DELIVERABLE REPORT

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D 5.2, Linearity of degrees of freedom in muscle space

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WP 5, Task 5.3, Linearity in muscle activity for multi-DoF control
Lead: UMG-GOE

1 DESCRIPTION OF THE TASK

The following description is taken from Annex I:

One of the main methods tested for prosthesis control will be regression of the EMG into forces or kinematics. For this purpose, a mapping is necessary and this is built usually on labelled data. However, it is not possible to calibrate/train the system on all possible combinations of DOFs across the full range of motions. To overcome this problem, the linear summation property in muscular activations will be tested extensively. The main rationale for such investigation is that single DOF training may be sufficient for multi-DOF control if the activations of each DOF sum linearly. This hypothesis is equivalent to the modularity or muscle synergy hypothesis. Moreover, within this linear framework, it is reasonable to expect that different postures can be compensated for by linear terms in the summation (this would be equivalent to identify a gravity-related synergy and some gravity-independent synergies). In addition to experiments in healthy volunteers as well as in amputees, motor control and EMG models will be used to interpret the experimental findings.

2 DESCRIPTION OF DELIVERABLE

The deliverable investigates the possibility to estimate combined motions (multiple DOFs active) from EMG with models that are trained on non-combined motions only.

3 IMPLEMENTATION OF WORK

The work was divided into two parts. The first part involved an offline analysis on EMG data that were recorded from able-bodied subjects and involved extensive combinations of two DOFs and precise data labels, obtained from a motion capturing system. The recorded data set involved continuously increasing the intensity for all movements that allowed for the investigation of the capabilities of proportional control for various algorithms. For the combined motions, different activation ratios of the involved motions were recorded, which allowed for significantly more sophisticated analyses compared to previous data-sets that involved only motion combinations with one activation ratio.

The second part involved closed-loop real-time tasks by subjects with amputation or congenital limb-deficiency. In this way the performance was evaluated when the user could adapt to the algorithmic output and potentially correct for lack of accuracy in the mapping. By performing real-world tasks with a physical prosthesis, potentially disturbing factors, such as gravity related activation, were included in the study.

3.1 Part I: Offline Investigation of Linearity in multi-DOF Muscle Activity

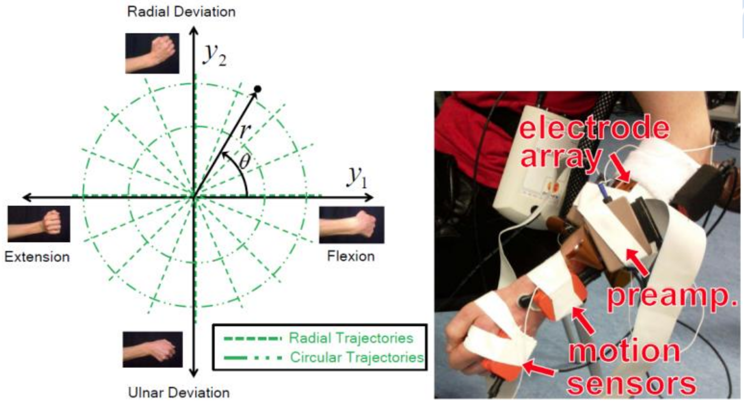
3.1.1 Introduction

To investigate the linearity in multiple DOFs systematically, accurate data-labels are required, i.e., a precise description of the motions is needed during EMG data acquisition. This is only possible by measuring the forces or kinematics of the motions, which is not possible in subjects with amputation or congenital limb deficiency. Therefore, the first part of the investigations is based on data acquired from able-bodied subjects. The data were previously acquired [7] while the analyses described below are new with respect to that previous study. The analyses were specifically designed to address the problem of linearity of DOFs in the muscle space.

3.1.2 Data Aquisition

EMG data were collected with an OT Bioelettronica amplifier (USB-Amp-II) at 2048 Hz sampling frequency and a 192 channel matrix electrode (ELSCH064NM 3-3, OT Bioelettronica). Accurate data labels were gained by recording the wrist angles with a motion tracking system (Xsens with MTx sensors, Fig. 1 (b)). The electrode array was placed on the proximal portion of the left forearm.

