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Toward Improved Sensorimotor Integration and Learning Using Upper-limb Prosthetic Devices

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***Abstract*—To harness the increased dexterity and sensing capabilities in advanced prosthetic device designs, amputees will require interfaces supported by novel forms of sensory feedback and novel control paradigms. We are using a motorized elbow brace to feed back grasp forces to the user in the form of extension torques about the elbow. This force display complements myoelectric control of grip closure in which EMG signals are drawn from the biceps muscle. We expect that the action/reaction coupling experienced by the biceps muscle will produce an intuitive paradigm for object manipulation, and we hope to uncover neural correlates to support this hypothesis. In this paper we present results from an experiment in which 7 able-bodied persons attempted to distinguish three objects by stiffness while grasping them under myoelectric control and feeling reaction forces displayed to their elbow. In four conditions (with and without force display, and using biceps myoelectric signals ipsilateral and contralateral to the force display,) ability to correctly identify objects was significantly increased with sensory feedback.**

I. Introduction

Motor learning requires sensory feedback. This tenet governs the ultimate utility of prosthetic and assistive devices used by amputees and physically impaired persons. Vision serves as a poor substitute for the haptic feedback missing from the terminal device of a prosthesis—visual processing and interpretation introduces undue cognitive loads and delays. When vision substitutes for kinesthesia or force sensing, manual performance is severely limited, even after extensive practice. Motor control schemes that normally require minimal attention no longer execute automatically. These observations are crucial to realizing recent investments in prosthetics technology: the utility of these new designs is limited not by mechanical dexterity but by lack of viable modes of control and sensory feedback. We aim to advance the science of sensory feedback and to drive prosthesis interface technologies in directions that are informed by an understanding of associated cognitive demand and brain activity.

While the need to relay sensory feedback regarding prosthesis posture and environment interaction has long been recognized, clinical experience has shown that cues must be provided in certain relationship with the brain's expectations [1]. Vision and other forms of sensory substitution fall short because users have difficulty associating sensations to their physical referents [2]. Perhaps the most promising technique involves directly interfacing to afferent peripheral nerves using signals derived from the prosthesis [3]. However, to inform the development of direct interface (both to the peripheral and central nervous system) we must uncover the underlying principles that govern the brain's ability to adapt to and use new interface paradigms.

Providing sensory feedback that restores kinesthetic processing and gives the brain access to afferents in lawful relationship to efferents can be expected to enhance and speed up learning of prosthesis use. Further, the considerable evidence that sensory and motor areas of the brain are dynamically maintained and continuously modulated in response to activity, behavior, and skill acquisition [4] can be brought to bear on the question of principles governing sensory processing.

In this paper, we evaluate alternative forms of sensing and action and their interaction that enhance the interface to powered prosthetic devices. Specifically, we provoke a mapping from information presented through haptic displays at the proximal part of the upper limb in able-bodied participants (representing the residual limb of an amputee) to activation in appropriate perceptual centers and brain regions. Our primary goal is to assess the role of force feedback on the function of peripheral (myoelectic) control of a prosthetic gripper, its ability to support dexterous manipulation in the absence of vision, and its impact on brain activity.

II. METHODS

A. Exoskeleton and gripper device

We have developed a prototype prosthesis that incorporates myoelectric control with haptic display of

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object interaction forces to proximal parts of the body (Fig 1A). The device can be adapted for an able-bodied person or a trans-radial amputee. In contrast to myoelectric prostheses for trans-radial amputees, our device features a brace or exoskeleton that spans the elbow and is motorized. The terminal device or gripper is also motorized and is instrumented for position control and force sensing. The experimental apparatus also includes scalp EEG electrodes (Neuroscan Synamps, 64 channel system), and fNIR (Drexel University, 16 sensor strip system).

