure 3 demonstrates that the decrease in percent fixation to hand occurred in both reach and transport phases in movement 3, while there was no difference in fixations towards the hand between controllers in any other movement. Therefore, when using the position-aware control strategy, participants had a reduced reliance on vision to monitor the hand in movement 3. Decreased fixations towards the hand were not accompanied by increased fixations towards the current target. A 3-way RMANOVA revealed no other significant interaction effects or main effects for percent fixation to current (Additional File 1).

Eye leaving latency

In general, the position-aware control strategy showed a trend towards shorter eye leaving latencies compared to the standard control strategy (Additional File 1). A 3-way RMANOVA revealed no significant three-way interaction between strategy, movement and event ($F(2, 12) = 3.625$, $p = 0.059$). There was no significant two-way interaction between strategy and movement ($F(2, 12) = 3.274$, $p = 0.073$) or strategy and event ($F(1, 6) = 0.411$, $p = 0.545$). However, there was a significant main effect of strategy ($F(1, 6) = 6.419$, $p = 0.044$) with a mean difference of -0.468 s. Figure 4 reveals that eye leaving latencies were consistently shorter across all movements and events with the position-aware control compared to standard control, with a largest difference of -1.081s (95% CI, -1.926 to −.236s) at drop off in movement 2. Therefore, there was a consistent trend for the position-aware control strategy to require a shorter time for the eyes to disengage visual attention from pick up and drop off targets than the standard control strategy.

Other eye gaze metrics

There were no other significant interaction effects or main effects for number of fixations to current or to hand, eye arrival latency at pick up, eye arrival latency at drop off, or eye leaving latency at drop off (Additional File 1).

