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User-in-the-loop Continuous and Proportional Control of a Virtual Prosthesis in a Posture Matching Task

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Abstract — **As the development of dexterous prosthetic hand and wrist units continues, there is a need for command interfaces that will enable a user to operate these multi-joint devices in a natural, coordinated manner. In previous work, we have demonstrated that it is possible to simultaneously decode hand and wrist kinematics from myoelectric signals recorded from the forearm in an offline manner. The goal of this study was to quantify the performance of this command interface during real-time control of a kinematic prosthesis. One subject with intact limbs controlled a virtual prosthesis and attempted to match a series of target postures using the proposed control scheme as well as using the movements of the intact limb. Initial results indicate that subjects can complete these target matching tasks in the virtual environment. Future work will evaluate the controllability of the proposed strategy relative to traditional control schemes.**

I. Introduction

Upper extremity prostheses can be effective tools for individuals with amputations. These devices typically have a somewhat awkward control interface that limits the user to operation of a single joint at a time, leading many amputees to choose not to use their prosthesis at all [1]. A number of approaches have been developed to map myoelectric signals (MES) to the desired movements of a prosthesis in a more natural manner. Pattern recognition techniques (e.g. linear discriminant analysis and fuzzy logic) have been used to identify discrete movement states, allowing a user to seamlessly operate the joints of a prosthesis in a sequential manner. Alternatively, the continuous prediction of movement trajectories with tools such as artificial neural networks (ANNs) may facilitate coordinated and simultaneous multi-joint control. Previous work by our group [2] and others [3,4] has shown ANNs to be capable of achieving highly accurate offline estimations of hand and wrist joint angle positions.

While the use of these statistical and artificial intelligence techniques in EMG control systems has been well researched, few if any of these algorithms have been clinically deployed. Recent clinical evaluations have demonstrated the value of using substitutes for a physical prosthesis during occupational training [5], leading several research groups to use "virtual arms" for quantifying pattern recognition based control [6-8]. While several dexterous prosthetic limbs are now commercially available, virtual environments remain a cost-effective tool for assessing the performance of advanced prosthetic control systems.

The goal of this study was to quantify the performance of an artificial neural network-based movement decoder during real-time control of a kinematic virtual prosthesis. One subject with intact limbs controlled a virtual hand and attempted to match a series of target postures using both the proposed myoelectric control scheme as his own movements and command signals.

II. Methods

MES data and hand kinematics were recorded from one male subject with an intact upper limb. The subject had no history of neuromuscular disorders. The MetroHealth Medical Center IRB approved the experimental procedures and the subject provided informed consent prior to participating in the study. Eight surface MES electrodes were positioned at equidistant locations around the circumference of the left forearm centered at approximately 30% of the distance from the medial epicondyle of the humerus to the styloid process of the ulna. In this study, we specifically examined three kinematic degrees of freedom: pronosupination, wrist flexion-extension, and finger flexion. The contralateral (i.e. left) limb was equipped with a CyberGlove II (CyberGlove Systems LLC, San Jose, CA, USA) to measure finger flexion and wrist flexion, and a torsiometer (Biometrics Ltd, United Kingdom) to measure pronosupination. Recording the kinematics in this manner (i.e. from the contralateral limb) provides a comparable baseline to data collected from amputees, where kinematic data must be recorded from the intact limb and MES data from the residual limb on the amputated side [3]. Trials were collected while the subjects performed a variety of isolated and coordinated movements involving the hand, forearm, and wrist. During all trials, kinematic and MES data were simultaneously recorded. In total, approximately 15 minutes of training data were collected.

The overall approach for data analysis and training the artificial neural network are illustrated in Figure 1. The MES data was segmented with 128 ms rectangular windows with 50% overlap between adjacent segments. Time-domain features [9] were then extracted from the segmented

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myoelectric data. The kinematic trajectories were normalized to a 0 to 1 scale and resampled to match the effective sample time of these time domain features.

