PROSTHETICS

Simultaneous control of multiple functions of bionic hand prostheses: Performance and robustness in end users

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Myoelectric hand prostheses are usually controlled with two bipolar electrodes located on the flexor and extensor muscles of the residual limb. With clinically established techniques, only one function can be controlled at a time. This is cumbersome and limits the benefit of additional functions offered by modern prostheses. Extensive research has been conducted on more advanced control techniques, but the clinical impact has been limited, mainly due to the lack of reliability in real-world conditions. We implemented a regression-based control approach that allows for simultaneous and proportional control of two degrees of freedom and evaluated it on five prosthetic end users. In the evaluation of tasks mimicking daily life activities, we included factors that limit reliability, such as tests in different arm positions and on different days. The regression approach was robust over multiple days and only slightly affected by changing in the arm position. Additionally, the regression approach outperformed two clinical control approaches in most conditions.

INTRODUCTION

A missing hand after amputation usually maintains its representation in the motor cortex, and most patients perceive their lost limb as if it was still present (*1*). Activating this so-called phantom hand causes contractions of the residual muscles in the stump, which can be detected by myoelectric potentials on the surface of the skin and used to control a prosthesis. Accordingly, electrically powered hand prostheses are typically controlled by two electromyographic (EMG) signals recorded from the residual limb. In conventional control, which has been commercially and clinically available since the 1960s (*2*), two bipolar EMG electrodes are integrated in the prosthetic socket at the flexors and extensors of the residual limb and used to proportionally control the velocity of closing and opening the prosthesis. This two-channel control is limited to one degree of freedom (DOF) at a time. To control more DOFs, the active DOF can be switched by a co-contraction or other heuristics (*3*), which are time-consuming or counterintuitive and do not allow for simultaneous control of multiple DOFs.

To overcome the limitations of conventional two-channel control, various machine-learning techniques have been proposed to extract control information from a greater number of channels (typically 4 to 10) (*4*–*6*). Most proposed approaches are based on signal classification that assigns EMG features to a discrete set of motions (*7*–*9*). This basic on/off control can be extended by including the proportional activation of each motion based on EMG amplitude (*8*, *10*). Classification in its basic form only allows for the sequential activation of individual prosthetic functions. It is possible to extend this concept to combined motions (*11*). However, this may reduce the classification accuracy and does not allow for independent velocity control of simultaneously activated DOFs.

Recently, regression-based approaches have been investigated for simultaneous and proportional myoelectric control (*12*–*17*). Regression does not map discrete movements but rather estimates a proportional activation for each DOF. This enables independent, simultaneous, and proportional control of all DOFs. For example, a prosthetic user can perform slow wrist rotation and fast hand opening simultaneously. Similar to classification approaches, labeled training data are required to train the regressor. Labels can be obtained by conducting bilaterally mirrored movements and measuring forces or kinematics on the intact side (*18*). Alternatively, visual cues can be provided for the user to follow, which can be applied also for bilateral amputees (*16*).

Despite research over four decades and very promising results in academia, the impact of machine-learning approaches on clinical practice is still limited. All major prosthetic manufacturers still rely on the conventional two-channel control; only one spin-off company (*19*) offers a classification-based controller as an add-on for various prostheses. The main reason for the limited transfer into clinical and commercial applications is the lack of robustness of advanced control approaches in real-world conditions (*20*). High performance obtained under controlled conditions usually decreased substantially when factors—such as a change in arm position (*21*), small electrode shifts (*22*, *23*), skin conditions (*20*), a mechanical load due to the weight of the prosthesis (*24*), or time between algorithm training and application (*25*)—were introduced. Most studies on machine learning–based myoelectric control were performed offline with recorded data, analyzing only a classification performance rate. Others were restricted to virtual control tasks, which exclude many robustness-related factors. Only a few studies evaluated classification-based systems with prosthetic users and in real prosthetic tasks. Almström *et al.* (*26*) evaluated a classification-based system with five prosthetic users in 1981. Two of the participants were using the prosthesis at home, but no evaluation of the functional performance was conducted. The authors reported a strong degradation of the controllability due to fatigue and repetitive hardware failures of the prosthetic prototype.

Amsüss *et al.* (*10*) conducted functional laboratory tests with four prosthetic users and tested two classification schemes and the conventional control that each participant regularly used. The performance with the classification-based systems was in some cases better

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and in some cases worse than the conventional control. However, a fair comparison was not possible because the reduced DOFs and the additional training due to daily usage simplified the tasks for the conventional control schemes. Recently, Kuiken *et al.* (*27*) evaluated a classification-based system in a home study on three prosthetic users. In that study, three participants with amputation used a classification-based prosthesis with seven functions and a customized classification-based controller prototype. Functional tasks such as the Southampton Hand Assessment Procedure (SHAP) test (*28*), the box-and-blocks test (*29*), and the clothespin relocation test (*30*) were evaluated and compared with a conventional control approach. To the best of our knowledge, a similar study for regression-based control is not yet available.

In this paper, we evaluated a two-DOF simultaneous and proportional control approach based on linear regression (LR) on five individuals with transradial amputation or congenital limb deficiency, with a specific focus on the robustness under challenging conditions. By conducting physical tasks with a real prosthesis and in different arm positions and by testing the trained regression model on two different days, we included the relevant factors that can potentially degrade the performance in daily use. We further compared the regression-based approach with two clinically well-established two-DOF control approaches [co-contraction control (CC) and slope control (SC)]. The performance was evaluated in the standardized box-and-blocks and clothespin relocation tests, with the latter extended to three different arm positions. We hypothesized that the LR approach (i) outperformed conventional control, (ii) was degraded when evaluated on a second day with the model trained on the first day, and (iii) was sensitive to arm position changes.

RESULTS

The regression-based (LR) and the two conventional control techniques (CC and SC) were evaluated in functional tasks. The performance in the clothespin relocation test for the five participants (one panel each) is provided in Fig. 1, with significant post hoc test comparisons marked (significance level $P < 0.05$ after Bonferroni correction). The left part in each panel shows the pooled results across all arm positions, whereas the right part shows position-specific results. Figure 2 shows the results of the box-and-blocks test, during which only the DOF "open/close" was required (significance level $P < 0.05$ after Bonferroni correction). For intuitive comparison with the clothespin relocation test, the outcome measure was converted into average time per block. Significant post hoc test comparisons are marked.

