Prediction of distal arm joint angles from EMG and shoulder orientation for prosthesis control

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***Abstract*— Current state-of-the-art upper limb myoelectric prostheses are limited by only being able to control a single degree of freedom at a time. However, recent studies have separately shown that the joint angles corresponding to shoulder orientation and upper arm EMG can predict the joint angles corresponding to elbow flexion/extension and forearm pronation/supination, which would allow for simultaneous control over both degrees of freedom. In this preliminary study, we show that the combination of both upper arm EMG and shoulder joint angles may predict the distal arm joint angles better than each set of inputs alone. Also, with the advent of surgical techniques like targeted muscle reinnervation, which allows a person with an amputation intuitive muscular control over his or her prosthetic, our results suggest that including a set of EMG electrodes around the forearm increases performance when compared to upper arm EMG and shoulder orientation. We used a Time-Delayed Adaptive Neural Network to predict distal arm joint angles. Our results show that our network's root mean square error (RMSE) decreases and coefficient of determination (R^2) increases when combining both shoulder orientation and EMG as inputs.**

I. INTRODUCTION

Current state-of-the-art upper limb myoelectric prostheses are limited in their ability to reach using coordinated joint movements. Generally, most multifunction prostheses use a mechanical switch to control individual degrees of freedom (DOFs) sequentially. This process usually allows for control of 2 degrees of freedom and more mentally burdensome systems are often abandoned by patients. However, there has been significant progress made by Kuiken, et al, through the use of targeted muscle reinnervation, a technique that restores control sites to high-level amputees from which electromyographic (EMG) signals may be measured. Such systems allow for two degrees of freedom–the elbow and a hand open/close–to be controlled simultaneously [1], or up to 10 different movements sequentially using pattern recognition [2]. These EMG-based neuroprostheses are limited in their ability to control coordinated elbow and wrist movements which are required in many activities of daily living, such as in reaching.

A recent study by Pulliam, et al used EMG recordings from the upper arm and chest to predict the angles of the elbow and forearm simultaneously [3]. Specifically, they implemented a Time-Delayed Adaptive Neural Network (TDANN) to predict the angles of elbow flexion/extension and forearm pronation/supination [4], [5]. Their results showed that across multiple types of reaching movements (single-joint movements, single-joint movements with a load, simultaneous DOF movements, and activities of daily living), the network could on average predict elbow flexion/extension within 10-15° and forearm pronation/supination within 20-25° of their actual values.

A separate study by Kaliki, et al suggests that when reaching, distal arm kinematics can be predicted by using shoulder orientation as the input to a neural network [6]. In this study, subjects were seated and asked to reach to a vertical handle that moved to uniformly distributed positions in the subjects reaching workspace. Motion capture was used to determine the joint angles at the shoulder, and their network resulted in R^2 values above 0.7, denoting a strong correlation.

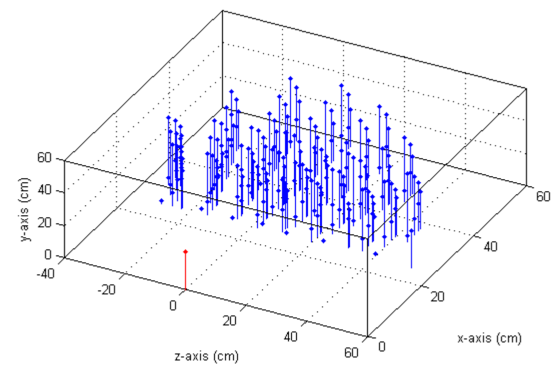

Fig. 1. Stem plot of 226 targets within subject's reaching workspace. Blue dots represent the target while the red dot represents the subject's shoulder center.

Our study aims to improve the prediction of distal arm kinematics by using the combination of shoulder orientation and EMG from the upper arm as inputs. In addition, we also hypothesize that by adding EMG inputs on the forearm, we will achieve a smaller RMSE and a greater R^2 since we retain information from distal arm musculature involved in reaching (as it would be with a targeted muscle reinnervated patient).

