Pilot Study for Myoelectric Control of a Supernumerary Robot During a Coordination Task

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Abstract. Robots are used in a wide variety of applications to augment the capability of humans. A relatively new category of assistive robots, supernumerary robots (SRs), create an additional, kinematically independent limb or appendage that may serve various functions. SR research has centered on device development and proof-of-concept but has generally not focused on the human interface and human-robot performance. In this pilot study, four subjects completed 80 cursor-to-target trials of a three-handed coordination task with a collaborative robot. The subjects used their two natural hands to control a cursor on a screen in 2-DOFs (degrees of freedom) and used a leg muscle signal to control the robotic hand. The robotic hand controlled the cursor in the third DOF. We calculated two metrics to assess coordination, the coordination score and the DOF activation. Subjects improved in the coordination score and DOF activation throughout the study duration. The subjects increased the percentage of trial time with 3-DOFs active and correspondingly decreased 1-DOF activation. The results indicated that subjects learned how to improve their coordination, while successfully completing trials and decreasing their trial completion time. The subjects tended to coordinate most of the time with their hands (41%) followed by all three limbs (19%). Future studies should focus on increasing the proportion of 3-DOF coordination for improved human-robot performance.

Keywords: Supernumerary robots · Human-machine interfaces · Myoelectric control

1 Introduction

Robots are used in a wide variety of applications including disaster response and minimally invasive surgery. In these cases, robots augment the capability of humans by extending their presence into an extreme or challenging environment. The research interest in human-robot collaboration has grown exponentially [1] and a related fiel has recently emerged: supernumerary robots (SRs). SRs are characterized by creating an additional, kinematically independent limb or appendage that may serve various functions. Of particular interest is SRs' potential to reduce risk and increase capability in challenging environments by providing a third, robotic arm for manipulation. The current state-of-the-art in SRs has focused on the development of the robot and less research

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has centered on the user interface and performance of the human-SR system. The experiments conducted with humans and SRs to complete a task have focused on specifi use cases and tasks that do not provide as much detail on the human-robot interaction.

SRs are distinct from other assistive robots and comprise a relatively novel fiel of research. Exoskeletons augment the abilities of existing limbs, prosthetics restore functionality by replacing lost appendages, and SRs can create limbs that are kinematically independent from the user. SRs may manifest as arms [2–7], legs [8, 9], or finger [10–15]. Current SRs have several potential use cases: body bracing [2, 8, 9], overhead tasks [3, 4], grasp assistance [11–13], and manipulation tasks [5–7] (a more detailed and potential usage taxonomy for wearable SR arms may be found in Ref. [16]). The research in this fiel has centered on device development and proof-of-concept but has generally not focused on the human interface and human-robot performance.

According to the classificatio framework proposed by Leigh et al. [17], human-robot systems that can be considered a single unit, may be classifie by type of support and control methods. SR development has focused on indirect control, or "Pseudo-Mapping" and "Shared Control" according to Leigh's framework, by predicting the human's intent (for examples see Refs. [3, 4, 11]). In contrast to using prediction to identify intent, there has also been some work on direct control of SRs (i.e., "Direct Control"). For example, a supernumerary finge used a combination of hand gestures to control position and muscle signals (i.e., myoelectric control) to modulate the grip strength [10]. A subsequent version of the supernumerary finge incorporated buttons and haptic feedback [12]. Another SR, a supernumerary arm, was commanded by foot position and toe fl xion to directly control 6-DOFs [6]. The selection of the control method, whether direct or indirect, may depend on the application including the role of the SR in the task. However, there has been little available guidance or knowledge regarding control methods and task allocation due to the novelty of the field Therefore, this study aimed to focus on direct control for a primary task, which has not been well-studied in the field

Direct control SRs that use Body-Machine Interfaces (BoMIs), such as gestures or muscle signals, need to use an existing part of the body, which may seem counter to the concept of SRs creating a limb. However, for tasks or applications where part of the body would not otherwise be used, it provides an opportunity to reallocate resources. Specificall , the lower limbs are available in seated tasks as demonstrated by Saraiji et al. [6] for the foot control of a 6-DOF SR. Furthermore, coordination between the hands and legs occurs in a variety of skilled tasks, such as the use of foot pedals by dentists and doctors. For example, in a virtual laparoscopic task at least one hand worked in coordination with the foot for 50% of the task time [18]. Similarly, instead of the foot controlling an instrument, the foot could also be represented as a hand. Abdi et al. compared two-handed and three-handed performance during a virtual task where subjects needed to catch falling objects [19]. The subjects controlled the third hand with their leg. The results showed that subjects missed fewer objects in the three-hand paradigm as task difficult increased [19]. A similar study assessed coordination between the hands and legs for various virtual tasks and deemed the control strategy feasible for SRs [20]. However, the experiment did not include any robot simulation or hardware. Overall, the incorporation of foot control for SRs has precedent from other field (refer to Ref. [21] for review of foot control in HCIs).

The purpose of this pilot study was to incorporate a direct control BoMI with a SR and assess the human's ability to coordinate between their hands and the lower limb while controlling the SR (the robotic, third hand). Subjects controlled the robotic, third hand through myoelectric control, where muscle activation was measured from the surface of the skin by a pair of electrodes, also known as surface electromyography (sEMG). The task was designed such that all three hands were needed to successfully complete the task. Simultaneous coordination of the hands was the goal communicated to the subjects, but it was possible to operate each hand independently. Instead of designing our own SR, we used a commercial, collaborative robot. We also did not constrain the SR to be physically attached to the human, since a wearable SR may not be necessary for every application. This study addressed current gaps in direct control interfaces and limb coordination for SR applications.