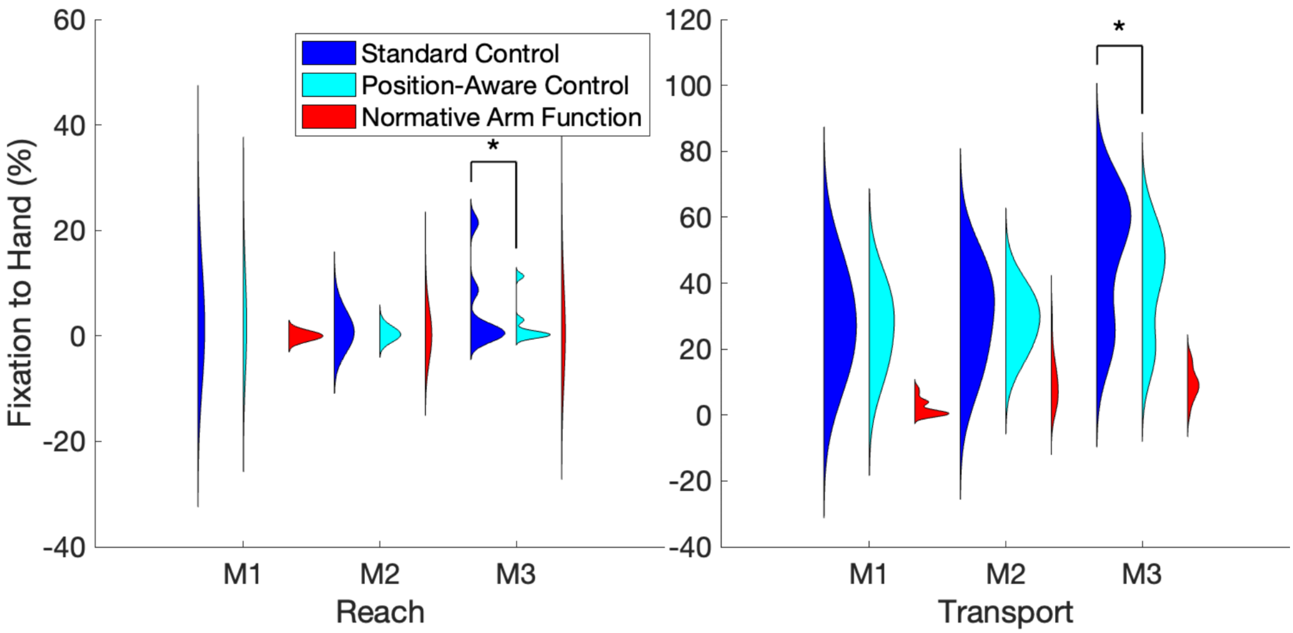

Fig. 3 Percent fixation to hand violin plots with standard (dark blue) and position-aware (light blue) control strategies for reach and transport phases of each movement (M1 = Movement 1, M2 = Movement 2, M3 = Movement 3) of the pasta box task. Normative values are represented by red violin plots. The asterisks (*) indicate statistically significant differences ($p < 0.05$) between standard and position-aware control in movement 3

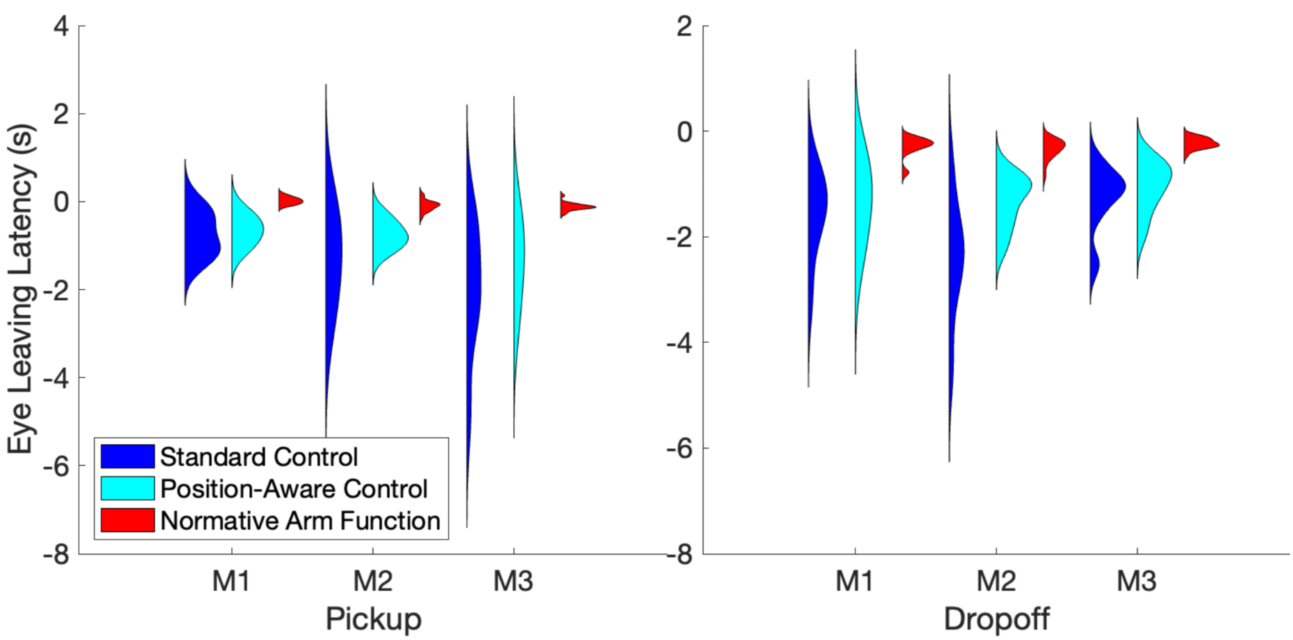

Fig. 4 Eye leaving latency violin plots with standard (dark blue) and position-aware (light blue) control strategies for pick up and drop off events of each movement (M1 = Movement 1, M2 = Movement 2, M3 = Movement 3) of the pasta box task. Normative values are represented by red violin plots

Duration

Total task duration

There was no statistically significant difference in total task duration between control strategies $t(6) = 1.629$, $p = 0.154$, $d = 0.616$. Participants had an average total task duration of 28.6 ± 7.8s with the standard control and a total task duration of 24.0 ± 4.9s with the position-aware control, a mean difference of 4.6s (95% CI, -2.3 to 11.6s). Although no statistically significant difference, there was a trend for movement times to be shorter with the position-aware control strategy. In movement 1, there was a mean difference of 1.0s (95% CI, -1.3 to 3.2s), in movement 2 there was a mean difference of 1.5s (95% CI, -0.5 to 3.4s), and in movement 3, there was a mean difference