Simultaneous control outperforms conventional control

Considering the position-pooled results of the clothespin test, in which both DOFs were needed, four of the five participants performed significantly better, with LR evaluated on the first day than with CC. The median time for transferring the three pins with LR was 12 to 22 s (participant medians; average, 18.6 s). With CC, the participants required 20 to 80 s (average, 37.4 s). Only for participant 4, there was no statistically significant difference between LR and CC. In comparison with SC (16 to 30 s; average, 21.8 s), two participants performed significantly better with LR, and the other three performed equally well. When directly comparing the two conventional methods SC and CC, four participants performed significantly better with SC; for one participant, there were no significant differences.

In the box-and-blocks test, the performance in a one-DOF task was evaluated (Fig. 2). Because the control is locked in a single DOF in CC, the participants tended to perform best with CC in this task, as expected. When evaluated on the first day, LR performed significantly worse than CC for two participants and significantly worse than SC for one participant. However, on the second day, there was no significant difference between LR and CC for any of the participants, and LR performed significantly better than SC for two participants. When directly comparing SC and CC, two participants performed significantly worse with SC. Movie S1 shows the tests for the different control methods.

Simultaneous control is robust against donning/doffing and session transfer

When LR was evaluated on the second day without retraining the model, the performance did not degrade in comparison with the first day in any of the tests. In the clothespin test, there was no significant performance difference between the two LR sessions in any of the participants (LR second day: median times, 11 to 21 s; mean, 16.6 s).

In addition, in the box-and-blocks test, the performance did not decrease from the first to the second session in any participant. Instead, the performance increased significantly for one participant. Participant 1 conducted the box-and-blocks test only in the second session because of fatigue in the first session caused by substantial amount of time spent adjusting the socket and testing the signal quality.

Simultaneous control is relatively robust against arm position change

Considering the effect of changing arm position in the clothespin test, SC showed the highest robustness, with no significant differences between the three positions for any participant. For LR, three participants showed no significant differences between arm positions, but two participants performed significantly worse in the upper arm position. CC was the approach most influenced by the change in arm position, with three participants performing significantly worse in some arm positions.

The number of dropped pins was generally low (Table 1). Depending on the control technique, between 0.73 and 1.47 pins were dropped on average in the 10 repetitions (30 transferred pins). There were no significant differences among methods or arm positions for any of the participants except for participant 2, who dropped a significantly higher number of pins with LR1 than with CC, particularly in the upper arm position.

DISCUSSION

We evaluated a regression-based simultaneous and proportional myoelectric control technique (LR) in comparison with two well-established conventional techniques (CC and SC) on five prosthetic end users. The evaluation was based on the standardized clothespin relocation and the box-and-blocks tests. The clothespin relocation test was extended to three arm positions to investigate the impact of this factor on the performance. With LR, the participants generally performed better than or similarly to the two tested conventional techniques.

LR was evaluated in two sessions, with a regression model trained in the first session only. We expected a degradation in performance due to donning and doffing, because it was previously reported for classification-based control in offline (*25*) and online (*31*) applications as well as for offline regression-based control (*23*). However, in the current online study, we did not observe any performance degradation of the regression-based control in the transfer session. Because we evaluated the performance only online, we cannot establish whether the regression model itself was robust against the factors related to the session transfer

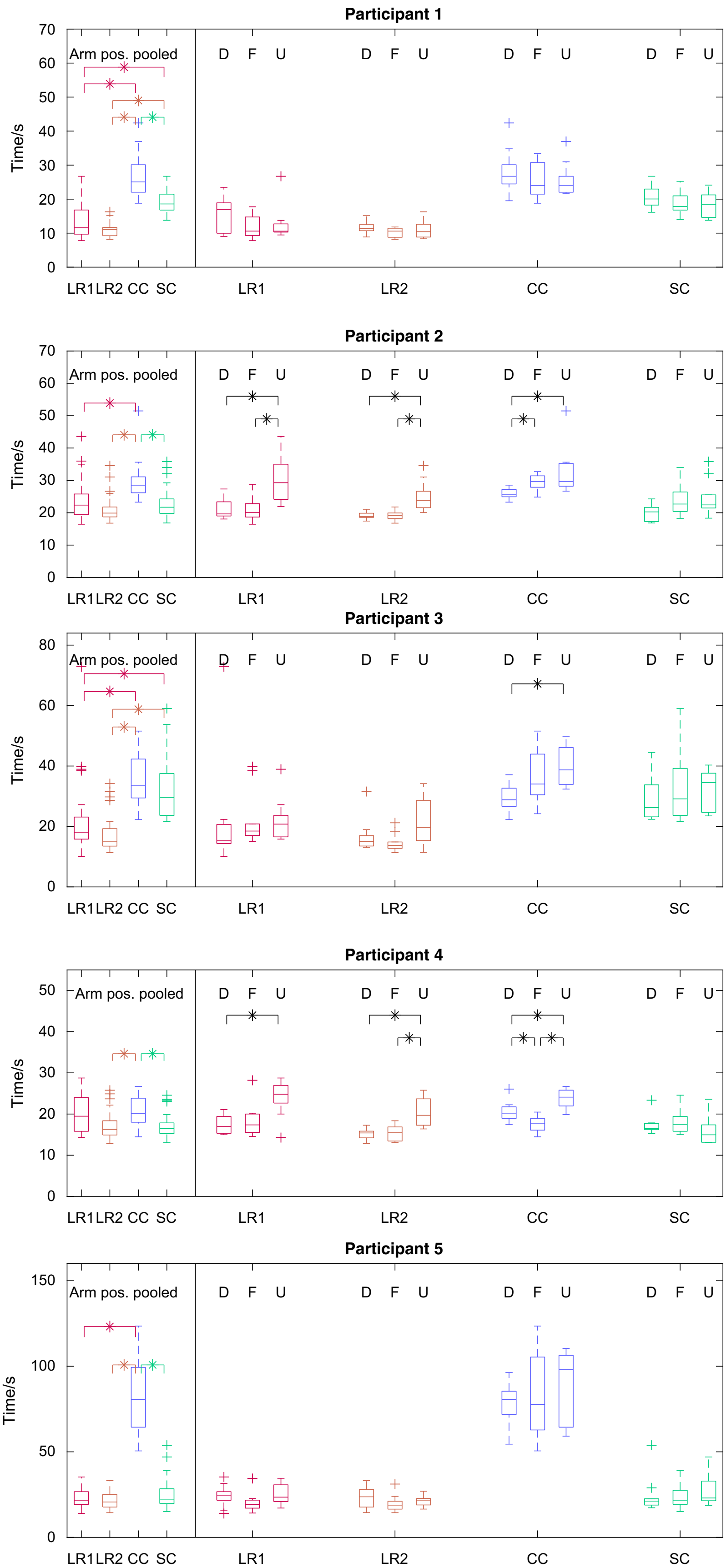

Fig. 1. Results from clothespin relocation test. The time required to transfer three pins from a horizontal to a vertical bar is shown. Performance of LR-based control on two different days without retraining (LR1 and LR2) and two conventional control strategies, CC and SC, is shown separately for each participant (one panel each). The three arm positions—down (D), frontal (F), and up (U)—are shown separately on the right and pooled on the left. The proposed regression-based control outperformed CC for all participants and performed similarly to or better than SC. It was robust against session transfer and less affected by a change of arm position than CC. Asterisks indicate significant differences; plus signs indicate outliers; error bars indicate 25th and 75th percentiles.