2 Materials and Methods

2.1 Subject Recruitment and Demographics

We designed a pilot experiment to investigate a three-handed, coordination task with two natural hands and a robotic, third hand. The protocol was approved by University of California Davis Institutional Review Board, and adult participants were recruited from the university. Exclusion criteria included history of neurological/neuromuscular disorders, limitations on arm and leg mobility, and failing coronavirus-specifi screening. We chose to limit the age range of the participants to 18 through 39 years old based on the risk rates published by the Centers for Disease Control and Prevention [22]. Participants had to show proof of a negative coronavirus test and pass a coronavirus survey addressing symptoms and exposure risk on the day of their scheduled experiment session.

To further reduce the risk of coronavirus transmission, in addition to the coronavirus-specifi screening, we remotely conducted the intake. At the start of the scheduled experiment session, the subject called the researcher to complete the coronavirus-specifi screening. After passing the screening, the researcher reviewed the consent form with the subject; both the subject and researcher could view and sign the form online. Consented subjects then completed a pre-session survey to collect demographic information. The remainder of the experiment protocol occurred in-person at the research location. The in-person protocol consisted of experiment instructions, sEMG setup and calibration, a maximum voluntary contraction measurement, the task, a second maximum voluntary contraction measurement, and a post-session survey.

Four subjects consented to participate in this pilot experiment. The subjects ranged in age from 20 to 25 years with an equal participation of females and males. One subject identifie their ethnicity as Hispanic, Latino/a, or Spanish and race as Asian. The remaining subjects were not of Hispanic, Latino/a, or Spanish ethnicity and identifie their race as White. Origin and race survey questions followed the guidance document provided by the Food and Drug Administration [23]. All subjects self-reported a right hand dominance, and leg preference was determined using the revised Waterloo Footedness Questionnaire (WFQ-R) [24]. The leg preference was used for sEMG electrode placement, and three subjects reported a right leg preference. The remaining subject indicated a similar preference between left and right, but a recent injury resulted in the selection of the left leg. The subjects had some prior experience that may have made them amenable to the experiment's task. One subject had prior experience with myoelectric control, and all subjects played video games. Two subjects had significan prior experience with robots and the other two subjects had little to none, but all subjects answered that they thought they would be comfortable around robots.

2.2 Experiment Setup and System Architecture

The pilot experiment aimed to observe coordination between two natural hands and a robotic, third hand controlled by sEMG from the leg. We decided to not allow direct, physical interaction with this robot (UR5e, Universal Robots [25]), but used a computer-based task for indirect, physical interaction and direct myoelectric control and integration with the actual hardware. The overall experiment task software framework was created using AxoPy [26], which provides basic infrastructure to design and run myoelectric control experiments. Communication with the robot controller used the Universal Robots Real-Time Date Exchange (RTDE) interface [27] and leveraged the API created by the University of Southern Denmark (SDU) Robotics [28].

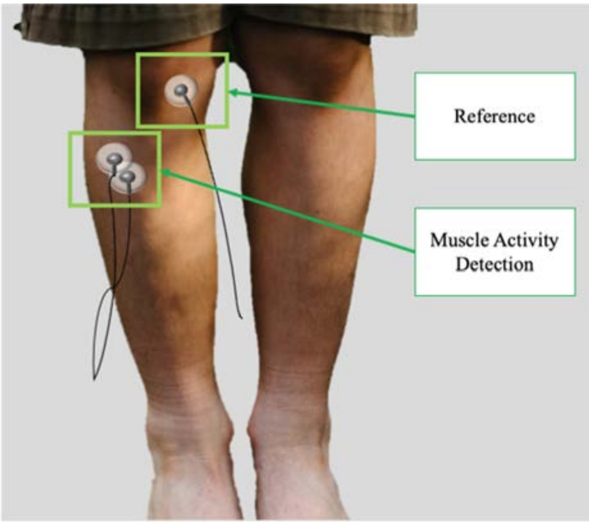


Fig. 1. Illustrative electrode placement on the tibialis anterior (image modifie from [29])

The subjects completed a cursor-to-target task visualized on a desktop monitor. They used their natural hands to input keyboard commands to control the cursor in 2-DOFs and used their leg muscle to command the robotic hand position in the third DOF. The cursor position on the screen in the third DOF reflecte the actual, scaled position of the robotic hand, or end effector. The ConMed 1620 Ag/AgCl center snap electrodes were placed approximately 2.5 cm apart on the tibialis anterior below the lateral tibial condyle to measure the muscle activation and a reference electrode was affi ed to the kneecap (see Fig. 1). The electrodes were placed on the preferred leg as indicated by the WFQ-R. The sEMG signal acquisition followed [30] and was processed as described in [31], where the signal was sampled at 4096 Hz for 256-sample windows with a 4^{th} order Butterworth filte (bandpass at 10 Hz and 500 Hz). The rms value for the window was normalized by each subject's calibration value and put in a moving average filte (length 0.5 s) to yield a processed signal update rate at 16 Hz. Commands and position data were exchanged between the experiment computer and robot controller at 16 Hz.

During the in-person portion of the experiment, the subjects sat at a desk in front of a desktop monitor. Subjects were instructed to adjust the chair height, so their feet rested comfortably on the floo and their thighs were approximately parallel to the floo . The robot was positioned within the fiel of view and off to the right of the desktop monitor. The subject and robot were separated by an adequate distance and stanchions were used as a physical barrier marking the keep out zone. The layout of the experiment room is shown in Fig. 2.