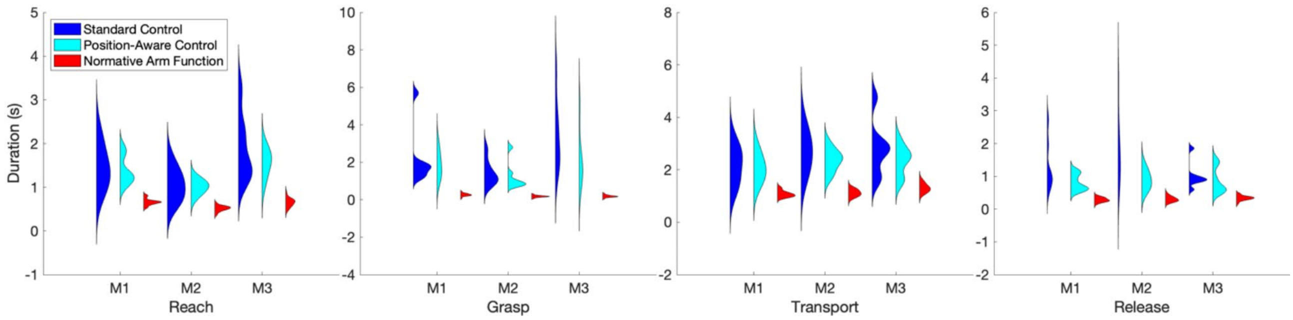

Fig. 5 Phase Duration violin plots with standard (dark blue) and advanced position-aware (light blue) control strategies for each movement (M1 = Movement 1, M2 = Movement 2, M3 = Movement 3) and phase of the pasta box task. Normative values are represented by red violin plots

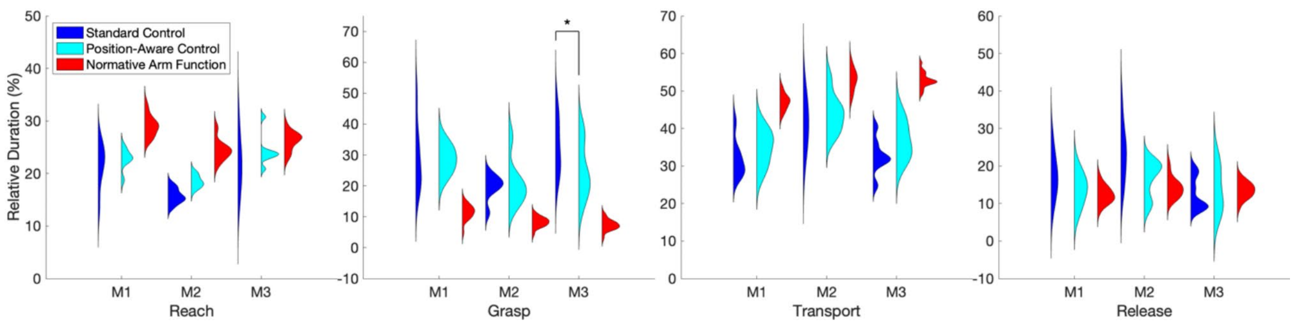

Fig. 6 Relative phase duration violin plots with standard (dark blue) and position-aware (light blue) control strategies for each movement (M1 = Movement 1, M2 = Movement 2, M3 = Movement 3) and phase of the pasta box task. Normative values are represented by red violin plots. Significant differences ($p < 0.05$) between control strategies are marked with an asterisk (*)

of 2.2s (95% CI, -0.6 to 4.9s) between standard and position-aware control strategies.