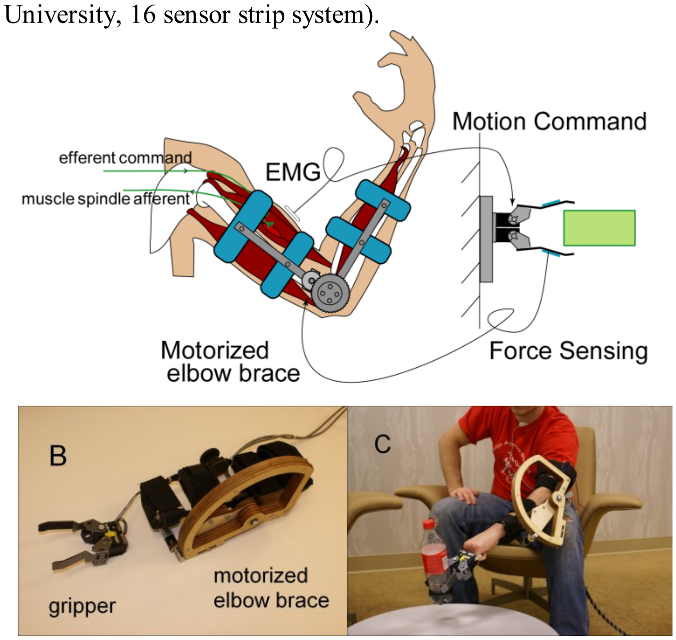

Fig. 1. Functional design of the experimental apparatus: A) Bicep EMG signal controls the aperture of the gripper while forces arising from object interaction control an extension torque about the elbow. B) A capstan drive rendered out of wood is attached to an elbow brace. C) Able-bodies persons can hold the gripper by a handle.

The elbow brace has a single axis of rotation that lines up with the elbow axis through the fitting of Velcro-tightened cuffs to the upper and lower arms (or residual lower arm). Dry EMG surface electrodes are integrated in the cuffs to pick up activation in the biceps muscle. A geared DC motor and capstan-drive transmission are incorporated into the elbow brace to create torque loads on the muscles spanning the elbow. The mechanical advantage associated with the capstan drive is 17:1, yielding a maximum torque of about 6 Nm.

The motorized gripper or terminal device operates under myoelectric control, and features strain guage based force sensors. Servomotors drive the fingers under position-control, employing position sensing and embedded control. Independent sensing on each finger allows internal forces to be distinguished from forces that act to accelerate an object or act against mechanical ground. In operation, grip forces sensed at the gripper are displayed as extension moments to the elbow through the action of the motorized elbow brace.

In the configuration for experiments with able-bodied persons, the gripper can be carried in the hand of the user (see Figure 1C). For experiments with amputees, the gripper can be mounted to the elbow brace. Alternatively, to attenuate the weight and inertia cues transmitted through the structure of the gripper to the hand or residual limb, the gripper can be mounted on a table. Our prototype device is designed to support experiments in which sensory feedback from the gripper is metered so that we may investigate the role of such feedback in motor performance and motor learning. Figure 2 shows a subject wearing the exoskeleton with EMG on the biceps, an EMG scullcap, and the fNIR system across the forehead.

Fig. 2. EEG and fNIR systems are used to monitor brain activity while a subject attempts to distinguish object stiffness using myoelectric control and torque feedback about the elbow.

A. Task and Experimental Protocol

In the present study, n=7 able-bodied subjects donned the exoskeleton on the left arm, and EMG measurements on either the ipsilateral or contralateral arm were used to command the gripper. Rather than being held, the gripper was mounted on a table out of view of the participant, and during the experiment, objects of varying stiffness were placed in the grasp of the gripper. Subject attempted to distinguish between the three objects using a single close and release motion. Participants were asked to complete a three alternative forced choice identification experiment with thirty trials per block, with correct answer feedback provided after each block. The availability of sensory feedback (in the form of gripper-sensed force displayed as torque through the motorized exoskeleton) was the primary experimental condition (presented in blocks). An additional blocked condition used EMG control from the ipsilateral or the contralateral arm. Each block consisted of thirty trials (during which knowledge of results was provided). Skill transfer from training to test was evaluated using a new set of two objects.

Hypothesis: We expect that the brain can achieve improved myoelectric control of a prosthetic gripper when interaction forces are reflected to a proximal joint of the body, in the absence of vision. To test this hypothesis we modulated the presence of force displayed according to remote force sensors and observed changes in object stiffness discrimination, prehension kinematics, and metabolic (fNIR) and electrophysiological (EEG) correlates of brain activity. First, participants rested in a silent room for 3 minutes to obtain Baseline data to be used for planned comparisons; next, each participant performed 30 trials using myoelectric control from their left arm with Grasp Force Feedback provided to their left arm. Knowledge of results (KR) was provided at the end of each trial by providing the correct name ('A','B', or 'C') of the object just presented. Subsequently, each participant performed 30 trials with KR but without Grasp Force Feedback. Then each participant performed 30 trials using myoelectric control from the right (contralateral) arm with KR but without Grasp Force Feedback. Finally, each participant performed 30 trials using myoelectric control from the right arm with KR and with Grasp Force Feedback provided to their left arm.