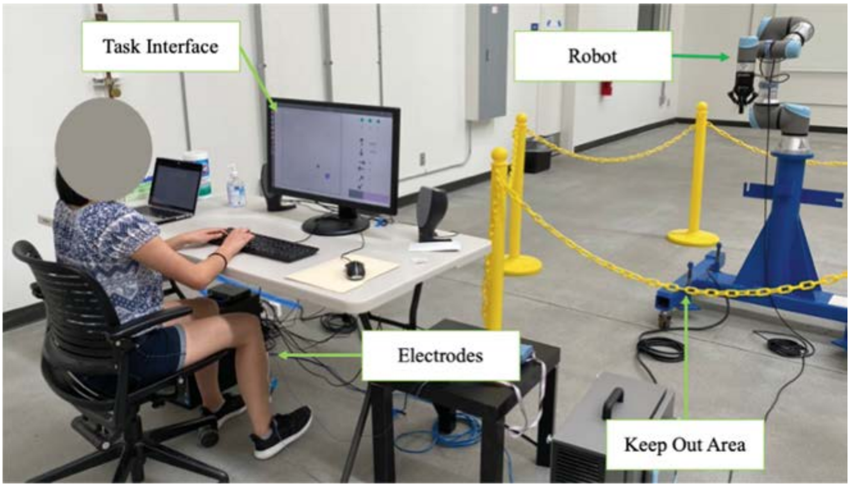


Fig. 2. Experiment room layout

2.3 Coordination Task

The subjects were informed during the experiment instructions that their task was to "move the cursor in three dimensions to select targets on a screen using three 'hands'" with the goal of simultaneous movement in 3-DOFs. The control method was deliberately chosen to require acquisition of a non-intuitive, complex control scheme to test the person's ability to acquire a new, complex motor skill. The development of an optimal control scheme could be the subject of future studies. In this pilot experiment, the subjects controlled the cursor motion using keyboard inputs with their hands and myoelectric control with their leg. Their left hands used keys *a* and *d* to move the cursor left and right along the x-axis, respectively. Each keypress increased or decreased the cursor speed in the x-direction meaning that a single press of key a would cause the cursor to continue moving left until either the cursor hit the task boundary and stopped, or a press of key d negated the leftward motion. The right hand manipulated the cursor motion along the z-axis, which was into and out of the screen. To show 3D motion in a 2D visualization, the cursor diameter decreased to show motion into the screen and the diameter increased for motion out of the screen. Key j decreased cursor diameter and key l increased the diameter. The cursor diameter was constrained from 0.15 to 2.45 times of the original diameter. The subjects' legs controlled robotic motion in the y-axis to move the cursor vertically. The subjects needed two commands, up and down, and communicated those commands by modulating their muscle activation. "Inputs" refer to muscle activations that exceeded a threshold; muscle activations below the threshold were considered "at rest." The fris input selected the command and the second input resulted in forward motion for the duration that the processed sEMG signal input remained above the threshold, l_1. A short input ($\leq$0.5 s) selected the "up" command and a long input ($>$0.5s) selected the "down" command. The robot moved at a constant velocity and therefore so did the cursor in the y-axis. The commands are summarized in Table 1.

Table 1. Summary of 3-DOF cursor commands

Axis	Direction	Command	Input method	Leg/Hand
x	Left	*a*	Keyboard	Left hand
	Right	*d*		
y	Up	*Short*	sEMG	Leg
	Down	*Long*		
z	In	*j*	Keyboard	Right hand
	Out	*l*		

The user interface included an information interface and a task interface for the cursor-to-target task (see Fig. 3). The information interface contained a set of status lights, the command key, and an sEMG signal bar. The status lights indicated in which DOFs the cursor was currently in motion by turning from gray to green. These lights could be helpful when the cursor moved at a low velocity, especially in the z axis, and provided a different visual representation of the subjects' goal, 3-DOF movement (i.e., keep all the status lights green). The subjects never had to memorize the cursor commands and could refer to the command key. The sEMG signal bar displayed their current processed signal value as an overlaid, dark gray bar. The light blue region and light pink region designated the rest area and active area, respectively.

In addition to the elements in the information interface, we used color feedback to provide additional information during the task. The cursor body had concurrent feedback to indicate the reception and interpretation of the sEMG signal. The cursor body changed from black to a dark gold when the sEMG signal crossed the threshold; the color would change to light blue if the firs input time exceeded 0.5 s to indicate a long input. The cursor body remained the color of the selected command during the second input. This concurrent color feedback was the same scheme as the manual rotate method in our prior study [31]. The other two forms of color feedback applied to the target. To select the target, the cursor needed to be at approximately the same depth, which was represented by diameter. The cursor was considered at the same depth if difference in scale between the cursor and target diameters was within 0.10 units. In preliminary testing, we tried a fi ed percentage of the target diameter, but the margins were too small for far targets and too large for near targets. Since it could be visually difficul to estimate the cursor depth, we used color feedback on the target body to indicate when the cursor and target were at approximately the same depth. The target was nominally light purple and turned green when the cursor was at depth. In addition to placing the cursor at the same depth as the target, the subjects needed to dwell on the target for 1 s to select it. The target turned orange when the cursor selected the target. If the cursor was not at the appropriate depth and overlapped with the target, the target would remain light purple. Table 2 contains information about the additional visual feedback elements.