or whether there was a degradation of the model that could be compensated by the user, as shown recently for signal degradation due to noise (*32*). However, none of the users reported feeling any difference in control on the second day or actively compensating for any changes. It remains to be shown whether the trained regression model is stable over a longer period, such as several months. If needed, the controller could be retrained in less than 3 min, if a recalibration function were included in the controller.

Degradation of performance due to a change in arm position was previously shown offline for classification-based (*21*) and regression-based (*33*) control. In our study, the change in arm position degraded the performance with LR only in two of the five participants. This could indicate that the effect of arm position is less problematic when evaluated online because the user can correct for shortcomings of the control algorithm, as indicated also in (*23*). Unexpectedly, the conventional CC was more influenced by the arm position change than LR. This was in accordance with the statement from a participant, who reported to have similar problems while using CC with his own prosthesis in daily life.

In most studies on advanced myoelectric control, CC is referred to as the clinical state of the art. However, SC is another equally well-established technique, being the standard setting in the MyoRotonic control unit (Otto Bock Healthcare GmbH, Duderstadt, Germany), in which all four functions are directly accessed without mode switching (similar to the classification-based approach). Although simultaneous motions cannot be conducted with SC and the absolute performance was often still below our proposed LR approach, the participants performed significantly better with SC than with CC and the control was robust to arm position change. Therefore, we believe that SC deserves more attention as a clinically established baseline technique when evaluating novel myoelectric control approaches.

The LR approach, on the other hand, offers a much higher functionality compared with the two conventional approaches. Both DOFs can be actuated simultaneously, and their velocity can be controlled independently. Moreover, it allows a smooth transition between motions as

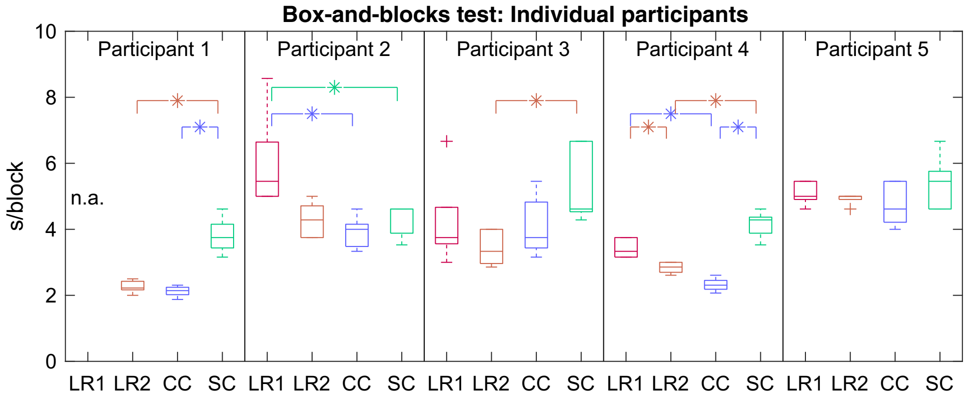

Fig. 2. Results from box-and-blocks test. The reported outcome measure is the average time per block. Performances of LR-based control on two different days without retraining (LR1 and LR2) and two conventional control strategies, CC and SC, are shown separately for each participant (one panel each). LR was robust across sessions, and its performance was similar to or better than the conventional control systems in the second day, although only one DOF was needed. n.a., not applicable.

Table 1. Number of dropped pins. Dropped pins for all control techniques and arm positions. Each technique/position combination involved 10 runs or 30 transferred pins per participant. That is, the number of dropped pins was relatively low, with almost no significant differences between techniques and conditions. D, down; F, frontal; U, up. Dash entries indicate no drops.

Method	**LR1**			**LR2**			**CC**			**SC**		
Arm position	**D**	**F**	**U**	**D**	**F**	**U**	**D**	**F**	**U**	**D**	**F**	**U**
Participant 1	1	—	—	—	—	—	—	—	—	—	1	1
Participant 2	2	—	6	—	—	2	—	—	—	—	—	2
Participant 3	—	2	3	2	1	5	—	2	2	2	5	1
Participant 4	1	—	1	—	—	—	—	—	—	—	—	—
Participant 5	5	—	1	2	4	—	1	1	5	—	1	2

in natural hand motions. We observed that some of the participants used this feature in the clothespin test, for example, initiating a wrist rotation before the hand was fully opened when releasing the pins. The fact that the performance with LR in the box-and-blocks test was comparable to those of conventional control techniques indicates that the additional functionality offered by LR did not complicate the control in tasks that required only one DOF (i.e., very few false activations of the second DOF).

It is not possible to investigate correlations between participant-specific factors such as the type of limb deficiency (amputee versus congenital) or length of the residual limb and performance due to the small sample size. However, the short residual limb and the fact that only four, instead of eight, electrodes were applied in participant 2 may have contributed to the relatively large influence of arm position in this participant. Moreover, the participant with the best performance in LR (participant 1) had the most experience with advanced control (mainly classification-based control). It is likely that this experience was transferred to the regression-based control. A similar training effect is likely present for the type of control used in daily life by the participants. Two of the three participants who performed equally well with SC as with LR (participants 2 and 4) use SC in their conventional daily life prostheses. Thus, they had substantially more training with SC than with the other methods. An additional potential training effect relates to the bilateral participant 4, who uses CC in one of his conventional daily-use prostheses. Among the five participants, he showed the best performance with CC.

One user decided to stop the experiment on the first day of the experiment before conducting the box-and-blocks test because of fatigue. However, this was due to the time needed for the final adjustments to the socket that required repetitively testing the signal quality during contractions. The socket tuning was not associated to a specific control method but related to the signal quality needed for all methods. We did not investigate the degree in which different control methods induced fatigue, but with comparable adjustments of the gain factors and thresholds, we would not expect a higher level of fatigue in LR than in conventional control.