B. *Assessments and data analysis*

Recordings of grip force (which drove the elbow extension torque) were graphed against EMG signal (which corresponded to grip position) to determine whether object stiffness could be distinguished by the available signals.

The EEG, EMG and joint angle trajectories for each block were low pass filtered at 2 Hz. The joint angle time series was numerically differentiated and low-pass filtered again. Each time series was down-sampled to 20 Hz and standardized to zero mean and unit standard deviation. The dataset was then segmented into trials from 5 s before movement onset to 10 s after movement onset, resulting in 29 trials (one trial was discarded due to artifacts) from the first block and 30 trials from the second block.

A linear decoder with memory was used for predicting the elbow joint velocity and the EMG envelope from the EEG data [5]. Such a decoder predicts the decoded variable to be a weighted sum of the EEG data from all electrodes at multiple time lags. In this study, the decoder used EEG data until 250 ms in the past to predict the current movement variable. The weights for each electrode and each time lag were computed using robust regression. A leave-one-out paradigm was used to cross-validate the model: the data from a single trial was left out as the testing set while the decoder weights were computed using the data from remaining trials. The predicted movement variable time series was then computed using the EEG inputs and the computed weights. The predicted time series was low-pass filtered at 2 Hz. The decoder accuracy was quantified as the correlation coefficient between the observed (measured) trajectory and the predicted trajectory. This process was repeated so that all trials were used once as the test dataset. Separate decoders were used for the two movement variables, EMG and joint angle velocity.

The statistical analysis corresponded to 2 X 2 Condition 1 (Grasp Force feedback vs. none) × Condition2 (ipsilateral vs. contralateral myoelectric signal source) mixed model ANOVAs with trial-blocks (average of 10 consecutive trials) as the repeated factor. For the kinematic, EEG (e.g., spectral content, joint signal analysis), force and hemoglobin/ deoxyhemoglobin and oxygenation from fNIR, data were analyzed using mixed model ANOVAs with trial-blocks as the repeated factor.

III. RESULTS AND DISCUSSION

Grip force data are shown versus EMG signals in Fig. 3 for 30 object grasps performed by one subject in the first experimental block (with grip force feedback, EMG from ipsilateral arm). From the plot, the variations in stiffness and maximum grip force achieved for the three grasped objects can be observed.

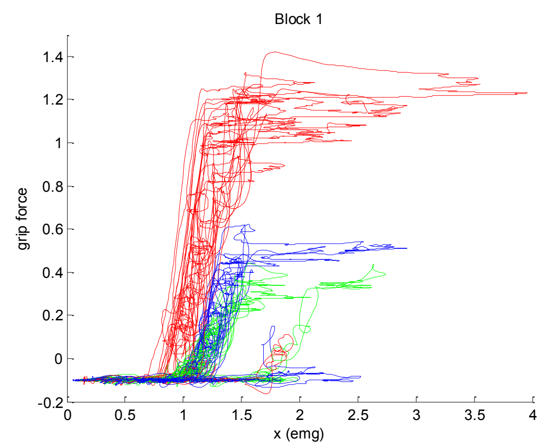

Fig. 3. Grip force vs. EMG showing stiffness variations in grasped objects. Red, blue and green lines delineate objects with decreasing stiffness.

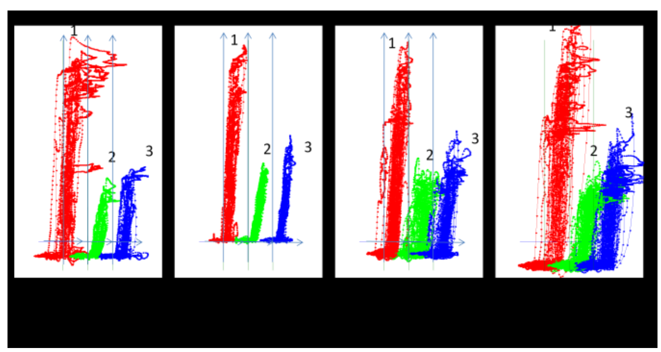

Fig. 4. Grip force vs. EMG for the first subject in all four experimental conditions (Blocks 1-4). Red, blue and green lines represent objects of varying stiffness

Figure 4. shows the same subject's grip force vs. EMG traces for all 30 trials sorted for object by color and x-axis offset (object *x* offset to the right by *x* EMG units, where $x=1,2,3$). The traces for Block 1 are the same as those in Figure 3. Evidently the presence of feedback and the positioning of the EMG sensor had little effect on this subject's observable behavior. Figure 5 depicts representative examples of the measured and predicted elbow joint velocities and EMG envelopes from 55-channel EEG for Block 1 (with grip force feedback) and Block 2 (with no grip force feedback). Figure 6 shows the median decoding accuracy obtained across Block 1 and Block 2

using the leave-one-out cross-validation procedure. These decoding results suggest that it may be possible to use EEG to control the gripper - a useful alternative when myoelectric control is not feasible or practical. We are now studying how practice affects the neural representation of elbow movement and/or EMG and thus decoding accuracy. We believe these results represent the first instance of decoding of EMG activity or elbow joint velocity from noninvasive EEG and opens the possibility of noninvasive neural interfaces to restore motor function in pediatric and adult populations.