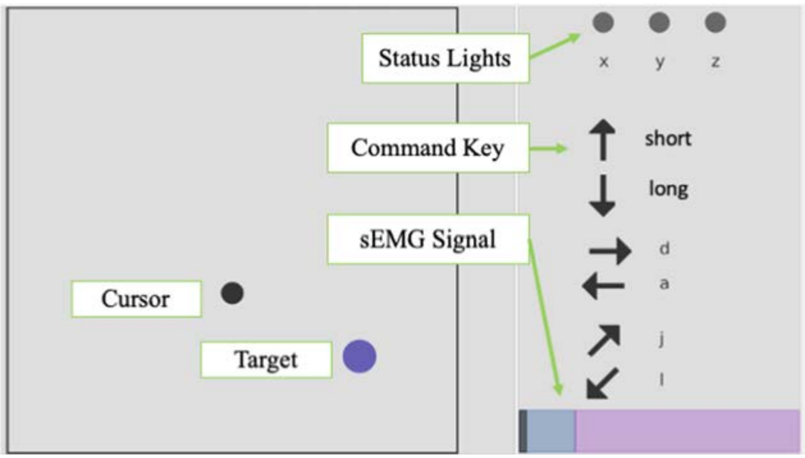


Fig. 3. The User Interface includes the Task Interface on the left-hand side and the Information Interface on the right-hand side.

The subjects completed 80 trials of the cursor-to-target task on the task interface. The task interface dimensions were normalized to have horizontal and vertical bounds of [–1,1] on a square, right-hand Cartesian coordinate system. At the beginning of each trial, the cursor started at the origin (i.e., center of the screen) with a diameter of 0.100 units. The cursor and target diameters were relative to the task interface dimensions. There were 16 unique target positions based on the target angles (45º, 135º, 225º, and 315º) and target diameters (0.025, 0.050, 0.150, 0.175) combinations, and all targets were positioned 0.80 units from the origin. A Block consisted of 4 trials and the subjects received a minimum 30 s break before starting the next Block; subjects could ask to rest longer. A set of four Blocks, or a Test, covered the 16 unique target positions in a pseudorandomized order. The fi e Tests each had the same pseudorandomized order of trials. The trials timed out after 30 s, which was based on preliminary testing. The total number of trials was determined by reviewing the results from our prior studies [31, 32], as well as our decision to reasonably minimize the duration of the in-person portion of the experiment due to coronavirus transmission concerns.

Table 2. Additional visual feedback during task

Object	Nominal color	Feedback color	Purpose
Cursor	Black	Dark gold	Indicates short input/up command
		Bright blue	Indicates long input/down command
Target	Light purple	Green	Cursor at target's depth
		Orange	Cursor selected target

3 Analysis

3.1 Coordination Metrics

To assess coordination between the hands and leg driving the robotic hand, we calculated a coordination score and DOF activation. The coordination score was calculated for each trial and was the weighted average of the time spent with 0-, 1-, 2-, and 3-DOFs activated. For each time step, points were added in proportion to the number of active DOFs. For example, if there were no DOFs active the time step would be assigned zero points. If any 1-DOF was active, then one point would be awarded. Each additional DOF earned another point. A fina coordination score of 1 meant that on average 1-DOF was active during the trial. Larger coordination scores would indicate a more coordinated performance. The coordination score did not detail which DOFs were active, only the number of DOFs. The DOF activation metric provided a fine analysis of which DOFs were used and the relative percentage for each trial. The DOF activation metric measured the proportion of the trial time spent with 0-, 1-, 2-, and/or 3-DOFs activated. This metric was calculated for the overall comparison between all DOFs, as well as within 1-DOF and 2-DOFs. For the DOF activation within 1-DOF, the metric assessed the proportion of the trial time that the x, y-, and z- axes were activated. The 2-DOF activation metric measured the proportion of trial time for xy, xz, and yz activation. These metrics were calculated for all trials, regardless of success.

3.2 Task Metrics

Two task metrics were used to evaluate performance: percent of successful trials and completion time. The percent of successful trials was calculated as the number of successful trials divided by the total number of trials in a Test (16 trials). The completion time was only calculated for successful trials. Both metrics were averaged over each Test.

4 Results

The coordination metrics and task metrics were calculated for all trials regardless of success, except for completion time. Comparing performance during unsuccessful trials and successful trials may reveal useful insights, however, the number of unsuccessful trials decreased substantially starting in Test 3. Across subjects, there were 25 unsuccessful trials (40% of the total trials) in Test 1 and 9 unsuccessful trials (14% of the total trials) in Test 2. The remaining Tests had a total unsuccessful trial count of 8 trials. Therefore, it was difficul to make meaningful comparisons between successful and unsuccessful trials.

4.1 Coordination Metrics

The coordination score was calculated for each trial and averaged over all subjects per Test. As shown in Fig. 4, the coordination score increased each subsequent Test with a slight decrease in the last Test. The average coordination scores ($\mu \pm \sigma$) in order of Test were 1.61 ± 0.37, 1.76 ± 0.27, 1.86 ± 0.26, 1.96 ± 0.23, and 1.89 ± 0.25. The coordination scores ranged from 0.61 in Test 1 to 2.42 in Test 5. The individual subject scores (averaged over all their trials) ranged from 1.65 to 1.93. The subjects did have a variety of experiences that may have been helpful for this task, such as prior myoelectric control and video game experience. Interestingly, the one subject with prior myoelectric control experience did not have the highest average coordination score. Overall, the subjects appeared to perform similar to each other in terms of the coordination score. There did not appear to be noticeable changes in the coordination score per Test when the results were disaggregated by trial success, target angle, or target depth. The slight decrease in the coordination score from Test 4 to Test 5 did not appear to be attributed to muscle fatigue. Two subjects reported feeling some muscle fatigue in their feet, but their maximum voluntary contractions decreased by less than 12% from before the task to after the task and remained well above the threshold.