Two DOFs, wrist flexion/extension and radial/ulnar deviation were investigated in this study (Fig. 1 (a)). This is because those two functions are relevant for prosthesis control and because it is easy to provide visual feedback to the subjects as explained below. The target movement trajectories used for the current investigations included moving the wrist from neutral position to 16 equi-spaced radial directions. The subjects were instructed to keep the fingers in a relaxed position and not to rotate the wrist (keeping the thumb pointing upwards). At the beginning of each session, the individual range of motion in both DOFs was measured. Then the paradigm was scaled accordingly so that the trajectories started at the center (neutral position) and reached the maximal range of motion for each direction. The time for moving from the center position to the outermost position was 3 s, followed by 2 s at the outermost position and 3 s for returning to the center position. The experiment was divided into 15 runs, where each run contained each of the 16 directions exactly once. During the recordings, the target wrist angles were displayed on a computer screen in real-time together with the actual angles obtained by the motion tracking system. This online feedback assisted subjects in better matching the target trajectories. Six able bodied subjects were included in this study.



(a) (b)

Fig. 1: (a): Visualization of the trajectories within the 2D space spanned by the two DOFs. (b): Experimental Setup involving EMG acquisition with an electrode array and motion capturing system.

3.1.3 Signal Processing

The EMG signals were filtered with a low-pass (500 Hz, 4th order Butterworth), a high-pass (20 Hz, 4th order Butterworth) and a band stop filter (45 - 55Hz, 2nd order Butterworth) to remove high-frequency noise, movement artifacts and power line interferences. Features were extracted from overlapping intervals of 200 ms, with an increment of 50 ms. In this investigation the amplitude-based log-var feature was used. This feature has a logarithmic relation to the more commonly used RMS, and models better the relationship between kinematics and EMG [1].

The mapping from EMG features into simultaneous and proportional 2-DOF control signals was performed with linear regression:

$$\hat{\boldsymbol{y}} = \boldsymbol{W}^{\boldsymbol{T}}\boldsymbol{x} \quad (1)$$

$$\boldsymbol{W} = (\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}})^{-1}\boldsymbol{X}\boldsymbol{Y}^{\boldsymbol{T}} \quad (2)$$

where $\boldsymbol{x}$ is a vector with the EMG features, $\hat{\boldsymbol{y}}$ the two-dimensional estimated labels, $\boldsymbol{W}$ the linear mapping matrix and $\boldsymbol{X}$ and $\boldsymbol{Y}$ matrices containing training features and labels.

3.1.4 Investigation of Linearity

In order to investigate to which extend the DOFs are linear independent in the muscle space, cross-validation was performed. The linear regression model was trained with parts of the data and independent data was used to test the performance of the model. Testing was done based on three runs including all 16 angles to evaluate the performance for non-combined and combined motions. Training was done in three conditions: 1) all 16 directions were used for training; 2) 8 directions (corresponding to 4 non-combined and 4 combined motions) were used for training; 3) only the 4 directions corresponding to non-combined motions were used for training. To exclude potential effects of the training-set size, 3 runs were used for training condition (1), six for condition (2), and twelve for condition (3), resulting in identical training-set sizes in the three conditions.

3.1.5 Results Offline Investigations

The results of part 1 are summarized in Fig. 2. The estimation error of the 2D wrist angles (in degree) is shown for the 2D motion space. Results were available for the 16 trajectories, that cover large parts of the 2D space spanned by the range of motion for the two investigated wrist DOFs. The points where no motion labels were available in the test-dataset were interpolated. The first row of Fig. 2 shows the results for the six subjects when the full set of training data was used for training. The estimation error for most subjects in most regions within the range of motion was smaller than 15 degrees. In some cases (e.g. subjects 1), the regions close to the border of the range of motion resulted in significantly worse performance. This was presumably caused by a non-linear relation at the end points of the motion range, where the required force increases rapidly while only little change in the joint angle occurs. The central row shows the case of reduced diversity in the training-set but still involving combined motions at equal activation ratio. Interestingly, the results are very similar to the first case, where all trajectories were used. The same applies for the results in the last row, estimated by the linear model that was trained with non-combined motions only. Therefore, most regions of combined motions were estimated relatively accurately (similarly to the case of full training set), even when the training was made exclusively with non-combined motions. Exceptions are mostly related to the borders of the range of motion. For some subjects (e.g. subject 6), regions of combined motions performed slightly worse than non-combined motions when trained with non-combined motions only but the difference was small in all cases.