Although standardized performance metrics were used, a comparison with other studies is difficult due to different experimental conditions (e.g., number of available DOFs) and the very large interparticipant variations that were observed within this study. With the classification-based control evaluated in (*27*), the three participants required 54.9 to 99.4 s (mean, 73.1 s) to transfer three pins in a first session, which is substantially longer than the times observed with our LR approach (LR1, 13.4 to 24.1 s; mean, 20.5 s). However, their prostheses allowed the control of seven functions compared with four in our case, which may render a reliable control more difficult. After a home-use period of at least 4 weeks, their performance improved to 14.1 to 37.6 s (mean, 24.2 s), which is still longer than we observed for LR (LR2, 10.9 to 21.5 s; mean, 17.6 s) but underlines the importance of longitudinal user training. In (*10*), where two different classification-based approaches with five to seven prosthetic functions (depending on the participant) were evaluated, the participants required about 10 to 50 s (mean, ca. 22 s) to move three pins in the clothespin test. This is a range similar to our LR approach, but the study included only participants who were experienced with classification-based control approaches and participated in a longitudinal training program for repeatable EMG patterns before the experiments. It is expected that with such a longitudinal training, the performance of our LR approach will improve.

A limitation of the applied control technique as well as of most other machine learning–based approaches is that the users need to be able to generate at least four different signal patterns. In our study, five of the eight screened individuals immediately fulfilled this condition without any rehabilitation training. With a specific longitudinal training, such as proposed in (*10*), the number of individuals who could benefit from our approach would most likely increase.

The overall feedback on the LR control from the participants was very positive. The users found the control very intuitive and esteemed the fact that they did not need to switch between functions or concentrate on the slew rate of their EMG signals. In future work, we will investigate the range of motion and the extent of compensatory motions depending on the controller.

Table 2. Participant characteristics. Dash entries indicate zero.

Participant	Type and affected side	Gender	Age	Years after amputation	Residual limb	Own prosthesis	Frequency of use	Experience advanced control
1	Amputation, left	M	56	35	Medium	1 DOF	Daily	Medium
2	Congenital, left	F	37	—	Short	2 DOF, SC	Daily	Little
3	Congenital, left	F	24	—	Long	—	—	None
4	Bilateral amputation, left side tested	M	58	7	Medium	2 DOF, SC/CC	Daily	None
5	Congenital, right	M	44	—	Long	1 DOF	Very seldom	Little

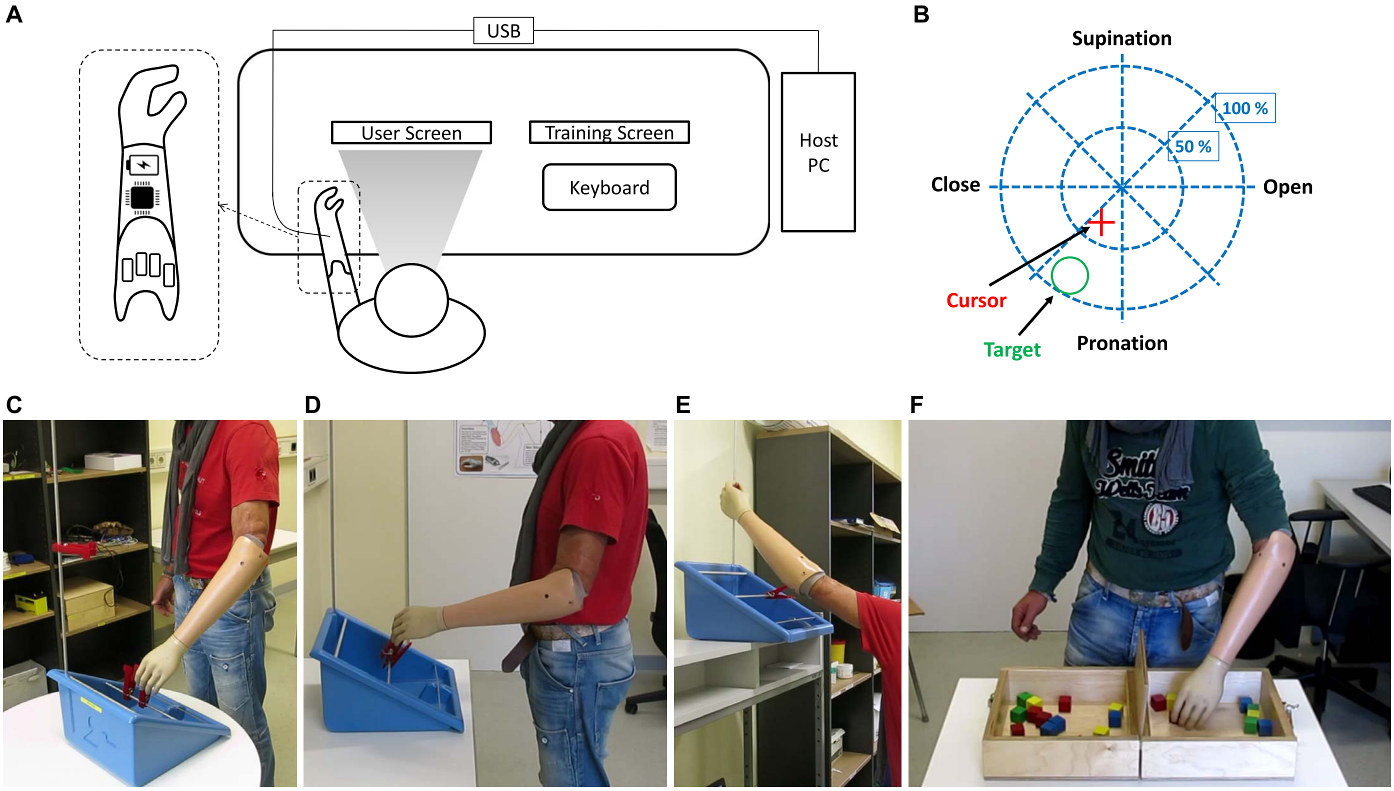

Fig. 3. Experimental setup. (**A**) Setup for PC-supported user training with regression algorithm. During training, the prosthesis was connected to a PC to record EMG signals while the user received instructions via the user screen. An initial regression model was applied for virtual control tasks for training the user in a game-like software framework and optional co-adaptive learning between the user and the algorithm. (**B**) Computer game for training the user in conducting noncombined and combined motions of different activation levels with the regression-based control. Evaluation in the clothespin relocation test, executed in arm positions down (**C**), frontal (**D**), and up (**E**). (**F**) Evaluation in the box-and-blocks test.