The coordination score improvements may be explained by increased 3-DOF activation and decreased 1-DOF activation, which was captured by the DOF activation metric (see Fig. 5). The largest changes occurred for 1-DOF and 3-DOF activation between Test 1 and Test 4. The 1-DOF activation decreased by 14 percentage points and 3-DOF activation increased by 16 percentage points, which may be explained as the subjects decreasing their 1-DOF control and learning to increase their 3-DOF control. In contrast, the 0-DOF and 2-DOF activation remained relatively constant between Tests 1 and 4 with a difference in percentage points of 3 and 1, respectively. At most, these differences in percentages for 0-DOF and 2-DOF activation account for less than 1 s of a trial. The changes across DOF activations from Test 4 to Test 5 translate to a time difference of less than 0.5 s. Therefore, the most meaningful changes in DOF activations occurred from Test 1 to Test 4 for the 1-DOF and 3-DOF activations. As with the coordination score, there did not appear to be noticeable changes in the coordination score per Test when the results were disaggregated by trial success, target angle, or target depth.

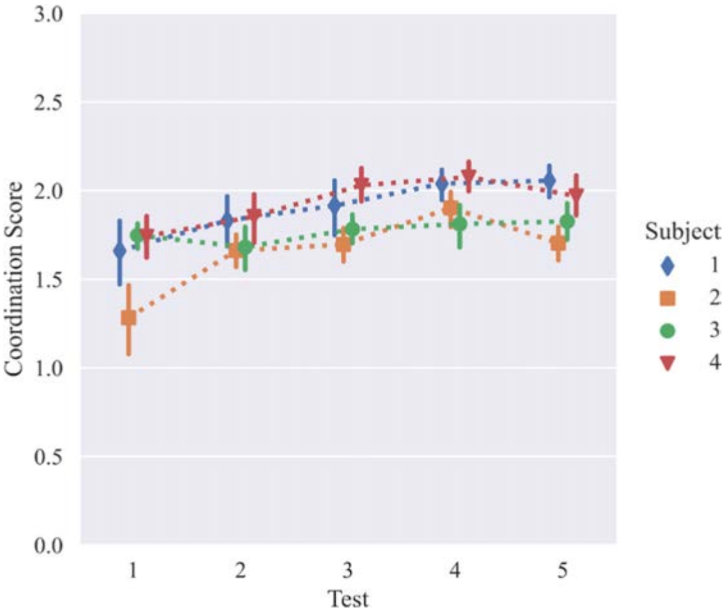


Fig. 4. The average coordination score for each Test (16 trials) is shown for individual subjects. Perfect 3-DOF coordination would achieve a score of 3.

In addition to the overall activation proportion between DOFs, it was also of interest to understand which axes were active within DOFs. As seen in Fig. 5, about half of the trial time was spent with 2-DOFs activated, and 1-DOF was activated between 16% and 30% of the trial time. Together the 1-DOF and 2-DOF activations accounted for most of the trial time. Within the 1-DOF activation during a trial, the activation tended to originate from one of the hands with keyboard inputs (see Fig. 6). It was relatively uncommon for 1-DOF activation with the leg, which occurred less than 10% of the time. For 2-DOF activation, the most likely pairing was for both natual hands together (*xz*-axes) for approximately 80% of the time (see Fig. 7). Coordination between the leg and left hand (*xy*-axes) occurred approximately 16% of time in 2-DOF activation, whereas the leg and right hand (*xz*-axes) coordination accounted for less than 4% of 2-DOF activation time. This analysis increased understanding of which axes were activated within a particular DOF activation case. However, it was also of interest to compare all combinations of DOFs and axes to determine an overall activation ranking. Each possible activation combination was ranked and percentage differences less than 1% were not considered different due to the small absolute time differences. The resulting 2-DOF activation order was both hands (*xz*, 41%), all three limbs (*xyz*, 19%), the left hand (*x*, 12%), and left hand-leg (*xy*)/right hand (*z*)/no activation all tied with each accounting for 8%. The right hand-leg (*yz*) and leg only (*y*) were 2% of the time each. These results indicated that subjects tended to coordinate their hands followed by all three limbs.

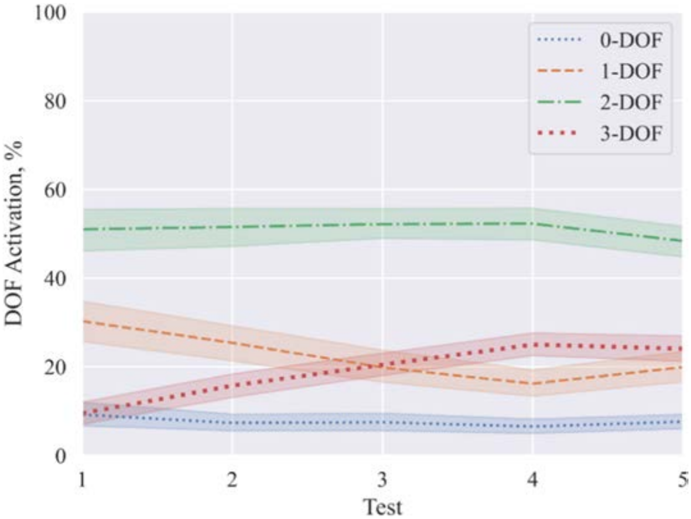


Fig. 5. The DOF activation metric is averaged across each Test (16 trials) for all subjects. The shaded region shows the 95% confidenc interval.