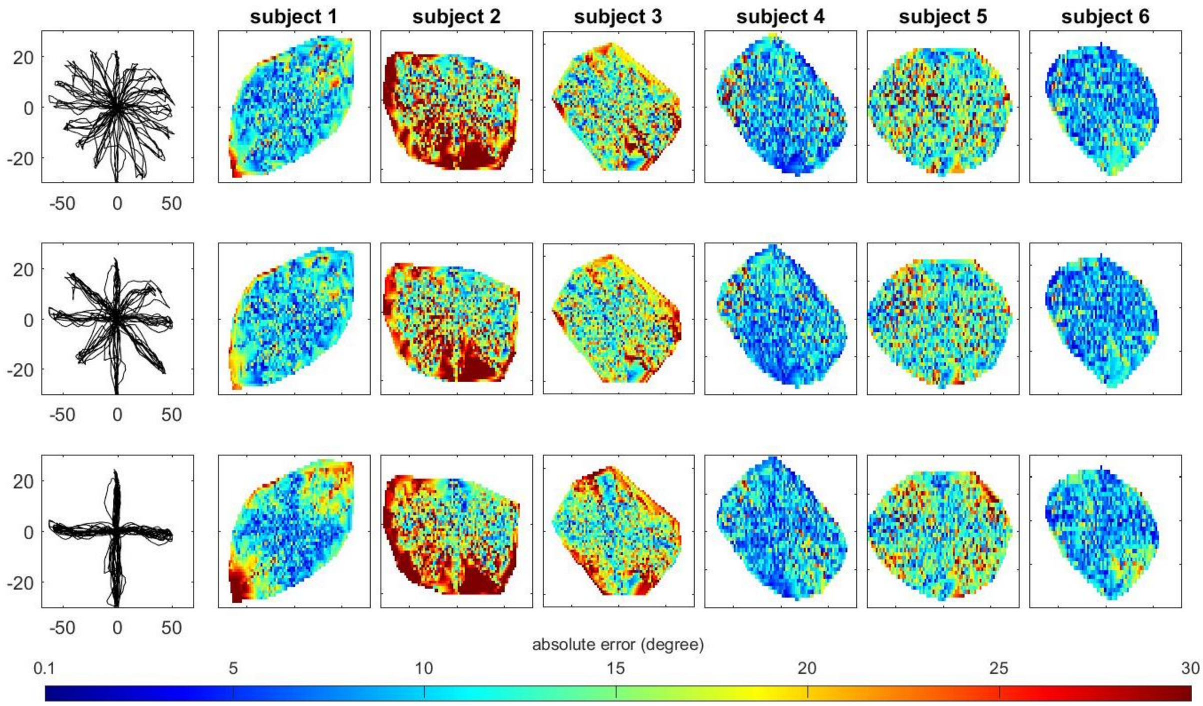


Fig. 2: Linear estimation error for regions of the 2D control-space including non-combined and all possible combinations. The left column shows the training trajectories used in this row and the other columns the absolute interpolated estimation error (in degrees). For most subjects the wrist angels are estimated well in all regions. The used training trajectory subset has almost no influence on the distribution of the error. Even if only non-combined motions are used for training (lower row), the estimation error is low, also in regions of combined movements, indicating a good linear separability.

3.2 PART II: CLOSED LOOP INVESTIAGTIONS IN REAL-WORLD TASKS

3.2.1 INTRODUCTION

In the open loop offline investigations, the subjects did not have the chance to correct their motions in case the estimation of the regressor was incorrect. Also, only able-bodied subjects were evaluated in part I. Therefore, the second part will focus on closed-loop real-time evaluation on subjects with amputation or congenital limb deficiency. As these prosthetic end-users have often problems to reliably conduct simultaneous motions, the linear mapping model was trained on non-combined motions only. Since neither kinematics nor forces can be measured for phantom motions of the amputated side, labels were obtained based on the visual cues that instructed the users.