Phase duration

Although no statistically significant differences were found in phase durations, there was a trend for phase duration across all movements to be shorter with the position aware controller (Additional file 1, Table 3), with the absolute differences most noticeable in movement 2 release and Movement 3 grasp. A significant three-way interaction ($F(1.974, 11.843) = 4.587$, $p = 0.034$) between strategy, movement and phase was revealed for phase durations. To follow this up, two-way interactions were run for strategy x movement at each level of phase. There was a statistically significant simple two-way interaction between strategy and movement for release ($F(2, 12) = 4.688$, $p = 0.031$). Pairwise comparisons revealed a mean difference of 0.866s (95% CI, -0.083 to 1.854s), $p = 0.066$ in release of movement 2 between standard and position-aware control strategies. Despite a non-significant difference at a Bonferroni adjusted $p < 0.05$, the magnitude of difference was large compared to other phases. In addition, a simple two-way interaction between strategy and movement for grasp was not found to be significant ($F(2, 12) = 3.080$, $p = 0.083$), however there was a large mean difference of 1.322s (95% CI, −0.407 to 3.050s) in grasp of movement 3 between standard and position-aware control strategies, which was not observed in any other phases (Additional File 1). Therefore, release in movement 2 and grasp in movement 3 demonstrated trends towards shorter phase durations with the position-aware controller compared to standard controller (Fig. 5).

Relative phase duration

Relative phase duration was significantly less for the position-aware controller in movement 3 grasp (standard $32.8 \pm 8.8\%$; position-aware $25.1 \pm 9.0\%$, $p = 0.002$). There was a trend in which the position-aware control strategy had a shorter relative duration of release in movement 2 (standard $23.3 \pm 7.6\%$, position-aware $16.7 \pm 4.9\%$, $p = 0.052$), which closely matched the normative value for relative release time as shown in Fig. 6. A 3-way RMANOVA revealed a significant three-way interaction between strategy, movement and phase ($F(6, 36) = 3.313$, $p = 0.011$). Follow up two-way interaction effects were run for strategy x movement at each level of phase. There was a statistically significant simple two-way interaction between strategy and movement for release ($F(2, 12) = 7.756$, $p = 0.007$). Pairwise comparisons revealed there was a mean difference of 6.686% (95% CI, −0.095 to 13.467%), $p = 0.052$ in release for movement 2 between standard and the position-aware control, although not significant at a Bonferroni adjusted $p < 0.05$ (Additional