Conclusion

In this study on five individuals, we demonstrated the feasibility of robust simultaneous and proportional prosthetic hand control, even under challenging conditions. The proposed two-DOF regression-based approach outperformed two clinically and commercially well-established control techniques, which confirms our hypothesis 1. No performance degradation was observed when the regression model was trained on the first day and tested on a second day, which surprisingly disproves hypothesis 2. This shows that this rather common pattern recognition problem does not apply to the presented method or that the degradation in the mapping could be fully compensated by the users. Hypothesis 3 is only partly confirmed, because the impact of changing arm positions was relatively weak (significant only in two participants) and less than in conventional co-contraction–based control. Besides better performance scores, the regression approach is more natural and more flexible, because all functions can be accessed intuitively and in combination, with their velocities being independently controlled. The regression-based control approach, therefore, has a high potential for successful transfer into clinical use. In the future, the LR approach should be evaluated over a longer period in daily life and on

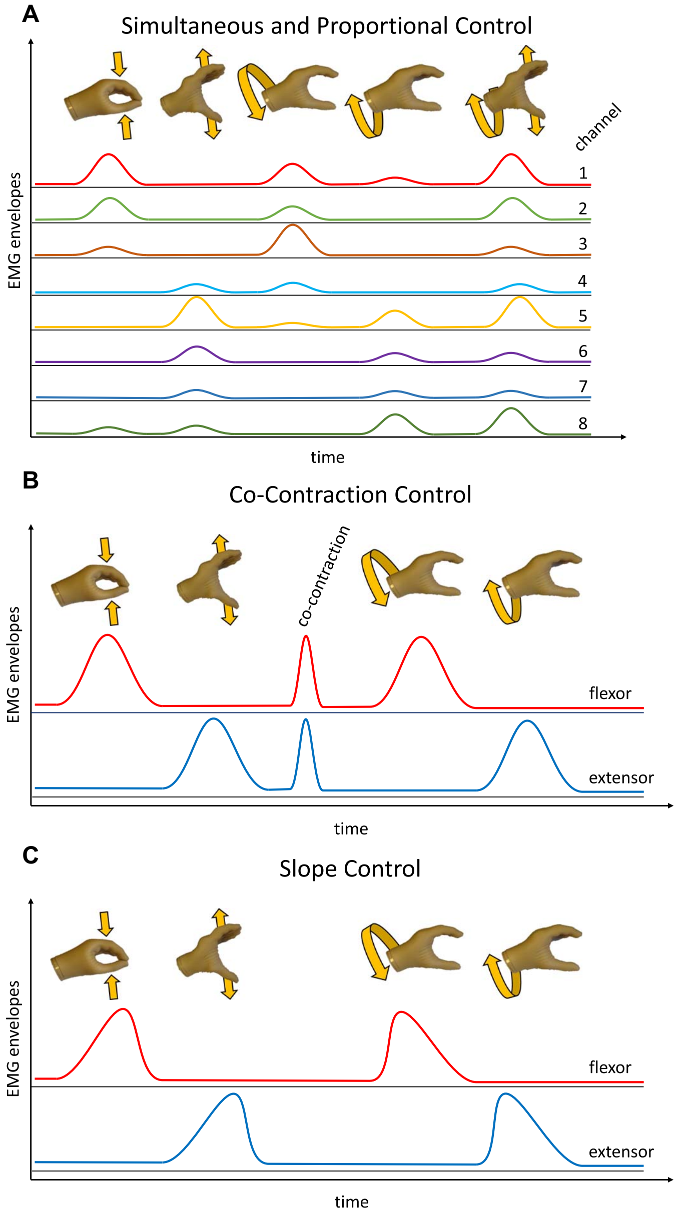

Fig. 4. Schematic explanation of the evaluated control techniques. (**A**) Regression-based control uses eight channels that are mapped into two DOFs that can be activated proportionally and simultaneously. (**B**) CC is based on two channels. For switching the active DOF, a short and strong co-activation is required. (**C**) In SC, which also uses two channels, the rate of increase in EMG envelope determines the activated DOF.

more users. In addition, a direct comparison with a classification-based approach and a more systematic evaluation of user satisfaction by questionnaires would provide further relevant information for translational work in myocontrol.

MATERIALS AND METHODS

Equipment, screening, and setup preparation

We recruited individuals with transradial amputations or congenital limb deficiencies. All candidates first participated in initial screening, in which eight equally spaced EMG sensors were attached circumferentially on their residual forearm at the level of the largest diameter. An intuitive graphical real-time representation of the root mean square signal of the eight channels was provided to the candidate and the experimenter, while the candidate was asked to perform various contractions with the residual muscles. All candidates with amputation reported vivid phantom representation of the missing hand and were motivated to conduct various phantom limb motions. The candidates with congenital limb deficiency were asked to move their residual wrist joint in different directions. On the basis of visual inspection, we included candidates that were able to generate four different EMG amplitude patterns. In total, eight candidates were screened, and five of them were included in this study. Two had a transradial amputation, and three had a congenital limb deficiency. An overview of the participants' characteristics is given in Table 2. The experiments were performed in accordance with the Declaration of Helsinki and approved by the local ethics committee (Ethikkommission der Universitätsmedizin Göttingen). All participants gave their written and oral informed consent before participating in the study.

For each participant, a customized experimental prosthetic socket was built. The construction process was based on well-established techniques for conventional prosthesis fitting. A plaster negative of the residual limb was taken, which was used to form a plaster positive from gypsum. Eight dummy electrodes were fixed on the positive mold on the targeted electrode positions (equally spaced at the level of the largest diameter). The final inner socket was built from thermoplastics using deep drawing. Eight conventional electrode modules (13E200, Otto Bock) were integrated into the socket, except for participant 2, for whom only four electrodes were integrated because of the relatively short and thin residual limb. A two-DOF prosthesis (grasping and rotation) was used (DMC hand with electric wrist rotator, Otto Bock). The prosthetic hand was mechanically connected to the inner socket either by a conventional outer socket (participants 1 and 2) or by a customized adapter that directly linked to the inner socket (participants 3 to 5).