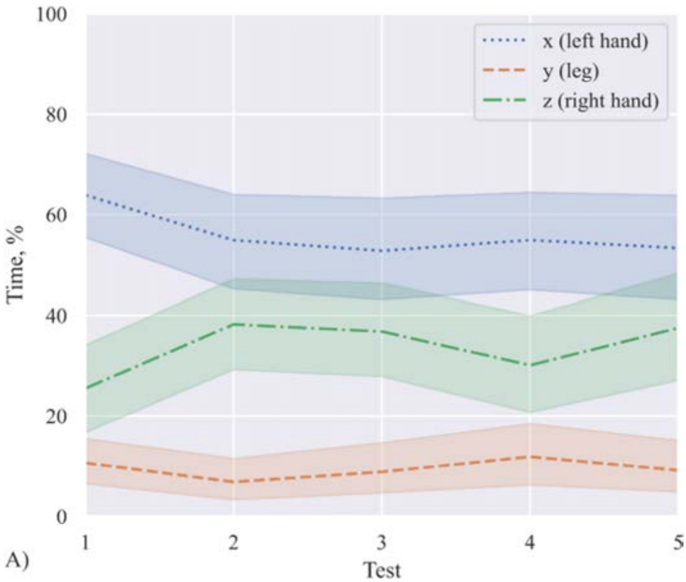


Fig. 6. The plots show the 1-DOF activation breakdown. The percentage of time is within 1-DOF activation time and not for the entire trial time. The shaded area shows the 95% confidenc interval. The results are averaged over all trials within a Test (16 trials).

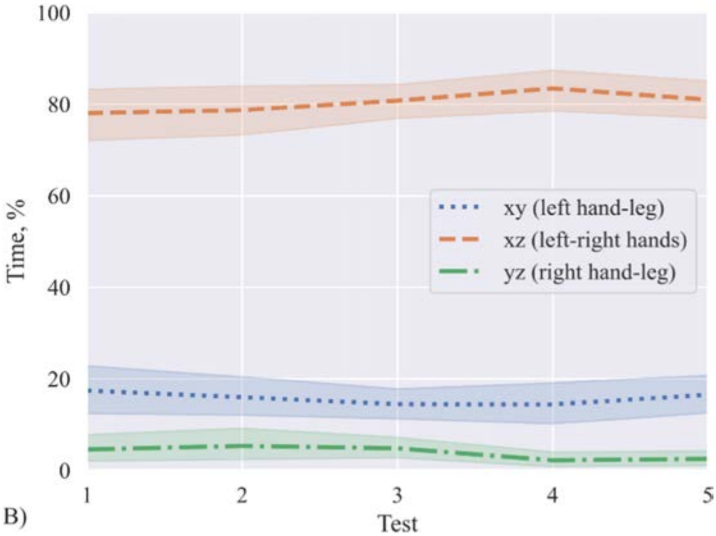


Fig. 7. The plots show the 2-DOF activation breakdown. The percentage of time is within 2-DOF activation time and not for the entire trial time. The shaded area shows the 95% confidenc interval. The results are averaged over all trials within a Test (16 trials).

4.2 Task Metrics

The percent of successful trials was calculated for each Test and generally showed improvement throughout the experiment (see Fig. 8). By Test 3, all subjects successfully completed more than 90% of the trials, and there were no unsuccessful trials in Test 4. The trend followed the coordination score, where there was a small decrease in the percent of successful trials for Test 5. There appeared to be relatively large differences in this metric between subjects for Tests 1 and 2. One subject only successfully completed one trial in Test 1 and seven trials in Test 2. Another subject successfully completed seven trials in Test 1 and then successfully completed all trials in the remaining Tests. The early differences in percent of successful trials may provide evidence of individual learning rates, however, the number of subjects was too low to make any definit ve conclusions. These results indicated that the number of trials was sufficien for learning how to complete the task.

The completion time continually decreased on average in each subsequent Test (see Fig. 9). The completion time was only calculated for successful trials, and trials had a maximum time of 30 s. In Test 1, the subjects used most of the allotted trial time with an average completion time of 21.98 ± 3.85 s ($\mu \pm \sigma$). The completion time decreased to less than half of the maximum trial time by Test 5 (11.84 ± 1.62 s). Although completion time looked to be leveling off, it was not clear if the completion time plateaued in Test 5, and it could be interesting to observe this metric over more trials. These results combined with the percentage of successful trials supported the reduced trial times compared to our prior study (60 s maximum trial time) [32].