With this linear model, first real-time controllability was evaluated in virtual tasks to obtain a performance estimation analog to the offline investigations. In a second step, the controllability and robustness in real-world prosthetic tasks was evaluated. The aim was to show that training on individual motions in amputees and real-life conditions of prosthesis use would allow the accurate and robust control of combined motions. Therefore, these results complement the offline analysis. The experimental protocol design, data collection, data analysis and results are all original. Ethical clearance for this investigation was obtained by the local ethics committee of the University Medical Center of Goettingen, where the data were collected.

3.2.2 Experimental Setup

The experimental setup for the prosthetic tasks consisted of eight conventional bipolar electrode modules (Otto Bock, 13E200), a conventional prosthetic hand (Otto Bock, DMC Hand) in combination with a rotation unit (Otto Bock, Electric Wrist Rotator), a custom controller, and a PC.

To utilize a portable, miniaturized solution for simultaneous and proportional control of the two prosthetic DOFs, an embedded system based solution was implemented. It consists of an ATMEL ATXMEGA32-A4U 8-bit microcontroller (MC) clocked at 32 MHz with the integrated calibrated RC-oscillator. This MC has an integrated A/D-converter with analog multiplexer that was used to sample the eight EMG signals. As the electrode modules already include temporal filters, rectification, and low-pass-filtering, no additional analog filters were required and a sampling rate of 25 Hz was sufficient. To control the grasping function of the prosthesis, two electrode signals were emulated by generating analog electrode outputs with the integrated pulse-width modulation (PWM) signal generators and external passive RC-low-pass for smoothening. To generate the high currents required for directly driving the motor of the rotation unit, a motor driver was used (ON Semiconductor, LV8548MC). The 3.3 V voltage supply required for the MC was generated from the prosthesis 7.2 V battery by a linear voltage regulator (Texas Instruments, TPS7233).

The implemented firmware provided two modes. For signal inspection, training and evaluation in virtual tasks, it could be connected via USB to a PC and used as a data-acquisition device. The visualization and control algorithm were in this case executed on the PC and the control signals could be sent back to the MC to control the prosthesis in real-time. Once the training was finished, the learned regression model could be uploaded to the MC and permanently stored in the integrated EEPROM. Then the system could be disconnected from the PC and used in autonomous mode (Fig. 2 green block), where the eight EMG signals were directly mapped into 2-DOF control signals.

3.2.3 Training of the Algorithm with Non-Combined Motions

For a successful application of machine-learning based myoelectric control systems, both the user and the algorithm need to be trained. First, the user performed various phantom-limb movements, while the EMG signals were visually inspected by the experimenter and the subject. Out of these, four distinct contraction patterns were selected based on visual inspection. Then, three runs of calibration data were recorded in neutral arm position, in which the subject followed predefined trajectories that consisted of non-combined movements only and were presented on the user screen as visual cues. A linear mapping model was generated based on the least mean-squares solution (Eq. 2). As shown in part I, this approach should allow for a generalization from non-combined to combined motions. This generalization was tested in this second part on patients.

3.2.4 Evaluation of non-combined and combined motions in virtual tasks

The model generated from non-combined motions was used for real-time control of a cursor within a two-dimensional coordinate-system in position-control mode. The user was given some time to familiarize with the control. Supported by a small computer game in which the user had to catch circular targets in 2D, the quality of the control was evaluated. By specific positioning of the targets (randomized order) non-combined and combined motions of two different contraction levels were evaluated (50% and 85% MVC). In this way, both the general performance of the linear model for non-combined motions and the capability to linearly extrapolate to combined motions was evaluated.

In cases when the performance of the model was insufficient, a co-adaptive learning-strategy was applied, in which the linear mapping model was adapted by considering additional data-samples obtained while playing the game. This has been demonstrated to be an efficient approach to train both the user and the algorithm simultaneously [2].