Regression-based simultaneous and proportional control

LR-based simultaneous and proportional control was implemented with a customized embedded system based on an Atmel AT-XMEGA32-A4U 8-bit microcontroller (MC) clocked at 32 MHz. The EMG envelopes of the eight electrode modules were digitized by the internal analog-to-digital converters of the MC. To interface the grasp function of the prosthesis, we generated two analog signals emulating the electrodes in conventional one-DOF application with the internal pulse-width modulators of the MC and external RC filters. To control the rotation in a proportional way, we applied an external motor driver (LV8548MC, ON Semiconductor).

For training, the embedded system was connected via an isolated universal serial bus (USB) bridge to a PC (Fig. 3). Supported by a real-time visualization of the EMG envelopes, the participant and the experimenter selected four muscle contractions to be mapped to the four prosthetic functions. The criteria to select suitable patterns were (i) dissimilarity, (ii) repeatability of the EMG patterns, and (iii) intuitiveness of the contraction. For all five participants, wrist flexion and extension were used for opening and closing the prosthesis as in conventional control. In all congenital participants, ulnar and radial deviations were used for prosthetic pronation and supination. Both participants with amputation used the phantom motions pronation and little finger flexion for the rotation function of the prosthesis.

PC-based training of the regression algorithm and the user was conducted on the basis of the protocol developed in (*34*). The participants first performed a series of contractions after visual cues and without any feedback to record calibration data to train the algorithm. In particular, the participants were asked to follow trapezoidal contraction profiles with a ramp-up phase (3 s), a static contraction phase at a strong but comfortable level (2 s), and a ramp-down phase (3 s). In total, three runs of training data were collected, where each run consisted of one profile for each of the four motions and 8 s of rest. The collected data were used to train a linear mapping model $\mathbf{W}$ from the eight-dimensional EMG envelopes $\mathbf{x}$ to the two-dimensional control signal $\hat{\mathbf{y}}$

$$\hat{\mathbf{y}} = \mathbf{W}^T\mathbf{x} \tag{1}$$

The <8 × 2> dimensional coefficient matrix of the mapping $\mathbf{W}$ was obtained with ordinary LR, that is, by minimizing the mean-squared error. If $\mathbf{X}$ and $\mathbf{Y}$ are matrices with the collected training data and labels, respectively, the solution is given in closed form by Eq. 2. For the labels, we relied on the visual cues that were given to the user during the recording.

$$\mathbf{W} = (\mathbf{X}\mathbf{X}^T)^{-1}\mathbf{X}\mathbf{Y}^T \tag{2}$$

A position control scheme was implemented to enable real-time control over a cursor within a two-dimensional coordinate system on the computer screen. Without contraction of the residual muscles, the cursor remained in the central of the screen. The stronger the user contracted, the further the curser moved away from the center. Each direction corresponded to one of the four chosen phantom movements. As shown previously (*13*), although only noncombined motions were included in the calibration data, combined motions could be estimated with the linear mapping function (Fig. 4A). In this case, the cursor moved diagonally, and its angle depended on the activation ratio of the two active contractions. After brief familiarization (<5 min), a systematic evaluation of the control capability was conducted using a computer game (Fig. 3B). Circles appeared in a random order in predefined positions (8 equally spaced targets at 50% contraction level and 16 targets at 80% contraction level). For each circle, the user was asked to move the cursor into the circle (radius, 15%) and remain inside the circle for 1 s. Between two targets, a "rest" target appeared at the origin and forced the user to relax. For participants 1 to 3, one run of co-adaptive learning was conducted in which the mapping coefficients were adapted continuously (i.e., every 40 ms) while playing the game. To avoid undesired adaptation for targets that could be reached with the current regression model, we started adaptation 5 s after the appearance of each target. For details on the calibration procedure and the co-adaptive learning, we refer to our previous study (*34*). Participants 4 and 5 did not conduct the co-adaptation runs because they could not maintain the contractions for stable algorithmic adaptation.

After training the algorithm and the user, the regression model was uploaded to the embedded system and used to control the prosthesis instead of a virtual cursor. As in conventional control, the prosthesis was controlled in velocity control mode. The stronger the user contracted, the faster the prosthesis moved. At relaxation, the prosthesis did not move back to a neutral position but remained in the current position. The mapping was instantaneous, and the update rate of the embedded system was set to 25 Hz; that is, every 40 ms, a new output was generated. Because of the conventional EMG electrodes that provide the conditioned EMG envelopes as outputs, no windowing or feature extraction was required. The additional latency introduced by our controller was far below the recommended maximal delay of 200 to 300 ms (*35*) and was not noticed by any of the users.

To fine-tune the velocity of the prosthesis, allowing for more precise control, and to reduce the risk of undesired prosthesis actuation, we individually adjusted two thresholds for each of the four prosthetic functions. The lower threshold determined the contraction level at which the prosthesis would start moving, and the upper threshold determined the contraction level at which prosthesis would move with maximum velocity. The procedure for adjusting the thresholds was as follows. After calibration and potential co-adaptation, the regression model and the default values of 10 and 100% for the lower and upper thresholds, respectively, were uploaded to the controller. We then asked the user to execute all four motions sequentially and at different velocities with the prosthesis while visualizing the real-time cursor in parallel. During these tasks, the user reported on the quality of the control, and the thresholds were adjusted to maximize functionality. For example, the upper threshold was decreased when the maximal velocity could be reached only with strong efforts, and the upper threshold was increased when it was difficult to execute slow movements. If a prosthetic function was continuously co-activated while a different, noncombined motion was intended, its lower threshold was slightly increased to reduce the risk of unwanted activations. The upper and lower thresholds were graphically visualized in the control panel. Thus, both the experimenter and user were fully aware of the applied thresholds. After adjustment, the applied range varied from user to user and between the different prosthetic functions. The ranges for the lower and upper thresholds across users were 10 to 30% and 60 to 150%, respectively. After a satisfactory setting was found, all parameters were saved on the EEprom of the MC and remained unchanged during the entire regression-based part of the experiment, including the second session on another day.

Conventional control techniques

Two well-established conventional control strategies, namely, CC and SC, were evaluated as reference methods. They are based on two EMG channels only, located on the extensors and flexors of the residual forearm. The same sockets as for the regression-based control were used, and the two electrodes with maximum EMG amplitudes during wrist flexion and extension were selected. For both reference methods, the commercially available MyoRotonic control unit Otto Bock was used and configured with the MyoSelect tool. Both methods allowed for proportional control: The stronger the user contracted the muscles, the faster the prosthesis moved or the higher the grip force in case an object was grasped. With both techniques, only one DOF could be controlled at a time. The selection of the active DOF (grasping or rotation) was specific for each method, as described in the following.