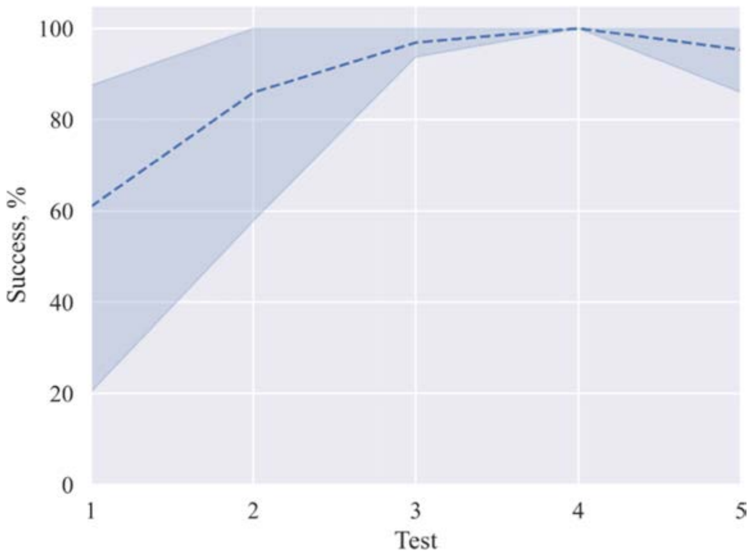


Fig. 8. The results for percentage of successful trials are averaged over the 16 trials within a Test. The shaded region indicates the 95% confidenc interval.

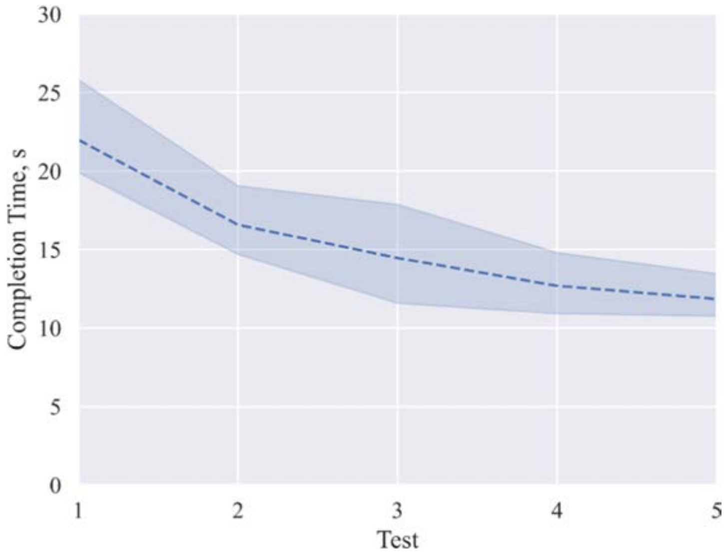
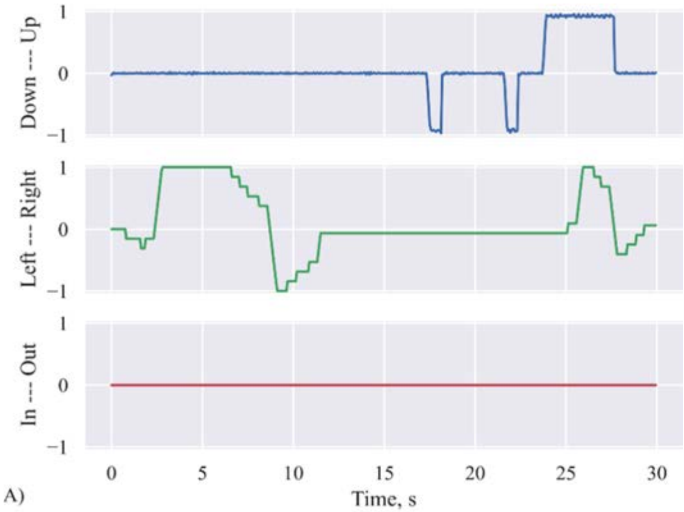


Fig. 9. The results for completion time are averaged over the 16 trials within a Test. The shaded area indicates the 95% confidenc interval.

4.3 Additional Analysis

The coordination metrics and task metrics provided a high-level assessment of the average subject performance; however, it was of interest to examine trial data in more detail. After reviewing data from low- and high-performance trials, one case was selected to highlight some of the changes in subject cursor control. The data shown in Fig. 10 compares the normalized cursor velocities in each axis for the same target in Test 1 (Fig. 10A) and Test 5 (Fig. 10B). In the Test 1 trial, the subject moved the cursor primarily one axis at a time, except towards the end of the trial. The trial was unsuccessful and timed out with no inputs in the *z*-axis (i.e., depth/in and out motion). Directional corrections



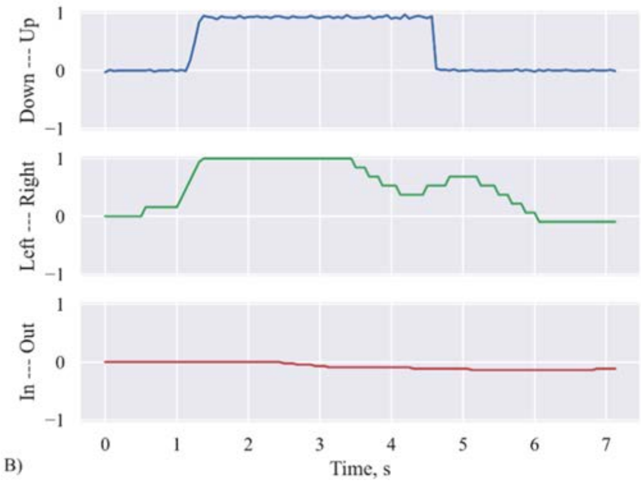


Fig. 10. Normalized cursor velocities are shown for each axis for the selected trial (diameter = 0.05, angle = 45°) in Test 1 (A) and Test 5 (B) for the same subject. The trial in Test 1 was not successful.

were made in both the x- and y- axes, as evidenced by the changing sign of the cursor velocities. In contrast, the trial data from Test 5 showed precisely timed inputs with minimal corrections. The subject correctly estimated the duration for the y-axis input, which was myoelectric control. The x-axis motion continued to the right once initiated with a gradual decrease and a minor correction to increase the velocity. The motion in the z-axis had the latest onset and smallest velocity but appeared to be sufficientl estimated to reach the target depth. The subject successfully completed the trial in 7.13 s. The subject may have been able to improve performance by holding the x-axis cursor velocity at the maximum for longer, ramping down the velocity quicker, and having an earlier onset for the z-axis cursor motion. Compared to the Test 1 trial data, it was evident that the subject improved in their precision and estimation of the cursor velocity in each axis. This subject had the highest coordination score averaged across all Tests and provided an example of the improvements that can occur throughout the pilot experiment.