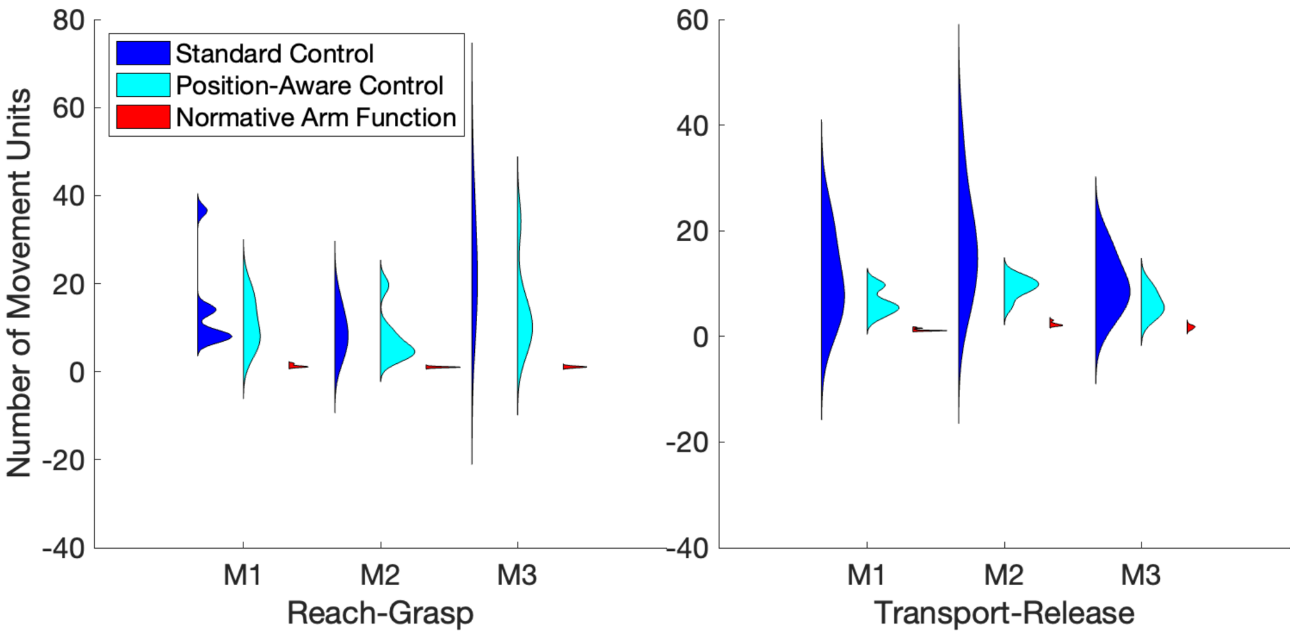

Fig. 7 Number of movement units violin plots with standard (dark blue) and position-aware (light blue) control strategies for each movement (M1 = Movement 1, M2 = Movement 2, M3 = Movement 3) and movement segment of the pasta box task. Normative values are represented by red violin plots

File 1). No other relative phase durations were found to be significantly different between standard and position-aware control strategies.

The large decrease in absolute release time for movement 2, in combination with a shorter total movement 2 duration of 5.5 ± 1.1s with the position-aware control compared to 6.9 ± 2.2s with standard control, contributed to the trending decrease in relative release time for movement 2. A large mean difference in absolute grasp time for movement 3, together with a shorter total movement 3 duration of 6.9 ± 1.7s with the position-aware control compared to 9.1 ± 2.9 with standard control, resulted in the significant decrease in relative grasp time for movement 3.

Hand kinematic measures

Number of movement units

There were fewer movement units in all movement segments with the position-aware control strategy than the standard control strategy, specifically in the reach-grasp of movement 3 (standard 23.7 ± 11.5, position-aware 13.8 ± 9.8, $p = 0.053$) (Additional File 1, Fig. 7). A 3-way RMANOVA revealed a statistically significant three-way interaction between strategy, movement and segment ($F(1, 6) = 10.622$, $p = 0.002$). To follow this up, two-way interactions were run for strategy x movement for each segment. A simple two-way interaction between strategy and movement for reach-grasp ($F(2, 12) = 4.730$, $p = 0.031$) was shown to be statistically significant, while there was no statistical significant interaction between strategy and movement for transport-release ($F(2, 12) = 2.068$, $p = 0.169$). Pairwise comparisons revealed a trending mean difference of 9.860 movement units in reach-grasp of movement 3 between standard and position-aware control strategies (95% CI, -0.169 to 19.889), ($p = 0.053$) (Additional File 1). In addition, although not statistically significant, there was a disproportionately large mean difference of 8.341 (95% CI, − 0.552 to 17.235) movement units in transport-release of movement 2 (Additional File 1). These values represented large differences in movement units that were not observed in any other movement segments, therefore when using the position-aware control strategy, participants likely had increased smoothness of hand movements in transport-release of movement 2 and reach-grasp of movement 3.

Other hand kinematic measures

There were no significant interaction effects or main effects for hand trajectory variability, peak hand velocity and grip aperture plateau (Additional File 1).

Discussion

This study aimed to explore whether the eye gaze behaviours of participants using a myoelectric prosthesis would change closer to normative visual behaviours when using an advanced position-aware control strategy that improved the reliability of control. In general, findings from the present study demonstrated that visuomotor performance did differ in the instance where the controller improved the limb position effect compared to the standard controller. Specifically, grasping the box in movement 3 required activating the prosthetic hand in an elevated cross body position that was at or above the participant's shoulder height, a position known to induce the limb position effect, and to be shown to have control improvements with the position-aware controller studied in this protocol [22].