For continuous prediction of the hand and wrist kinematics, a time delayed artificial neural network (TDANN) was trained offline using a backpropagation algorithm in MATLAB (Mathworks Inc, Natick, MA, USA) to map the relationship between the time domain MES features and the three joint angles. A two-layer feed forward structure with a nonlinear tangent-sigmoidal activation function for the hidden layer and a linear output layer was utilized. Three input time delays were used to capture the dynamic relationship between the MES features and joint angular position. The data was split into training, validation and testing data sets. Validation is used during the training to monitor the error generated by data not used for training. When this error increases, the TDANN is memorizing the training data set and the network is losing its ability to generalize. The testing data set is used to evaluate the performance of the TDANN after the training is finished. Offline TDANN performance on this testing data set was quantified by calculating the normalized root mean square error (NRMSE) and the variance accounted for (VAF) between the experimentally recorded joint angle trajectories and the corresponding trajectories predicted by the TDANN. The details of this approach have been previously presented [2]. Once trained, the TDANN was then used to generate a real-time controller implemented in Simulink/xPC target (Mathworks Inc, Natick, MA, USA). The output of the TDANN is mapped proportionally to the joint angular position of the prosthesis. Custom code was used to automate the data analysis (i.e. segmentation and feature extraction), TDANN training, and generation of the real-time controller. These steps can be completed in approximately 10 minutes.

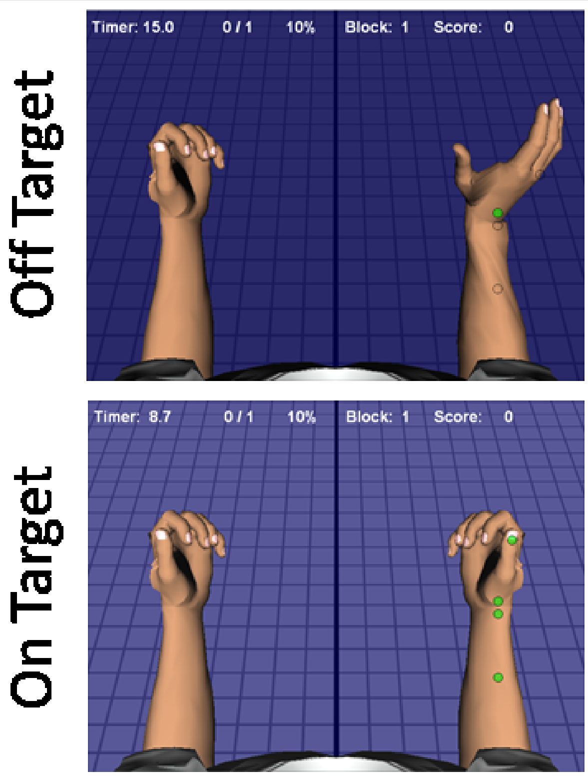

Figure 1. Screenshots from the virtual environment. The top panel shows the display when the controlled limb (right) does not match the target limb (left). The bottom panel shows the display when the controlled limb matches the target configuration.

In the same experimental session after the offline analyses were completed, the subject viewed a kinematic simulator in which a target posture was displayed next to a controlled virtual arm. The subjects' EMG signals were sampled and fed through the TDANN. The estimated joint angles were then filtered and displayed via the virtual hand. The subjects were instructed to modulate their muscle activation patterns to match the configuration of the virtual hand with the target hand. A screen capture from the simulator is shown in Figure 1. Several indicators (i.e. the green dots on the right arm) are used to cue when each respective degree of freedom is on/off target. When all degrees of freedom are on target, the background of the virtual environment lights up as an additional cue. Subjects had 15 seconds to match the target posture within a certain tolerance and hold it for a dwell time of 1 second. All joints had the same angular tolerance – this was initialized to 15 degrees. 10 blocks of 10 randomized targets were presented and the posture matching task difficulty (i.e. the joint angular tolerance) was adapted at the end of each block to attempt to achieve an overall success rate of 70%. The users' performance was quantified by calculating the path efficiency [10] for targets successfully reached and monitoring the tolerance levels achieved over the 10 blocks. For comparative purposes, this kinematic posture matching task was performed with two command interfaces: (1) the proposed artificial neural network joint angle decoder and (2) the actual movements of the intact limb.