The subjects were provided with instructions that explicitly stated the goal of 3-DOF coordination. However, prior to the pilot study, it was not clear if subjects would aim to continually improve their coordination, or if they would choose to maximize the cursor velocity and move in 1-DOF at a time. The coordination score results (see Fig. 4) and DOF activation results (see Fig. 5) confirme that subjects did try to improve their coordination. Concurrently, their percent of successful trials increased, and completion time decreased. We tested the correlation between completion time and coordination score using the Pearson correlation coefficient r, for all successful trials. The resulting value, $r = -0.50$, indicated a moderate, negative correlation between completion time and coordination score (see Fig. 11). Increased coordination scores had a moderate tendency to also correlate with decreased completion times. These results provide evidence that increased coordination also correlated with increased efficien y when completing the task.

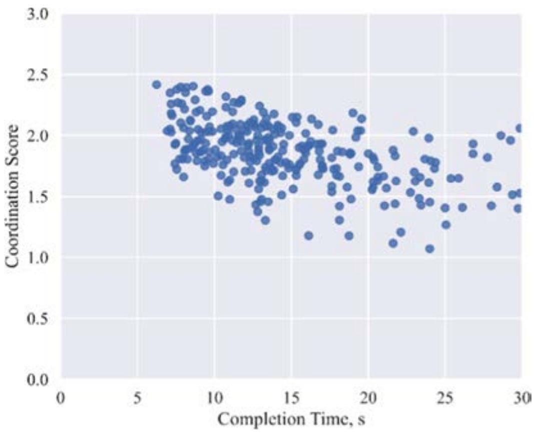


Fig. 11. Completion time versus coordination score for all successful trials

5 Discussion

The results from this pilot experiment showed increased coordination and task performance over its duration. The subjects were instructed to aim for 3-DOF coordination. The average coordination score in Test 4 and 5 was approximately a 2, which can be interpreted as an average of 2-DOF control during the trial. The goal was for subject to achieve 3-DOF coordination, and the highest coordination score was a 2.42 in Test 5. The average 3-DOF activation was 19% of the trial time. All subjects responded affirmat vely when asked if they felt that "…you coordinated your hands and leg well." It may be beneficia in a future study to encourage subjects to increase their 3-DOF coordination. This encouragement could be achieved by showing the subjects their coordination score during or after each trial to give them a quantitative assessment of their performance. Another option would be to only allow cursor motion when all 3-DOFs are active as a training tool. This restriction could be removed during a subset of trials to evaluate their 3-DOF coordination retention.

The cursor and target both employed color feedback to provide additional information to the subjects during the task. Three of the subjects felt that the cursor color changes helped them confir the command selection prior to cursor motion. The remaining subject said they largely ignored the color feedback and focused on resulting cursor motion. All subjects agreed that the target color feedback for depth aided them in aligning their cursor with the target. One subject further detailed that the target color feedback enabled them to time their actions. In contrast, the subjects minimally used the status lights and sEMG signal bar on the Information Interface. This information was not particularly surprising since it was expected that the subjects would allocate most of their visual attention to the Task Interface. However, the additional information was available as needed and the subjects did use the information occasionally to better understand myoelectric control (e.g., confirmatio of crossing the threshold) and axes statuses.

This pilot experiment provided insights regarding the task design. The number of trials and trial duration was selected based on preliminary testing and the results from our prior studies [31, 32]. The results from the task metrics generally support these selections for the given task design. As discussed, it would be of interest to revise the training design to encourage increased 3-DOF coordination as compared to the modest improvements in coordination seen in this study. A task with direct, physical interaction may provide additional motivation and more obvious connection to the robot. Another change that should be considered in future studies is the muscle site. The tibialis anterior was originally selected due to its good signal quality and use in prior experiments (e.g., [33]). Subjects primarily fl xed their foot or raised their toes to activate the muscle, and some reported fatigue in their foot. Overall, this study provided initial results and insights for myoelectric control of a collaborative robot during a computer-based task.

6 Conclusions

This pilot study expanded upon our previous work and demonstrated the sEMG system with a collaborative robot. The knowledge gained from previous studies helped us devise a task with a reasonable level of difficult . Subjects appeared to follow the instructions and tried to coordinate their inputs, but the 3-DOF coordination remained relatively low. Different options have been discussed for encouraging increased 3-DOF coordination in future studies. The robot performed in a reliable and safe manner, which built confidenc for future experiments with direct interaction. The metrics in this pilot experiment centered on coordination and task performance, and the other metrics we have previously used to address interaction factors like trust and cognitive workload should be incorporated in future studies. Although the robot did not physically interact with the subjects, the robot was integrated with the experiment software and established a basic infrastructure for future robotic myoelectric control experiments. Overall, this pilot experiment provided some interesting and encouraging results upon which to build more complex experiments in the future.

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