Co-contraction control

Conventional CC consists of a state machine that is locked either in the grasping state or in the rotation state (Fig. 4B). In the grasping state, EMG activity in the extensor muscles opens and activity in the flexor muscles closes the prosthesis proportionally. To change the active state, the user performs a short and strong activation of both muscle groups at the same time. When the controller detects this co-contraction, the user is informed by an auditory signal about the state change. Then, activity of the extensor muscles supinates the prosthesis, and activity of the flexor electrode pronates it. With another co-contraction, the controller switches back into the grasping state.

The gain factors of the electrodes were adjusted by visualizing the EMG envelopes with the Otto Bock according to the guidelines of the conventional fitting process. A co-contraction can only be detected when initiated from rest (i.e., low activity in both EMG channels). In lifted arm positions, involuntary muscle contractions are present to compensate for the weight of the prosthesis. A baseline activation above the threshold for detecting the co-contraction could compromise the control if the electrode gain is set too high. Therefore, during calibration, the control was tested in all arm positions while monitoring the EMG envelopes with the MyoBoy, and the best compromise between a reliable detection of the co-contraction in all arm positions and a sufficient gain to reach a suitable speed was chosen.

Slope control

In SC, also known as rate coding, the two electrodes have the same functions as in CC (Fig. 4C). For example, the electrode on the extensor muscles is used for opening and supination. However, the controller does not remain locked within one DOF. Instead, for each contraction, the rate of increase (slope) of the EMG envelope determines the type of motion. A slow change in EMG is mapped into opening/closing and a fast change into rotation. This is implemented with two thresholds and a timer. When the EMG signal exceeds the lower threshold, the timer is started. If the second threshold is also exceeded within 80 ms, then the prosthesis performs a rotation. Otherwise, grasp is performed.

Also in SC, the user needs to return to the rest state to change the active DOF. Therefore, the same problems as in CC, related to involuntary muscle contractions in challenging arm positions, arise when high gain factors are selected. Thus, the gains were optimized with the MyoBoy while testing the control in all arm positions.

Evaluation

To evaluate and compare the performance, reliability, and robustness of the investigated control strategies, we performed two standardized clinical tests. The first test was derived from the clothespin relocation test, in which three pins (10 N grip force) of the Rolyan Graded Pinch Exerciser are relocated from a horizontal to a vertical bar (*30*). As outcome metric, the time to transfer all three pins was measured. This test required the use of all prosthetic functions (hand closing for grasping the pin, supination for displacement to the vertical bar, hand opening for releasing, and pronation for grasping the next pin). Because a change of the arm position has been reported to negatively affect performance, especially for advanced myoelectric control approaches based on classification (*21*) and regression (*33*), we included this factor in our evaluation. Unlike previous studies, the clothespin test was therefore performed in three different arm positions: down, frontal, and up (Fig. 3, C and D). The participants performed the test in blocks of five repetitions for each arm position and repeated this procedure twice (i.e., 30 runs were measured for each method in one session).

The second test was the standardized box-and-blocks test (*29*), which required the participant to transfer as many blocks as possible from one box to another in 60 s (Fig. 3E). For this task, only the DOF opening/closing was required, and unintended wrist rotations would decrease the performance. Because the blocks could not be reached in all arm positions and to keep the experimental time within an acceptable range, this test was conducted with one arm position, which allowed the participants to access the blocks comfortably. For a better comparability with the clothespin test results, the outcome metric (blocks per minute) was expressed as the average time needed to transfer one block. Note that the statistical analysis provides the same results when conducted on the original metric.

EMG patterns may vary due to small shifts in electrode placement after donning and doffing the socket (*22*, *36*), changing skin conditions (*20*), or time between training and testing (*31*). Hence, if the patterns change with respect to the ones used for training the model, then the performance of machine learning–based myoelectric control techniques can substantially degrade over time (*25*, *31*, *37*). For this reason, the regression-based simultaneous control was evaluated on two different days (second session typically 2 to 3 days after the first session), without retraining the regression model for the second test (LR2). The two conventional control techniques are not model-based and hence were only tested on one day.

The order in which the control techniques were evaluated was randomized to avoid a bias due to increased user experience with the experimental tasks. In addition, the order of arm positions for the clothespin relocation test was randomized but remained the same across methods within each participant.

Statistical analysis

The number of participants in this case series was not large enough for a robust statistical inter-user analysis. Therefore, results are reported for each participant individually. To estimate the effects between the conditions within each participant, we performed intra-user statistical analyses. Because the data were not normally distributed according to the Kolmogorov-Smirnov test, nonparametric tests were used. For the clothespin test, in the first analysis, one Kruskal-Wallis test per participant compared the time needed (30 trials per method) between the four methods—LR1, LR2, CC, and SC—ignoring the arm position. Upon significance (set to $P < 0.05$ for all analyses), Bonferroni-corrected post hoc Wilcoxon rank sum tests assessed the pairwise differences between methods. In the second analysis, for each method, one Kruskal-Wallis test per participant tested for an effect of arm position (10 trials per condition). Upon significance, pairwise post hoc tests were performed as described above. For the box-and-blocks test, the average time per block was analyzed with a Kruskal-Wallis test per participant (five trials per method) and related post hoc tests, as described in the first analysis step above.

SUPPLEMENTARY MATERIALS

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Movie S1. Regression-based control of myoelectric hand prosthesis in comparison with conventional control.

REFERENCES AND NOTES

1. V. S. Ramachandran, W. Hirstein, The perception of phantom limbs. *Brain* **121**, 1603–1630 (1998).
2. E. D. Sherman, A Russian bioelectric-controlled prosthesis. *Can. Med. Assoc. J.* **91**, 1268–1270 (1964).
3. A. Muzumdar, *Powered Upper Limb Prostheses: Control, Implementation and Clinical Application* (Springer, 2004).
4. M. A. Oskoei, H. Hu, Myoelectric control systems—A survey. *Biomed. Signal Process. Control* **2**, 275–294 (2007).
5. P. Parker, K. Englehart, B. Hudgins, Myoelectric signal processing for control of powered limb prostheses. *J. Electromyogr. Kinesiol.* **16**, 541–548 (2006).
6. B. Peerdeman, D. Boere, H. Witteveen, R. H. in `t Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, S. Misra, Myoelectric forearm prostheses: State of the art from a user-centered perspective. *J. Rehabil. Res. Dev.* **48**, 719–737 (2011).
7. K. Englehart, B. Hudgins, A robust, real-time control scheme for multifunction myoelectric control. *IEEE Trans. Biomed. Eng.* **50**, 848–854 (2003).
8. C. Castellini, P. van der Smagt, Surface EMG in advanced hand prosthetics. *Biol. Cybern.* **100**, 35–47 (2009).

