USER-SPECIFIC MIRROR TRAINING CAN IMPROVE MYOELECTRIC PROSTHESIS CONTROL

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ABSTRACT

State-of-the-art transradial prostheses can provide intuitive and proportional myoelectric control by training an algorithm to correlate surface electromyographic signals from the residual forearm muscles to intended movements of the amputated hand. One training paradigm, “mimicked training,” relies on amputees mimicking a prosthetic hand with their missing hand such that the corresponding muscle activations are correlated to the preprogrammed kinematics of the prosthetic hand. A second training paradigm, “mirrored training,” relies on unilateral amputees mirroring their contralateral hand with their missing hand such that the muscle activations are correlated to the kinematics of the contralateral hand (determined via a motion capture). Prior work with intact participants demonstrated that the kinematics of a given hand are more closely related to that of an individual’s contralateral hand as opposed to the preprogrammed kinematics of a prosthesis. This abstract continues our investigation into the training data for myoelectric prostheses by exploring the impact of these training paradigms on real-time prosthetic control with amputees completing a functional task. For one out of three participants, mirrored training significantly improved task performance. These preliminary results demonstrate that mirrored training may provide more dexterous control through task-specific, user-chosen training data. These results can guide myoelectric training for proportional and dexterous control.

INTRODUCTION

The current standard of care for upper-limb amputees is unsatisfactory and, as a result, up to 50% of upper-limb amputees abandon their prostheses, citing poor and unreliable control as a primary reason. One approach to providing more intuitive and reliable control is to leverage supervised machine-learning algorithms that correlate residual muscle activity to motor intent. These supervised machine-learning algorithms require a training session in which a patient-specific training dataset is collected. The training dataset consists of synchronized muscle activity and the intended kinematic positions of the prosthesis.

To date, most research has focused on improving the machine-learning algorithm [1]–[8]. However, the quality of the training data is also a critical component of the run-time performance of machine-learning algorithms [1], [2], [9]. There are two widely used approaches (i.e., training paradigms) to collecting training data for prostheses. One training paradigm, herein referred to as “mimicked training”, relies on amputees mimicking preprogrammed movements of a prosthesis with their missing hand such that the corresponding muscle activations are correlated to preprogrammed kinematics of the prosthesis. A second training paradigm, herein referred to as “mirrored training”, relies on unilateral amputees mirroring their contralateral hand with their missing hand such that the muscle activations of the missing hand are correlated to the kinematics of their intact contralateral hand (determined via motion capture). Our prior work with intact participants demonstrated that the kinematics of a given hand are more closely related to that of an individual’s contralateral hand as opposed to the preprogrammed kinematics of a prosthesis [9]. This suggests that mirrored training provides more accurate training data and therefore should provide better prosthesis control than mimicked training.

Here, for the first time, we specifically tested whether or not mimicked or mirrored training would lead to improvements in real-time prosthetic control. Using two widely used algorithms, a linear Kalman filter and a non-linear convolutional neural network, we compared the performance of mimicked and mirrored training with amputees performing the Clothespin Relocation Task (CRT) [10]. We show that there is minimal difference in the subjective workload of each training approach and that user preference varies. However, we also show that the training paradigm may have significant impact on task performance for some participants. These results imply amputees should be given a choice between both paradigms or that a combination of the two may yield best control.

METHODS

Human Subjects

A total of three transradial amputees with prior myoelectric experience were recruited for this study. Two of three participants were male and all participants were between the ages of 55 and 65 years old. Informed consent and experimental protocols were carried out in accordance with the University of Utah Institutional Review Board.