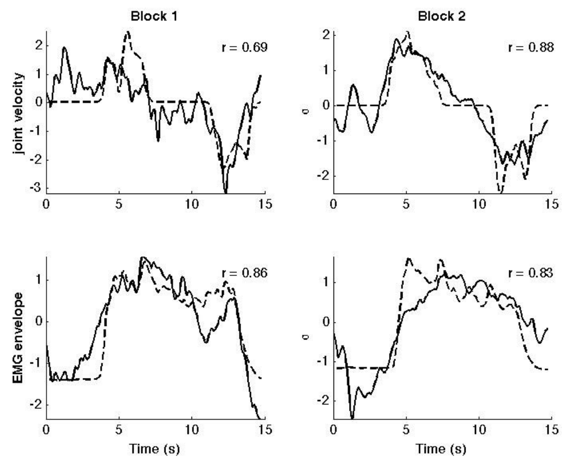

Fig. 5. Block 1 is with grip force feedback and Block 2 is without grip force feedback. Measured joint velocity and EMG envelopes are represented by the dashed line while the predicted values are indicated by the solid lines.

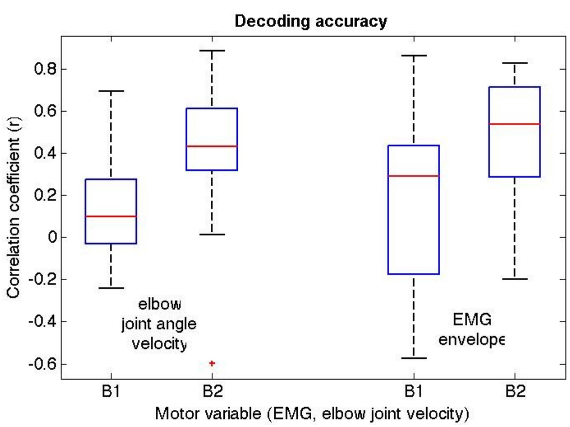

Fig. 6. Median decoding accuracy and quartiles of elbow joint velocity and EMG envelope across blocks 1 and 2 for subject 1.

Subjective percent classification was assessed using a 2 X 2 (EMG Control Limb X Force Feedback Limb) ANOVA with repeated measures on both factors. Results show significant main effects of arm side of EMG control [F(1,6) = 16.19, p 0.007, ES = 0.79] and Force Feedback Limb [F(1.6) = 25.70, p = 0.002, ES = 0.66] and are illustrated in Figure 7. Results indicate that the presence of force feedback provided via the exoskeleton proportional to the grip force greatly enhanced performance of the stiffness identification task. Additionally, EMG control via the ipsilateral limb resulted in better identification than when EMG control originated from the contralateral limb. These findings suggest the importance not only of sensory feedback, but of human-machine confluence and intuitive control of the smart prototype prosthesis.

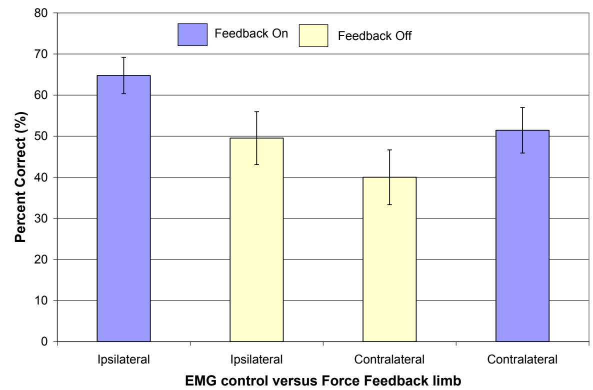

Fig. 7. Mean object identification performance in the three alternative forced choice stiffness identification experiments. Results are the average percent correct across seven participants, with standard errors shown with error bars. Four blocks of thirty trials were presented to subjects, with a combination of ipsilateral or contralateral EMG control/force feedback and force feedback turned on or off..

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