Eye gaze behaviour is inextricably tied to hand movement and the goal of the object movement. When control is unreliable and there is no confirmatory tactile or proprioceptive feedback, vision must compensate by fixating the hand and object to provide confirmatory feedback on success of the object movement. In the present study, we explored whether eye behaviour would reflect identified improvements in control or not. For movement 3, we found a significant reduction in percent fixation to hand when using the position-aware controller. The mean difference of 5.5% is meaningful in that the resultant 20% is closer to the normative reference value of 11–12% for this specific movement [28], and the effect is within the range of the reduction in fixation to hand (2 to 9%) shown with the provision of tactile and kinesthetic feedback in a multimodal prosthetic system [14]. It was likely that the reduced reliance on vision to monitor the prosthetic hand occurred because participants trusted that the hand would not open unexpectedly while transporting the pasta box from the pickup location to the drop off location. During movement 3 there were also smoother movements in reach and grasp (significantly less NMUs) and significantly less relative time spent grasping when using the position-aware controller, reflecting more confidence in reaching and grasping the box, consistent with the reduced visual fixation required to the hand.

We had expected that the position-aware control strategy, resulting in more confidence in grasp, would lead to significantly shorter eye leaving latencies, indicating the ability to disengage the eye fixation sooner. Indeed, although statistical significance was not reached in the analysis of each pick up and drop off movement, every value trended in the hypothesized direction, and overall, there was a positive main effect of control strategy with an absolute difference of almost 500ms in favor of the position-aware control strategy. Given the time scale of eye movement behaviour, this absolute difference is meaningful. During typical scanning the eyes move about 3–4 times per second, so an extra 250ms is about one extra fixation (or, one additional sample of visual information) [34]. Given that normal visuomotor behaviour with reach and grasp involves one fixation to the area of interest [27], this additional fixation time is relevant in understanding how a specific control strategy may have affected the ability to disengage the eyes closer to what would be considered normative behaviour. The magnitude of change in the ELL is similar to that found for a transhumeral prosthesis user when provided with kinesthetic and tactile feedback, where there was a 230ms improvement in ELL at drop off and a 500ms improvement in ELL at pickup [35].

In addition to movement 3 grasp, movement 2 release required the cross-body activation of hand open to place the box on the shelf. Differences in relative phase duration for release in this movement showed there was about a reduction in the relative duration of the release phase with the position-aware controller (16.75), close to the normative value of about 14% [28]. As mentioned above, the eye leaving latency at drop off, although not statistically significant, had a magnitude of difference of over 1 s quicker disengagement when using the position-aware controller in this specific position that challenged the release control. An increased difficulty to release the box is expected to result in inability to disengage visual attention from drop off locations, whereas with a better control strategy and improved ability to release objects should reduce the time needed for the eyes to shift away.

The unpredictability of myoelectric control draws visual attention towards the prosthesis to ensure that the hand performs as intended [16]. It is uncertain if this visual demand can be alleviated with additional movement training. Bouwsema et al. [8] have shown that some experienced prosthesis users with high functional skill level had gaze behaviours that were consistent with novice users. Parr et al. [2] demonstrated that when novice prosthesis users were provided with explicit movement-based training instructions, no changes in gaze behaviour were observed over multiple training sessions, despite faster movements. Parr et al. [36] proposed that the unreliable nature of prosthetic devices continually prevents normal sensorimotor mapping rules from developing. Typically, individuals with intact limb function rely on vision in the initial stages of motor learning, however the reliance on vision can usually be overcome as skill acquisition progresses and sensory feedback information becomes integrated into the motor control loop [37, 38]. Interestingly, in our cohort of novice users of myoelectric prostheses, limited training with an advanced position-aware myoelectric controller revealed the noted changes in visuomotor performance. It needs to be investigated if further training over multiple testing sessions would demonstrate greater changes in visual attention if participants adopt even more proficient control and increased confidence in the prosthesis.

Although researchers have commonly reported completion times and success rates to assess the functional performance of myoelectric prostheses [39–41], these metrics do not provide a complete understanding of the underlying mechanisms driving these changes in overall performance [25, 26]. In line with previous work, grasp and release phases were disproportionately prolonged for prosthesis users [10]. With improved control strategies, these phase durations could be reduced, with smoother movements, and fewer unwanted wrist rotations and changes in grip aperture [22]. The position-aware control strategy that improved hand kinematic performance in phases where the pasta box was moved to and from the highest shelf of the pasta box task with a myoelectric prosthesis did result in changes in visuomotor behaviour consistent with greater confidence in control. Therefore, this rationale lends motivation for including visuomotor performance to examine patterns of eye and hand movements during functional task evaluation with novel controllers.