Training Data Recording

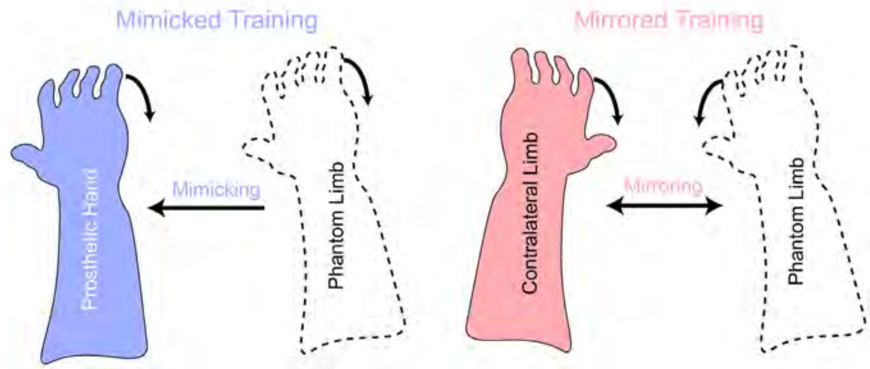

Figure 1: Overview of the mimicked training (left) and mirrored training (right) for collecting training data for myoelectric prostheses. During mimicked training, the user is watching a prosthesis move while simultaneously mimicking the movement of the prosthesis with their phantom limb. During mirrored training, the user performs bilaterally mirrored movements, such that the motion of their intact contralateral hand mirrors that of their phantom limb.

Training data for the machine-learning algorithms, was collected across a total of four training sessions. Participants performed two sessions (1.5 minutes each) of mirrored and mimicked training respectively Fig 1. Prior to the training sessions, participants were instructed to perform the CRT with their intact hand to understand what movements would be necessary to complete the task. Participants were instructed to only perform two movements: open/close of the hand (simultaneous flexion/extension of D1-D5) and pronation/supination of the wrist. Participants then donned the prosthesis (LUKE Arm, DEKA), and performed a session of mirrored training at their own pace using self-selected movement patterns. Training data from this first mirror-training session was used to train an algorithm and participants were allowed to temporarily control the prostheses. The participant then performed a second self-directed mirror-training session. The same two stage training process was then repeated for mimicked training.

Signal Acquisition

Infrared hand images of the contralateral limb were converted to 3D hand coordinates using custom MATLAB software. Joint angles were calculated based on an orthogonal palm vector. A total of two joint angles were calculated for the contralateral hand: D2 flexion/extension and wrist pronation/supination. The joint angle of D2 was used to measure grasping (i.e., simultaneous flexion/extension of D1-D5). Joint angles in the training data were normalized from -1 (maximum extension) to 0 (rest), and from 0 to 1 (maximum flexion) for each mirror-training session. The rest position of each joint was determined by the average angle while the participant relaxed for 15 seconds prior to each training session.

Surface electromyography (sEMG) was recorded from the surface of the residual limb using a custom EMG sleeve [11]. Thirty-two monopolar sEMG electrodes were sampled at 1 kHz using Micro2+Stim Front-Ends and a Summit Interface Processor (Ripple Neuro LLC). The 300-ms smoothed Mean Absolute Value (MAV) was calculated at 30 Hz for the 32 monopolar electrodes, as well as for all possible differential pairs (i.e., 496 differential pairs) [5].

Machine-Learning Algorithms

A total of two machine-learning algorithms were used in this study. The first was an eight-layer convolutional neural network (CNN). The CNN predicts kinematic position based on a spatiotemporal "image" of sEMG activity over the last 10 samples in time, described in more detail in [1]. The CNN utilizes convolution to learn complex spatiotemporal relations within EMG activity that correlate to kinematic position. The second algorithm used in this study was a modified Kalman filter (MKF), as described in [5]. The MKF provides an efficient recursive algorithm to optimally estimate the position of the bionic hand when the likelihood model (i.e., the probability of EMG activity given the current kinematic position) and prior models (i.e., the state model of how kinematics change over time) are linear and Gaussian. The inclusion of prior information about the system state enables an efficient recursive formulation of the machine-learning algorithm and effectively smooths noisy estimates in a mathematically principled way.

Modified Clothespin Relocation Task

The CRT provides a simple way to assess the ability of individuals to simultaneously grasp and rotate their wrist. The CRT involves moving a clothespin from a horizontal bar to a vertical bar. Clothespins are placed eight inches down the length of the horizontal bar and 8 inches up the vertical bar. If the participant drops the clothespin or takes longer than one minute the attempt is considered a failure.

Participants were instructed to complete the CRT with the prostheses under four different conditions: 1) using the CNN trained with data collected via mirrored training, 2) using the CNN trained with data collected via mimicked training, 3) using the MKF trained with data collected via mirrored training, 4) using the MKF trained with data collected via mimicked training. Participants performed the task six times for each of the four aforementioned conditions. The four conditions were tested in pseudo-randomized counter-balanced blocks to minimize order effects. During each block, participants were given eight attempts to move the clothespins. A block was finished after three successfully transfers or if all eight attempts were used. After the final block for a given condition, the participants completed the NASA Task Load Index (TLX) survey of subjective workload as well as a survey of embodiment adapted from [12]. At the end of the experiment, participants were asked to rate the four decodes from best to worse.