II. METHODOLOGY

A 25-year old unimpaired adult male volunteered for the reaching experiment. His physical measurements were taken

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and his reaching workspace was partitioned as in [6]. This resulted in 226 reaching targets (Fig. 1). The subject was seated in a chair in front of an Adept One SCARA robot arm (Adept Technology, Inc., Pleasanton, CA) used to present the targets to the subject. Attached to the robot arm's end effector was a vertically oriented handle for grasping. For the safety of the subject, the robot arm was restricted from moving within 25 cm from the subject's shoulder center along the global x-axis. Starting with the forearm on an arm rest, palm down, elbow bent at 90° with respect to the humerus, the subject was instructed to push a button to trigger simultaneous recording of EMG and motion capture, and to reach to and hold a vertical handle at a normal pace. After 5 seconds, the subject was instructed to let go of the handle and return to the arm rest. As soon as the subject placed his arm on the arm rest, he was instructed to push a button to stop the recording of the trial.

A. Experimental Setup

Using a DelSys 16-channel Bagnoli system, 13 bipolar surface EMG electrodes were positioned on the subject's arm: 6 equidistant around the circumference of the forearm, 2 on the long and short heads of the biceps, 2 on the long and lateral heads of the triceps, and 3 on the anterior, middle, and posterior deltoid (Fig. 2). The subject wore a wrist brace to restrict movement of the wrist during reaching tasks.

An OptiTrack motion capture system (NaturalPoint, Inc., Corvallis, OR) was used to determine the location of bony landmarks. Specifically, reflective markers were placed over the radial styloid, ulnar styloid, lateral epicondyle, olecranon, and acromion. From the locations of these markers, the angles for the shoulder, elbow, and forearm were calculated according to ISB standards [7]. Rotation about the global x, y, and z axes corresponded to shoulder abduction/adduction, internal/external rotation, and flexion/extension, respectively. Rotation about the forearm's y-axis (lateral epicondyle to ulnar styloid) corresponded to forearm pronation/supination, and rotation about the forearm's z-axis (radial styloid to ulnar styloid) corresponded to elbow flexion/extension. Clinically meaningful Euler angles were extracted to determine the orientation for the shoulder (YXY) and the forearm (ZXY) according to ISB standards. A hardware trigger was used to sync the recording of motion capture and EMG data.

B. Data Processing

All data were processed using MATLAB (MathWorks, Inc., Natick, MA). EMG data were recorded at 1000Hz. After acquisition, the data were filtered with a 5th-order Butterworth high-pass filter with a cutoff frequency of 10Hz to remove movement artifacts. Due to excessive noise, one of the forearm channels was removed. The EMG data was windowed at 200ms with an overlap of 75ms to make an effective timestep of 125ms. Four time-domain features were extracted from each channel, namely mean absolute value, waveform length, number of zero crossings, and number of slope sign changes [3], [8].

Fig. 2. Placement of EMG electrodes on subject.

Motion capture data were recorded at 100Hz. After the motion capture data was cleaned, the data were filtered using a 4th-order high Butterworth high-pass filter with a cutoff frequency of 15Hz to remove movement artifacts. Out of the 226 trials, one trial had to be omitted from analysis due to noisy marker data. To reduce data size, the data were then downsampled to 8Hz. To allow a full window width for the EMG data, the first sample was offset to 200ms before sampling every 125ms afterwards. The 3 Euler angles for the shoulder and 2 for the forearm were then extracted.

The data were reorganized so that the EMG features for each channel and shoulder Euler angles could be used as inputs to the neural network. The targets for the neural network were the 2 forearm Euler angles described previously, corresponding to elbow flexion/extension and forearm pronation/supination.

C. Neural Network Training

A two-layer TDANN was created using MATLAB's neural network toolbox. This type of network was used to effectively capture the sequential nature of motion capture and EMG time-series data. The network used a hidden layer size of 20 and had an input delay of 7 [3]. Initial weights and biases were randomly assigned. Repeated random subsampling [3] was used to separate the data into training (65%), validation (15%), and test (20%) sets. The network used Early Stopping to prevent the network from overfitting the data by discontinuing training if the performance of the validation set failed to improve after 6 weight updates. Otherwise, training would stop after 1000 weight updates.

III. Results

The neural network was trained with 5 different sets of inputs: 1) shoulder orientation, 2) EMG without forearm channels, 3) EMG with all channels, 4) both shoulder orientation and EMG without forearm channels, and 5) both shoulder orientation and EMG with all channels. RMSE and R^2 values for each network are shown in Table I.