9. J. M. Hahne, B. Graimann, K.-R. Muller, Spatial filtering for robust myoelectric control. *IEEE Trans. Biomed. Eng.* **59**, 1436–1443 (2012).
10. S. Amsuess, P. Goebel, B. Graimann, D. Farina, A multi-class proportional myocontrol algorithm for upper limb prosthesis control: Validation in real-life scenarios on amputees. *IEEE Trans. Neural Syst. Rehabil. Eng.* **23**, 827–836 (2015).
11. A. J. Young, L. H. Smith, E. J. Rouse, L. J. Hargrove, Classification of simultaneous movements using surface EMG pattern recognition. *IEEE Trans. Biomed. Eng.* **60**, 1250–1258 (2013).
12. N. Jiang, K. B. Englehart, P. A. Parker, Extracting simultaneous and proportional neural control information for multiple-DOF prostheses from the surface electromyographic signal. *IEEE Trans. Biomed. Eng.* **56**, 1070–1080 (2009).
13. J. M. Hahne, F. Bießmann, N. Jiang, H. Rehbaum, D. Farina, F. C. Meinecke, K.-R. Müller, L. C. Parra, Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control. *IEEE Trans. Neural Syst. Rehabil. Eng.* **22**, 269–279 (2014).
14. S. Muceli, D. Farina, Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-freedom. *IEEE Trans. Neural Syst. Rehabil. Eng.* **20**, 371–378 (2012).
15. A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, P. A. Parker, Support vector regression for improved real-time, simultaneous myoelectric control. *IEEE Trans. Neural Syst. Rehabil. Eng.* **22**, 1198–1209 (2014).
16. A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, P. A. Parker, Real-time, simultaneous myoelectric control using visual target-based training paradigm. *Biomed. Signal Process. Control* **13**, 8–14 (2014).
17. M. Ortiz-Catalan, B. Håkansson, R. Brånemark, Real-time and simultaneous control of artificial limbs based on pattern recognition algorithms. *IEEE Trans. Neural Syst. Rehabil. Eng.* **22**, 756–764 (2014).
18. J. L. G. Nielsen, S. Holmgaard, N. Jiang, K. B. Englehart, D. Farina, P. A. Parker, Simultaneous and proportional force estimation for multifunction myoelectric prostheses using mirrored bilateral training. *IEEE Trans. Biomed. Eng.* **58**, 681–688 (2011).
19. Coapt LLC, *Complete Control* (Coapt LLC, 2017); http://coaptengineering.com.
20. N. Jiang, S. Dosen, K. R. Müller, D. Farina, Myoelectric control of artificial limbs—Is there a need to change focus? *IEEE Signal Process. Mag.* **29**, 148–152 (2012).
21. A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, Ø. Stavdahl, Resolving the limb position effect in myoelectric pattern recognition. *IEEE Trans. Neural Syst. Rehabil. Eng.* **19**, 644–651 (2011).
22. A. J. Young, L. J. Hargrove, T. A. Kuiken, The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift. *IEEE Trans. Biomed. Eng.* **58**, 2537–2544 (2011).
23. H. J. Hwang, J. M. Hahne, K. R. Müller, Real-time robustness evaluation of regression based myoelectric control against arm position change and donning/doffing. *PLOS ONE* **12**, e0186318 (2017).
24. C. Cipriani, R. Sassu, M. Controzzi, M. C. Carrozza, Influence of the weight actions of the hand prosthesis on the performance of pattern recognition based myoelectric control: Preliminary study, in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, 30 August to 3 September 2011 (IEEE, 2011), pp. 1620–1623.
25. S. Amsüss, L. P. Paredes, N. Rudigkeit, B. Graimann, M. J. Herrmann, D. Farina, Long term stability of surface EMG pattern classification for prosthetic control, *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, 2013, 3622–3625.
26. C. Almström, P. Herberts, L. Körner, Experience with Swedish multifunctional prosthetic hands controlled by pattern recognition of multiple myoelectric signals. *Int. Orthop.* **5**, 15–21 (1981).
27. T. A. Kuiken, L. A. Miller, K. Turner, L. J. Hargrove, A comparison of pattern recognition control and direct control of a multiple degree-of-freedom transradial prosthesis. *IEEE J. Transl. Eng. Health Med.* **4**, 2100508 (2016).
28. C. M. Light, P. H. Chappell, P. J. Kyberd, Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: Normative data, reliability, and validity. *Arch. Phys. Med. Rehabil.* **83**, 776–783 (2002).
29. V. Mathiowetz, G. Volland, N. Kashman, K. Weber, Adult norms for the Box and Block Test of manual dexterity. *Am. J. Occup. Ther.* **39**, 386–391 (1985).
30. A. Hussaini, P. Kyberd, Refined clothespin relocation test and assessment of motion. *Prosthet. Orthot. Int.* **41**, 294–302 (2017).
31. M. M.-C. Vidovic, H.-J. Hwang, S. Amsüss, J. M. Hahne, D. Farina, K.-R. Müller, Improving the robustness of myoelectric pattern recognition for upper limb prostheses by covariate shift adaptation. *IEEE Trans. Neural Syst. Rehabil. Eng.* **24**, 961–970 (2016).
32. J. M. Hahne, M. Markovic, D. Farina, User adaptation in myoelectric man-machine interfaces. *Sci. Rep.* **7**, 4437 (2017).
33. N. Jiang, S. Muceli, B. Graimann, D. Farina, Effect of arm position on the prediction of kinematics from EMG in amputees. *Med. Biol. Eng. Comput.* **51**, 143–151 (2013).
34. J. M. Hahne, S. Dähne, H.-J. Hwang, K.-R. Müller, L. C. Parra, Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control. *IEEE Trans. Neural Syst. Rehabil. Eng.* **23**, 618–627 (2015).
35. T. R. Farrell, R. F. Weir, The optimal controller delay for myoelectric prostheses. *IEEE Trans. Neural Syst. Rehabil. Eng.* **15**, 111–118 (2007).
36. L. Hargrove, K. Englehart, B. Hudgins, A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control. *Biomed. Signal Process. Control* **3**, 175–180 (2008).
37. J. He, D. Zhang, N. Jiang, X. Sheng, D. Farina, X. Zhu, User adaptation in long-term, open-loop myoelectric training: Implications for EMG pattern recognition in prosthesis control. *J. Neural Eng.* **12**, 46005 (2015).

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