In this research, we aimed to explore whether visuomotor behaviours respond to myoelectric control interventions during an experimental task that closely resembles everyday tasks. We employed a functional task that was designed specifically to challenge users in multiple planes of movement and require visual fixations across these planes of movement. In doing so, we have highlighted the challenges of cross-body movements, while no other movements demonstrated differences in visuomotor performance between control strategies. Importantly, the use of eye tracking has enabled us to further assess the visuomotor compensations of myoelectric prosthesis use. Reduced visual fixations towards the hand can allow more natural feedforward visuomotor planning of movement, which may ultimately make the prosthesis more useable. Future work should consider the functional workspace of the experimental task and the inclusion of eye tracking metrics in control comparison studies, as these metrics have presently been shown to be sensitive to control interventions.

Limitations

The number of significant findings were limited in power. Although we observed trends in transport-release for movement 2 and reach-grasp for movement 3, these findings likely were not statistically significant due to the small sample size. In addition, participants of this study were without limb difference and performed experimental tasks using a simulated myoelectric prosthesis. The effect of limb loading has been shown to differ in intact limb individuals and individuals with amputation, which can be explained by anatomical differences. Individuals with intact limbs have greater moments across the elbow to support the weight of the anatomical hand, resulting in different muscle activation patterns than individuals with a transradial amputation. Future work should investigate whether the visuomotor behaviours of individuals with upper limb amputation would likewise be sensitive to myoelectric control interventions.

In this experimental design, participants were given the opportunity to practice using the prosthesis prior to the recorded trials, but training over multiple days was not provided. We postulate that the observed visuomotor behaviours may have been representative of mid-skilled prosthesis users, as demonstrated in prior work [42]. It is possible that with repeated testing over multiple days, participants may have been able to learn to develop a more reliable feedforward control strategy, as with normal patterns of motor learning, thereby further reducing the reliance on vision. Presently, we have only described the effects of modulating prosthesis control on improving visuomotor behaviour without considering the role of sensory feedback. However, successful object manipulation relies on both feedforward and feedback control mechanisms [43]. Notably in prosthesis use, control is not often optimal, thus sensory feedback may provide an equally important role in determining prosthesis performance [44–46] and may further aid in developing typical patterns of visuomotor behaviour.

Conclusions

This work explored how visuomotor behaviours change when individuals operate a simulated myoelectric prosthesis using a standard control strategy compared to a position-aware control strategy. More reliable control with the position-aware myoelectric control strategy likely increased users' confidence in the prosthesis and enabled users to visually fixate less on their prosthesis, particularly in movements requiring an extended cross-body arm position engendering the limb position effect. Therefore, a more reliable prosthesis that performs as intended has the potential to reduce the visual demands associated with prosthesis use, thereby making myoelectric prostheses more useable. Moreover, eye tracking served as a purposeful tool in understanding the changes in gaze behaviours of prosthesis users. Future work should thus consider the inclusion of eye tracking in future prosthesis control comparison studies.

Abbreviations

AOI	Area of interest
DOF	Degree of freedom
EAL	Eye arrival latency
ELL	Eye leaving latency
EMG	Electromyography
GaMA	Gaze and movement assessment
IMU	Inertial measurement unit
NASA-TLX	NASA Task Load Index
RCNN	Recurrent convolutional neural network

Supplementary Information

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Supplementary Material 1

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Author contributions

JH, HW, AS, and KC were involved in the study design. KC, HW, and AS carried out data collection. The data were processed by KC and HW, and analysed by KC. The manuscript was written by KC and edited by JH, HW, AS, CC, and PP. All authors read, reviewed, and approved the final manuscript.

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Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This study was approved by the University of Alberta Health Research Ethics Board (Pro00086557). All participants provided written informed consent to participate in this study.

Consent for publication

All participants provided written informed consent for publication.

Competing interests

The authors declare no competing interests.

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