Evaluation in real-world tasks with physical prosthesis

Once a satisfactory mapping model was reached and the entire 2D unity-circle could be firmly accessed by the user, the model was uploaded to the controller and used for prosthesis control. The performance was evaluated with the standardized clothespin relocation test that involves both prosthetic functions (open/close and rotation). In this test, the time for moving three red pins (10 N grip force required) from a horizontal to the vertical bar of the Rolyan Graded Pinch Exerciser was measured. As regression-based control approaches can be influenced by the position of the arm ([3], [4]), the test was conducted in three different arm positions (arm down, half up, arm up; Fig. 3). Also the time between training and evaluation as well as between donning and doffing of the electrodes can negatively impact the performance [5]. Therefore, the regression-based control was evaluated on two different days, using the model trained in the first day.

As a comparison, two conventional control systems with two bipolar electrodes located on the extensors and flexors of the residual forearm were evaluated (using the conventional Otto Bock Myorotonic controller). Co-contraction control (CC) consists of a state machine where a short contraction of both muscle groups triggers a switch of the active DOF. In slope control (SC), the active function is selected based on the slope of the EMG envelope when the contraction is initiated. Slowly increasing EMG-amplitudes are mapped into open/close of the prosthesis, and quickly raising signals into pronation/supination of the prosthetic wrist [6].

In this way, the benefits of simultaneous and proportional myoelectric control including combined motions in comparison to conventional approaches that require a sequential control of the individual (non-combined) motions was evaluated.

Subjects

This study was conducted on three patients, whereof two subjects had a congenital limb deficiency and one subject had a transradial amputation. Prosthetic test sockets were constructed that integrated eight equally-spaced electrodes at the location of largest diameter of the residual limb (for one congenital subject with very short and thin residual limb only four electrodes were used due to space constrains).

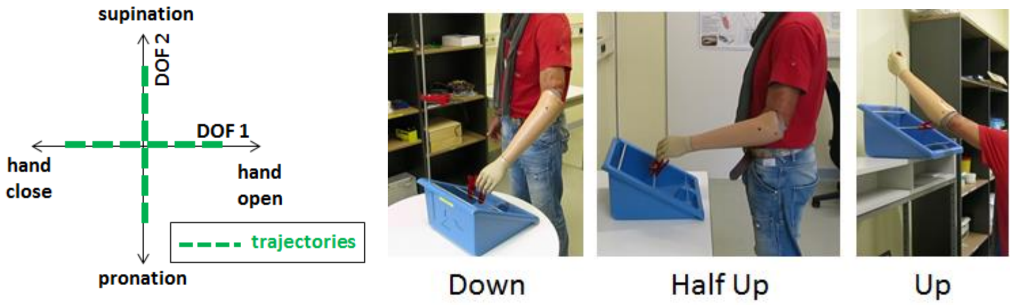


Figure 1: Evaluation in the clothespin relocation test, executed in three different arm positions

4 RESULTS

Fig. 4 shows the results of the virtual control task. As seen in the left column (performance after calibration based on visual cues with non-combined motions only), the subjects were able to reach many targets of non-combined and combined regions. On the other hand, subject 1 and 3 were not able to access all regions. However, this problem was not restricted to combined motions but affected both non-combined and combined motions, indicating rather a calibration problem than a problem of linearity across DOFs. It may be caused by an inaccurate execution of the motions during the calibration phase (e.g. improper timing or inconsistent contraction strength). As indicated by the right column of Fig. 4 (test after adaptation), the initial problem were mostly solved by applying the co-adaptive learning procedure. Subject 1 still did not hit all targets in this condition, but, as indicated by the black trace, this problem was related to an insufficient dwell time while all regions could be reached.