While all of the networks had small RMSE and R^2 values greater than 0.7 (indicative of a strong correlation), the combined use of motion capture and EMG outperformed the

TABLE I

PERFORMANCE OF NEURAL NETWORK FOR 5 DIFFERENT SETS OF INPUTS. FE = FLEXION/EXTENSION, PS = PRONATION/SUPINATION.

TDANN Inputs	Input Size		FE		PS	
			$RMSE$ (°)	R^2	$RMSE$ (°)	R^2
Shoulder orientation	3	Training	5.56	0.90	5.74	0.96
		Validation	5.98	0.88	6.40	0.95
		Test	5.89	0.89	6.48	0.95
EMG (without forearm)	28	Training	7.94	0.80	8.39	0.92
		Validation	9.32	0.72	10.05	0.89
		Test	9.18	0.75	9.59	0.90
EMG (all channels)	48	Training	5.54	0.90	7.52	0.94
		Validation	8.27	0.79	8.66	0.92
		Test	8.48	0.76	8.56	0.92
Shoulder orientation + EMG (without forearm)	31	Training	3.16	0.97	3.88	0.98
		Validation	4.07	0.95	5.48	0.97
		Test	4.11	0.95	5.38	0.97
Shoulder orientation + EMG (all channels)	51	Training	3.65	0.96	3.54	0.99
		Validation	5.42	0.91	5.08	0.97
		Test	5.57	0.91	5.10	0.97

networks with each input separate. For elbow flexion, the combination of motion capture and EMG without the forearm channels had lower RMSE (3.16, 4.07, 4.11) and greater R^2 values (0.97, 0.95, 0.95) for the training, validation, and test sets, respectively, when compared with motion capture alone (RMSE: 5.56, 5.98, 5.89; R^2: 0.90, 0.88, 0.88) and EMG without forearm channels alone (RMSE: 5.96, 7.74, 7.52; R^2: 0.88, 0.81, 0.82). Similar results were obtained for forearm pronation/supination.

Furthermore, the results show that when forearm EMG was added, the network performed slightly better for forearm pronation/supination (RMSE: 3.54, 5.08, 5.09; R^2: 0.99, 0.97, 0.97). We did not see an improvement in elbow flexion/extension after forearm EMG was added (RMSE: 3.65, 5.42, 5.67, ; R^2: 0.96, 0.91, 0.91).

Fig. 3 depicts the outputs of the TDANNs compared to the actual elbow flexion/extension and forearm pronation/supination joint angles for one of the target reaches.

IV. DISCUSSION

The low error and the high correlation of the network can be attributed to the use of a TDANN which takes successive timesteps of data as inputs and the fact that the reaching task only involved a particular kind of reaching. This type of network is better-suited for time-series data, and we suspect this to be the reason for the better predictive results when compared to the cascade-correlation neural network used by Kaliki [6]. Since training is done offline, a neural network is well-suited for online usage since outputs require a relatively small number of multiplications of the inputs and weights.

While the reaching workspace itself was well-represented by the targets, the reaching task was the same for every target (start with elbow bent at 90°, palm down, reach to a vertical handle). This could explain the relatively small performance gain achieved by adding forearm EMG to predict pronation/supination. Elbow flexion/extension likely did not see a performance gain from adding forearm EMG due to the larger influence of the biceps and the omitted noisy EMG channel over brachioradialis. Different and more complex types of movements such as those used by Pulliam [3] will likely lower the performance of the TDANN. However, our preliminary results suggest that the incorporation of shoulder orientation as one of the inputs in the TDANN could improve the results reported by Pulliam. In addition, incorporation of muscles corresponding to targeted muscle reinnervation sites, such as the forearm, may have a more pronounced effect.

It is unknown whether it is necessary for the predicted angles to be 100% accurate or if "body English" would be enough to compensate for the error. Though our results achieved small error, the time-series predictions were noisy, and may need to be constrained in order to be feasible for prosthesis control. Metrics that measure how much the prosthesis deviates from unimpaired reaching will need to be explored. Joint angle and angular velocity constraints will also need to be applied. State estimation techniques such as Kalman filtering may also minimize error.

Since many of the muscles in the arm work synergistically when reaching, both knowledge about the orientation of a segment and the relative force of the muscles should present unique information about the kinematics of the rest of the arm. While our neural network does not elucidate the innate muscular synergies of reaching, nor does it directly include any information about the dynamics of the arm, it does perform fairly well at predicting the joint angles of the distal arm. However, future study into the actual neural control strategies implemented by our central nervous system may lead to even more precise kinematic control.

