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Simultaneous, Proportional, Multi-axis Prosthesis Control using Multichannel Surface EMG

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Abstract— **Most upper limb prosthesis controllers only allow the individual selection and control of single joints of the limb. The main limiting factor for simultaneous multi-joint control is usually the availability of reliable independent control signals that can intuitively be used. In this paper, a novel method is presented for extraction of individual muscle source signals from surface EMG array recordings, based on EMG energy orthonormalization along principle movement vectors. In cases where independently-controllable muscles are present in residual limbs, this method can be used to provide simultaneous, multi-axis, proportional control of prosthetic systems. Initial results are presented for simultaneous control of wrist rotation, wrist flexion/extension, and grip open/close for two intact subjects under both isometric and non-isometric conditions and for one subject with transradial amputation.**

I. Introduction

PROSTHETIC hand and upper limb controllers allow the user to move different joints of the prosthesis with a small number of control inputs. These inputs often include switches, force sensors, and two to four myoelectric (surface EMG) signals, and some modern controllers also include variable speed and/or proportional control of joints to create smoother and more graceful movements. However, most clinically available upper limbs only allow users to select and control a single joint in the limb at a time. Even in advanced limbs, serial activation of the joints results in slow unnatural motion. These devices require significant levels of user training and continue to be cognitively demanding even after extended use.

The fundamental problem with simultaneous multi-axis limb control is that there are usually not enough independent control signals available [1,2]. Moreover, user control signals that are available may require body or muscle movements that do not intuitively map to movements of the limb without substantial training. In cases of middle and lower levels of forearm amputation, many of the upper forearm muscles that originally controlled the hand and wrist are often spared. In principle, surface EMG signals from these muscles could be used to control the joints of a hand and wrist prosthesis with muscle activation patterns similar to those of the original limb. This potential for natural, simultaneous control of multiple joints of a hand and wrist prosthesis has encouraged many researchers to investigate methods for extracting individual forearm muscle signals from surface EMG. This is complicated by the mixing of EMG signals from several muscles at the skin surface, the movement of muscles relative to the electrodes during contraction, variability in electrode placement, unintended co-contraction of adjacent muscles, and motion artifacts.

In this paper, we present a novel method for estimating simultaneous, proportional control signals from the forearm muscles of the residual limb, using an array of surface EMG electrodes. This method is based on the orthonormalization of spatial distributions of EMG energies of single-contraction recordings. Initial results for control of wrist rotation, wrist flexion/extension, and grip open/close are presented for two intact subjects and one subject with transradial amputation. These techniques are being developed to allow individuals with transradial amputation to better control next generation prosthetic hand and wrist systems.

II. Methods

A. Data Acquisition

Surface EMG recordings were made from two intact subjects and one subject with transradial amputation using 22 electrodes positioned around the upper forearm and spaced uniformly at 2-3 cm in two rows with a sparser third row of four electrodes (Fig. 1). Electrodes were placed for coverage of the forearm without deliberate consideration for

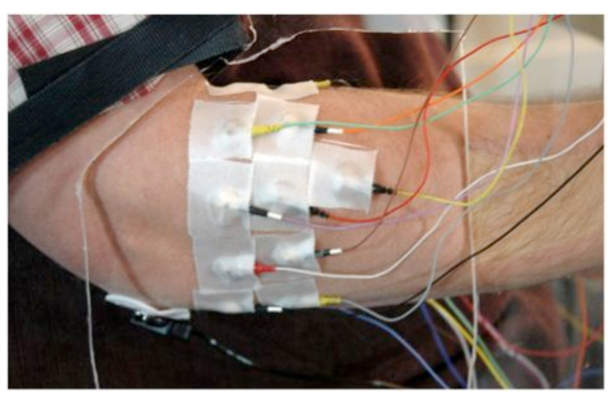

Fig. 1. EMG electrode montage used in the experiment. Electrodes were placed approximately uniformly in two or three rows without consideration for their relation to muscles of interest.

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their positions relative to the underlying musculature. Each electrode signal was recorded relative to a common reference electrode placed at the elbow and sampled at 400 Hz. Data collection procedures were conducted according to protocols approved by the University of Utah Institutional Review Board.

The subjects were instructed to follow a scripted visualization of the desired motions prompting them to produce one of six timed single contractions (hand open/close, wrist pronation/supination, flexion/extension), then pairs of simultaneous contractions (e.g. wrist pronation + wrist extension) and, finally, triple contractions (e.g. wrist pronation + wrist extension + hand open). The script prompted the subjects to repeat each contraction eight times and to sustain the contraction at constant force for 2.5 seconds.

For the intact subjects, two sets of experiments were performed: isometric and unconstrained.

In isometric tests, the hand and the arm were tightly taped to a rigid frame to reduce the movement of forearm muscles relative to the EMG electrodes and to reduce classification errors resulting from these movements. This potential source of error was tested by repeating the same data collection procedure without restraining the forearm. The intact subjects were instructed to move each joint through a full range of motion for each instructed contraction during this second set of experiments.