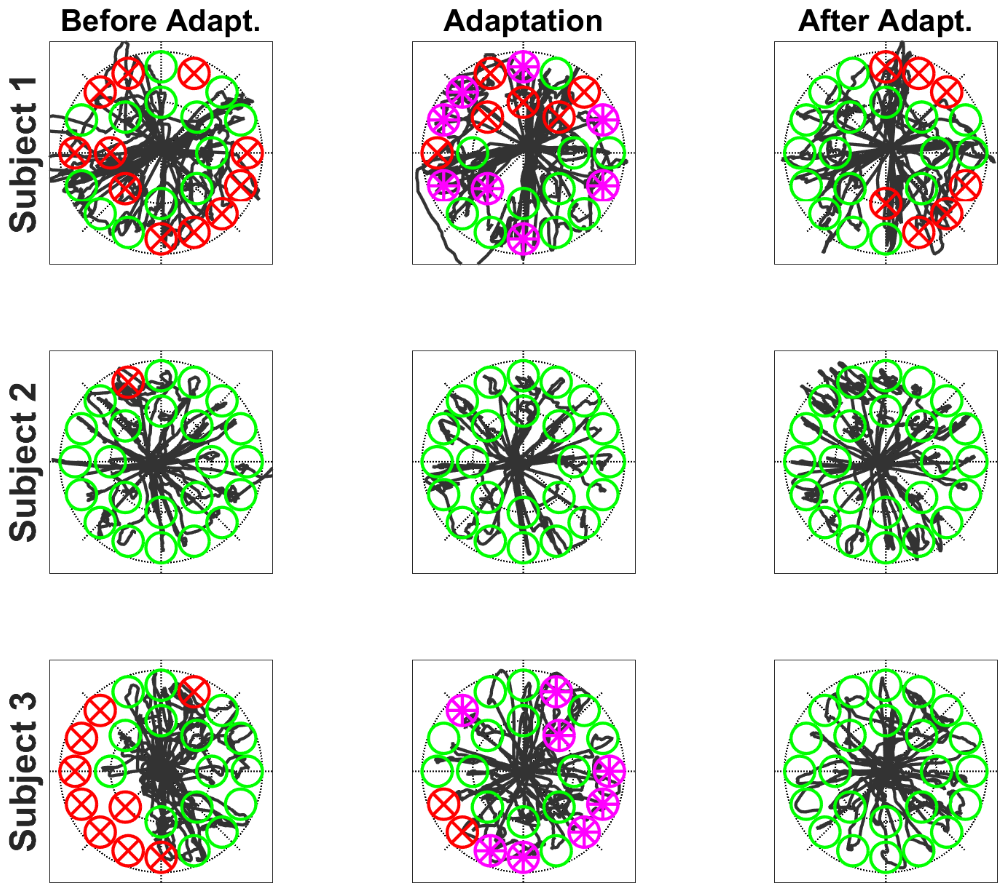


Fig. 4: Results of virtual control tasks obtained with a linear mapping model. The black curve indicates the trace of the cursor that was controlled by the user, green circles positions of successfully hit targets, red circles missed targets and purple circles adaptation cases. The left column shows results for the model trained with non-combined motions only, the middle column the adaptation step and the right column a test after adaptation.

