ROBUSTNESS OF REGRESSION-BASED MYOELECTRIC CONTROL IN A CLINICAL SETTING

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ABSTRACT

A miniaturized low-cost, low-power embedded system for regression-based simultaneous and proportional myoelectric control of a hand prosthesis with two degrees of freedom is presented. In a case study on one subject with transradial amputation, this system outperformed two commonly used conventional control techniques. Furthermore, the robustness of the approach against changing arm position and across sessions without retraining the regression model was demonstrated.

INTRODUCTION

Myoelectric signals are commonly used to control electrically powered hand prostheses [1]. Recent developments in mechatronics have led to a number of commercially available dexterous prosthetic hands with many degrees of freedom (DOFs) including individually actuated fingers [2]. However, the progresses in control are behind these developments. Most prostheses are still controlled with very simple techniques, based on two EMG signals from antagonistic muscles of the residual limb. These techniques allow for proportionally controlling only one DOF at a time. Cumbersome heuristics, such as selecting the active DOF by a co-contraction or based on the slope of the EMG onset, are used to control more DOFs sequentially.

Multiple functions can be controlled by using machine learning techniques. In particular, classification-based approaches have been investigated for many years [3]–[5]. Basic classification approaches offer only simple on/off control and a sequential activation of DOFs, but are often extended to include proportional control [6] and simultaneous activation of multiple functions [7]. Recently, regression-based control approaches (RC) have gained increasing interest. With these approaches, simultaneous and proportional control of multiple DOFs is possible [8], [9].

However, the impact of machine-learning based control on clinical practice has been limited. So far only one company offers a classification-based control system as an add-on for prosthetic hands [10]. One reason for the limited impact is related to robustness problems of most machine-learning approaches under real-world conditions. In daily use, factors such as altered arm positon [11], small electrode shifts [12], changing skin conditions [13] and time between training and use [14] can influence the signals and degrade the performance significantly.

For this case study, we implemented a linear-regression based control of two degrees of freedom on a miniaturized embedded system that fits into a prosthetic socket and allows for evaluating the control in real-world conditions. The performance was tested with the standardized clothespin relocation test, in varying arm positions and across different days without retraining the linear mapping model. A comparison with two conventional control techniques was also performed.

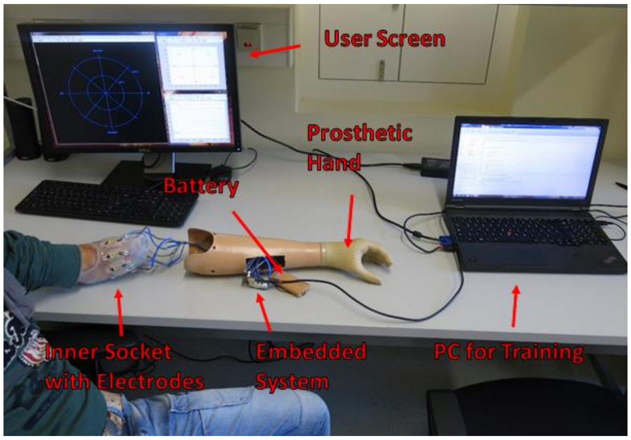

Figure 1: Setup for PC-supported training of user with regression algorithm.

METHODS

Regression-Based Control on Embedded System

The experimental setup (Fig. 1) 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 implement a portable, miniaturized solution for simultaneous and proportional control of the two prosthetic DOFs, an embedded system was developed (Fig. 2). 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 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 and training (see below), 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 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.

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

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

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

where $\boldsymbol{x}$ is a vector with the eight EMG envelopes, $\hat{\boldsymbol{y}}$ the two-dimensional control output, $\boldsymbol{W}$ an $< 8 \times 2 >$ transformation matrix and $\boldsymbol{X}$ and $\boldsymbol{Y}$ matrices with training data and labels.

To suppress unintended motions, activation thresholds where applied for each of the four prosthetic functions at which the prosthesis would start actuating with lowest speed. Upper thresholds were defined at a comfortably reachable maximal regression output for each prosthetic function, which were mapped to the maximal prosthetic speed. The pre-defined values for the activation and upper thresholds were 0.1 and 1. They were adjusted before the experimental evaluation to optimize controllability.