V. CONCLUSIONS

In this paper we have shown that by combining the inputs of shoulder orientation and EMG we can achieve better results in predicting the angle of elbow flexion/extension

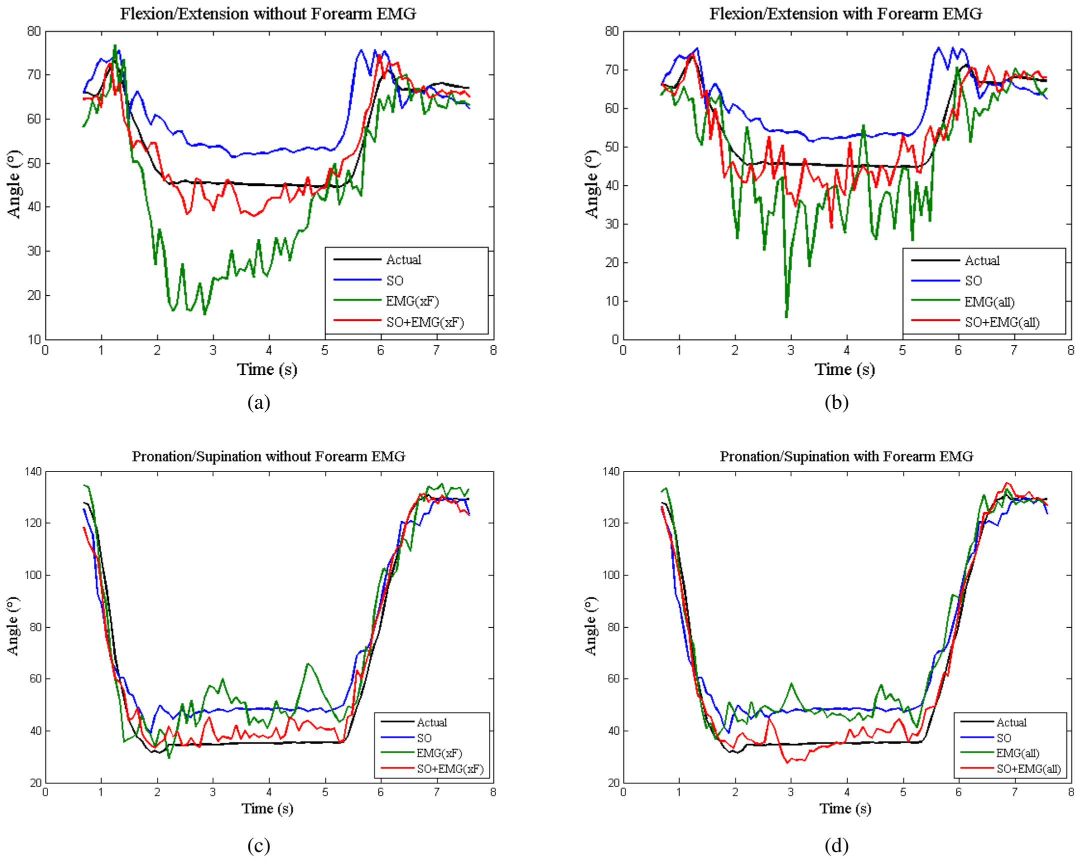

Fig. 3. Results for Flexion/Extension (a) without forearm EMG, and (b) with forearm EMG, and Pronation/Supination (c) without forearm EMG, and (d) with forearm EMG over a single trial. SO = Shoulder Orientation, xF = without Forearm.

and forearm pronation/supination in reaching movements. Furthermore, the results suggest that the incorporation of EMG from targeted muscle reinnervation sites may improve the prediction of distal joint kinematics. While these results are preliminary, this combination of inputs could potentially improve the prediction of multiple DOF-movements, such as in reaching.

Ultimately, the goal of this research is to implement multiple DOF-control strategies in transhumeral prostheses. Future work will investigate more complex arm movements from more subjects and control strategies that better represent the interaction between the nervous system and the arm.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 0903622. The authors would like to thank Dennis Matthews, Aaron Becker, Miles Johnson, Or Dantsker, Matt Petrucci, Iris Hsu, and Whitney Akhtar for their support with setup and equipment, Lauren Smith for her help with anatomy, and Elizabeth Hsiao-Wecksler for the EMG system.

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