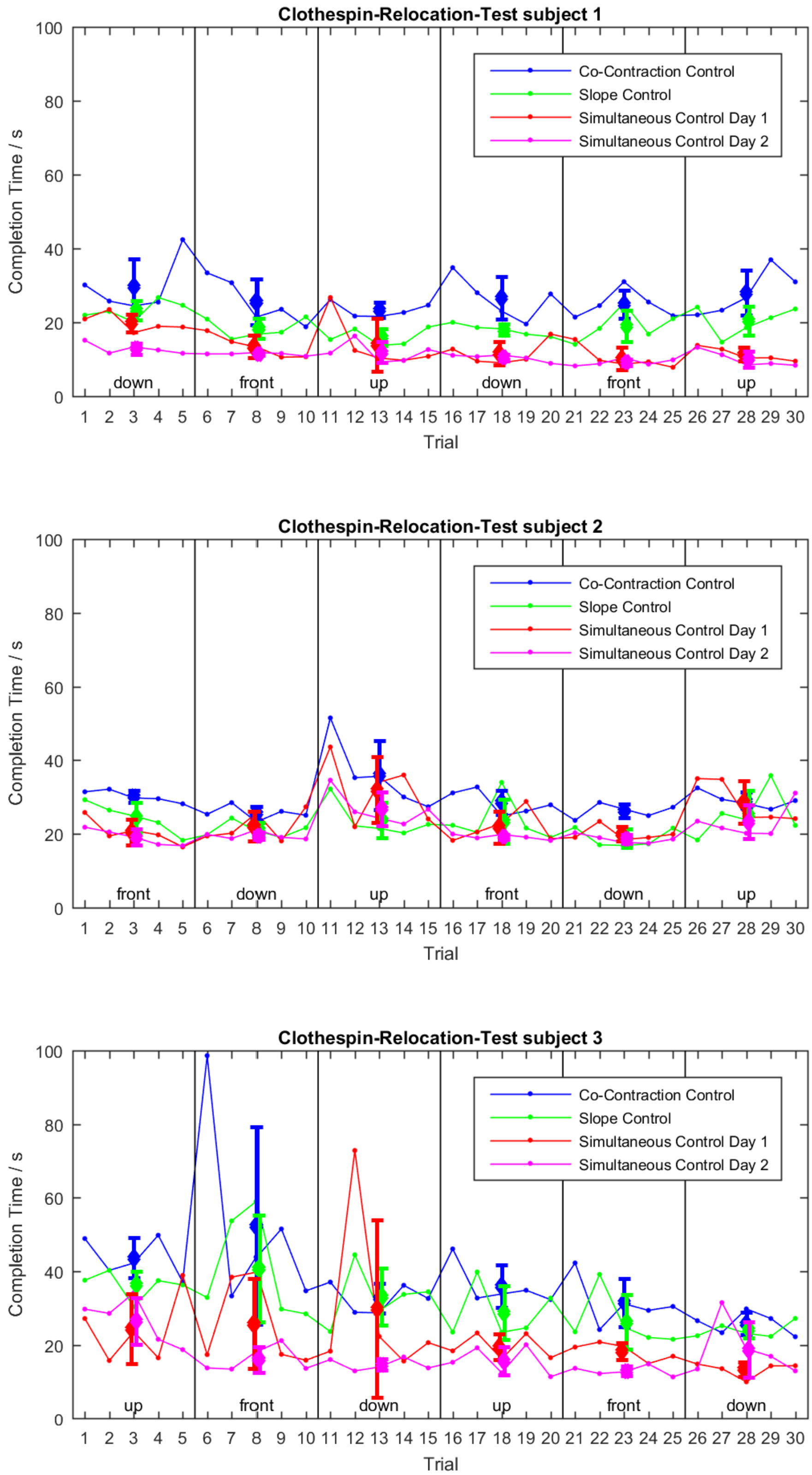


Figure 5: Performance of two conventional control systems and regression based simultaneous and proportional control evaluated on two different days. Three arm-positions were evaluated in the clothes-pin relocation test.

The completion times needed in the clothespin test are shown in Fig. 5. The proposed regression-based simultaneous and proportional control outperformed the two conventional control techniques CC and SC. The time for completing the task with RC was approximately half the time needed with CC. SC performed slightly better than CC but could on average not reach the performance of RC. On the first day there was an improvement within the first ten trials of RC, most likely due to learning effects of the user. Remarkably, the impact of arm-position change was relatively small and RC was not more strongly affected by this factor than the conventional control system techniques. Also the session transfers of the regression model had no negative impact. When evaluated on the second day without retraining the model, RC reached consistently similar results as on the first day. This is a demonstration that extending the control to multiple DOFs simultaneously with RC did not negatively impact on the robustness.

4.1 Conclusion

The work within this deliverable was divided in two parts. Conclusions from the combined results are summarized as follows:

- 2 DOFs are linearly separable in the muscle space as was assessed offline directly (part I) and online indirectly (by showing controllability of combined motions with individual motion training) (part II)
- Calibration with visual cues and non-combined motions in amputees where no kinematics nor forces can be used as labels is a feasible approach for training for simultaneous and proportion control
- When training on individual motions in a conventional way is not sufficient, co-adaptive training is beneficial for patients.

5 Subcontracting

No subcontracting was needed – all work was done by UMG.

6 References

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