Data Analysis

Data were screened for normality. A two-way analysis of variance (factors: algorithm and training paradigm) was performed for each participant individually. No significance differences were observed for the algorithms, so a subsequent pooled analysis was performed to look at the effect of training paradigm. Because the number of completed clothespin transfers varied based on success rate, an unpaired t-test was used to compare between the mimicked-training and mirrored-training data.

RESULTS

Mirrored Training Can Improve Speed on the CRT

We saw no significant difference between mimicked training and mirrored training on the overall success rate of transfers for the CRT. However, in general, mirrored training decreased the transfer time on the CRT for two of the three participants, although this was only significant for one of the three participants. Participant one saw a 12% improvement in speed with mirrored training ($p = 0.19$, unpaired t-test), participant two saw a 57% improvement in speed with mirrored training ($p < 0.05$, unpaired t-test), and participant three saw a 5% decrease in speed with mirrored training ($p = 0.68$, unpaired t-test; Fig 2).

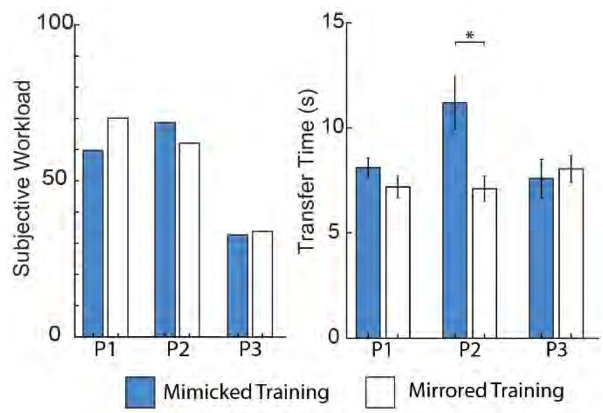

Figure 2: Differences between mimicked training and mirrored training during the CRT. Subjective workload varied among participants, but no differences were greater than the minimum detectable change. Transfer time decreased with mirrored training for participants one and two, but this trend was only significant for participant two.

No Detectable Difference in Subjective Workload or Embodiment between Mimicked Training and Mirrored Training

Subjective workload during the training sessions was comparable between mimicked training and mirrored training (Fig 2). Mimicked training has a slightly lower subject workload score for participants one and three, but none of the differences in subjective workload were greater than the minimum detectable change of 15 points [13]. Similarly, there were no significant differences or meaningful trends in the embodiment scores between the training paradigms. User preference between the training paradigms also varied. Participant one favored mimicked training, participant two favored mirrored training, and participant three had no preference.

DISCUSSION

Task-specific and accurately labeled training data is critically important for algorithm performance. Here, we compare the impact of two different training paradigms on the run-time performance of two commonly used machine-learning algorithms for use on a real-world functional task. Overall, we that subjective workload was similar between the training paradigms and that user preference varied. Mirrored training is capable of providing significantly better prosthetic control algorithm, but this improvement is unique to individuals.

Prior work showed that mirrored training provides more accurately labeled kinematics than the mimic approach [9]. The results presented here suggest that the more accurately labeled kinematics can also translate to improved run-time prosthetic control. We hypothesize that the benefits of more accurately labeled kinematics from mirrored training will become more pronounced with more complex machine-learning algorithms and more complex task.

The results presented here suggest that users should be given a preference in the training paradigm. However, there are several other important factors to consider when selecting a training paradigm. For example, mirrored training is only available to unilateral amputees and requires additional motion capture equipment and calibration to ensure accurate kinematics. That said, the work presented utilized a Leap Motion (Ultrahaptics) that cost less than $100 USD, requires low computational power and no extensive technical knowledge to use. The ability to allow users to collect their own self-selected training data could prove useful when training on complex activities of daily living. Task-specific training has been shown to improve performance on activities of daily living [2]. Furthermore, this approach empowers amputees to be control of their personal data and the type of movements they can perform with their bionic limb.

The ability of mirrored training to significantly improve run-time performance for some participants warrants further investigation. Future work should replicate these findings with additional participants, multiple training sessions and more complex tasks to more precisely quantify the impact of training paradigm on run-time prosthetic control.

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