III. Results

Figure 2 shows the success rate, path efficiency for successfully reached targets, and angular tolerance values over the ten blocks when the subject was controlling the virtual arm with both the TDANN estimator (i.e. myoelectric control) and with the movements of his actual limb (i.e direct kinematic control). In each panel, the solid black line represents the metric for control with the actual limb movements and the solid gray line represents the metric for control the movements estimated from MES signals.

It can be seen that the tolerance for direct kinematic control decreases initially since the subject was able to reach all 10 targets (maintaining a 100% success rate) for the first 5 blocks, and then reaches a plateau at 5°. The tolerance for myoelectric control, however, increases initially and reaches a plateau at 20°. Path efficiency, however, does not exhibit a clear difference between myoelectric control and kinematic control.

IV. Discussion

We have developed a control strategy for a transradial prosthetic limb the uses MES signals recorded from the forearm musculature to estimate three hand and wrist

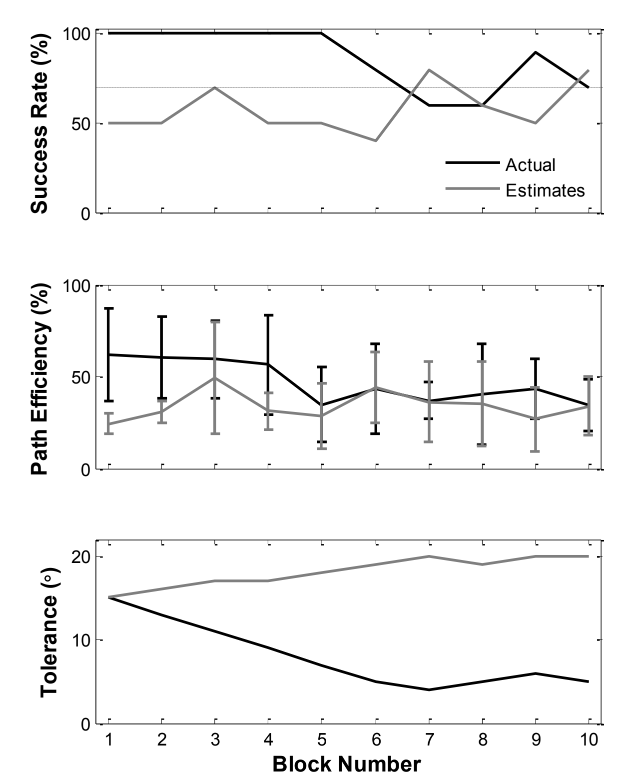

Figure 2. Block performance of kinematic posture matching task for both direct control using actual movements (black) and movements estimated from MES signals (gray). Shown are overall success rate (top panel), path efficiency (middle panel), and angular tolerance (bottom panel).

movements in real-time in a continuous and simultaneous manner. A single subject with intact limbs was able to use this scheme to control a virtual arm and complete a series of kinematic target matching tasks. In order to achieve the 70% success rate set in this study, however, the target tolerances increased to approximately 20 degrees when using the proposed scheme. This level of accuracy is likely to be too low for prosthetic control applications. We are currently pursuing several strategies for improving the controller's performance. The most significant challenge during the kinematic matching task was holding the virtual arm in a specified position for the required dwell time of one second. We are currently developing a probability-based method for adaptively filtering the estimated movements [2]. We are also evaluating continuous velocity estimation, rather than position estimation. This has the potential advantage of decreasing the cognitive effort required to maintain a desired position.

Additionally, it is worth noting that the functional implications of this study are yet unclear. While the performance comparison between using the proposed control strategy and using the actual movements is interesting, a more relevant comparison would be to evaluate this scheme relative to more traditional approaches, such as two-site, two-state control with a mode switch [11], or even other advanced approaches utilizing pattern recognition [8]. Future evaluations will include these command and control interfaces as well. Also, this experiment used an able-bodied subject with fully intact muscles, and the subject was not actually operating a prosthesis or performing a functional task. Both of these factors can be expected to affect performance in realistic conditions [7,12]. Future testing will evaluate the ability of individuals with amputation to control multi-joint myoelectric prosthesis during functional activities either simulated in a dynamic virtual environment with haptic feedback [13] or performed with a physical device.

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