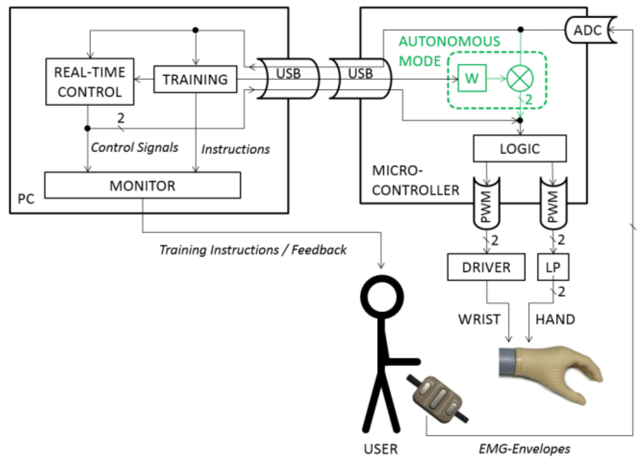

Figure 2: Block diagram of the regression-based myoelectric control system

Training of user and algorithm

For a successful application of machine-learning based myoelectric control systems, both the user and the algorithm need to be trained. The training protocol was based on the co-adaptive learning paradigm developed in [15]. First, the user performed various phantom-limb movements. Out of these, four suitable contraction patterns were selected based on visual inspection of the EMG signals. 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. An initial linear mapping model was generated based on the least mean-squares solution (Eq. 2). It has been shown that this approach allows for a generalization from non-combined to combined motions [16]. This model 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, he was trained and evaluated in the execution of non-combined and combined motions. In the next step, the 2D game was repeated while the linear mapping model was adapted using recursive least squares, so that both the user and the model could improve concurrently.

After 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.

Experimental Evaluation

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 is measured. As both classification- and regression-based control approaches can be influenced by the position of the arm ([17], [18]), 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 [14]. Therefore, the regression-based control was evaluated on two different days, using the model trained in the first day.

As a comparison to the RC, two conventional control systems based on 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 [1].

This case study was conducted on one male subject with transradial amputation (56 years old, 35 years after amputation). The study was approved by the ethics committee of the University of Göttingen and informed consent was obtained from the participant. A conventional prosthetic socket was constructed that integrated eight equally-spaced electrodes at the location of largest diameter of the residual limb.

Figure 3: Evaluation in the clothespin relocation test, executed in three different arm positions

RESULTS

The completion times needed in the clothespin test are shown in Fig. 4. 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 better than CC but could 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 arm-position did not impact the performance of RC nor of the conventional control techniques. Even when RC was evaluated on the 2nd day with the regression model of the first day, no degradation in performance occurred (see Fig. 4, in magenta).

With RC, one pin was dropped in trial 2 or the first day (arm position down). With SC, one pin in run 23 (arm position half up) and one in run 26 (arm position up) were dropped. In CC, no pins were dropped.

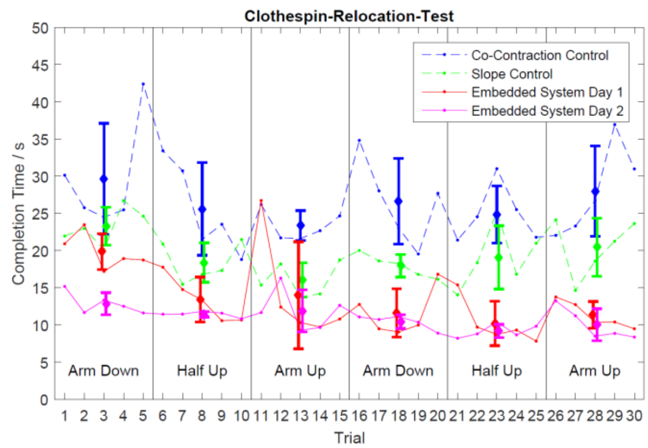

Figure 4: Performance of the regression-based control versus the two conventional control systems, evaluated in the clothespin relocation tests in varying arm-positions.

DISCUSSION AND CONCLUSION

We presented a miniaturized controller for autonomous simultaneous and proportional control based on a linear mapping. In a case study with one transradially-amputated subject, the system was evaluated in a practically relevant task. By varying the arm position and testing the co-adaptively-trained linear mapping model of the first day on a second day, the robustness against three important factors of non-stationarity was demonstrated (arm position, donning/doffing the socket and time between training and application).

The proposed approach outperformed two commonly-used conventional control strategies. The advantage over CC is that the user does not need to perform a time-consuming co-contraction for switching the active function. SC is also sub-optimal since the slope can only be detected in the onset of the contraction and the user needs to relax for a short moment before using another function; in the proposed RC, no break between grasping and rotation is required. A strong advantage over both CC and SC is that even simultaneous motions are possible. This leads to very natural and fluent motion patterns and a fast task execution. In fact, it was observed that the subject made use of simultaneous motions and initiated the rotation already while releasing a pin.

As the current study is limited to a single subject, a follow-up study with a larger number of subjects and over a longer period is still needed to prove clinical feasibility. If successful, the proposed technique has the potential for a clinical transfer in the near future.

ACKNOWLEDGEMENTS

This work was supported by the European Union's Horizon 2020 research and innovation program under grant agreement number 687795 (project INPUT)

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