The last experiment was performed on a subject with transradial amputation of the left forearm five years post amputation subsequent to an electrocution burn injury. In the experiment, the residual limb was not mechanically constrained. The subject was instructed to produce the same permutations of wrist and hand motions.

B. *Signal Processing*

The basic assumption behind the signal processing algorithm was that spatial distributions of EMG power of the myoelectric signal (MES) of complex contractions could simply be modeled as a linear combination of the distributions of EMG powers of the constituent single contractions produced in isolation. As variances of independent random signals combine linearly, this assumption is equivalent to independence of motor unit action potentials.

The collected data were separated into disjoint subsets to be used for the *training* and *testing* stages of the experiment (Fig. 2).

Thus, after the initial band-pass and notch filtering, MES signals $\mathbf{x}(t)$ were converted into their short-time power signals $\mathbf{s}(t)$ using the Teager energy operator [3]:

$$\mathbf{s}(t) = \mathbf{x}^2(t) - \mathbf{x}(t-\Delta t)\mathbf{x}(t+\Delta t) \tag{1}$$

The whitening matrix $\mathbf{W}$ was estimated from the power signals $\mathbf{s}(t)$ of the training dataset by means of principal component analysis to obtain whitened power signals $\hat{\mathbf{s}}(t)$ for all further processing:

$$\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{s}(t) \tag{2}$$

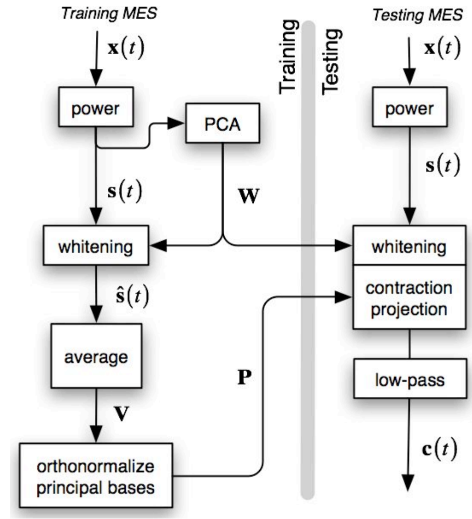

Fig. 2. Signal processing used in the experiments. The training procedure computes the whitening matrix and the orientations of the principal contractions.

The whitening of the power signals was found to be key to successful separation of constituent single muscle contractions.

Then the average spatial distributions of energies produced during the six single contractions are averaged to form their contraction vectors:

$$\mathbf{v}_j = \left\langle \int_{\text{start contraction}}^{\text{end contraction}} \hat{\mathbf{s}}(t)\,dt \right\rangle \tag{3}$$

Here $j \in \{\text{pronate, supinate, open, close, extend, flex}\}$ denotes one of the six single contractions and $\langle \cdot \rangle$ denotes an ensemble average.

Finally, the contraction vectors $\mathbf{v}_j$ are orthonormalized to produce the contraction basis $\mathbf{P}$:

$$\mathbf{V} = \left[\mathbf{v}_1 \quad \mathbf{v}_2 \quad \dots \quad \mathbf{v}_6\right] \tag{4}$$

$$\mathbf{P} = \mathbf{V}\left(\mathbf{V}^T\mathbf{V}\right)^{-1/2} \tag{5}$$

In the testing phase, the incoming signal is whitened, projected onto the contraction basis set $\mathbf{P}$, and low-pass filtered by the convolution kernel $h_{LP}(t)$ to reduce noise, introducing additional delay of as little as 50-80 ms:

$$\mathbf{c}(t) = \left[\mathbf{PWs}(t)\right] * h_{LP}(t) \tag{6}$$

The contraction vector signal $\mathbf{c}(t)$ then represents the contraction strength of each of the six principal contractions.

C. *Performance Evaluation*

The contraction signal $\mathbf{c}(t)$ produced by the algorithm in the testing phase was compared to the contraction requested from the subject at the corresponding time. The fidelity value was computed as the averaged normalized intensity of the commanded contractions minus the averaged intensity of uncommanded contractions with 1 denoting perfect command and -1 corresponding to a prevalence of incorrectly interpreted contractions. The results were averaged over three two-second contractions.

III. Results

A. Isometric contractions

Figure 3 depicts all possible permutations of the three principal contractions excluding the co-contractions of opponent muscles as requested from the subjects in the course of the experiment. Starting with single contractions in sets 1-6, the experiment progresses to double and triple combinations of principal contractions.

Ideally, the contractions detected during the testing phase of the experiment, will form the same pattern.

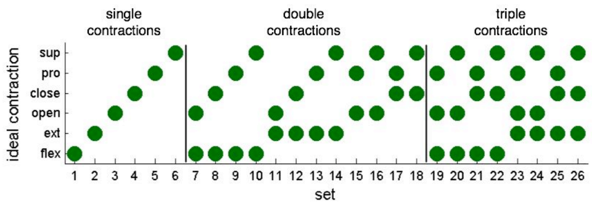

Fig. 3. Averaged contraction vectors and corresponding fidelities for subject 1 for isometric contractions.

Figures 4 and 5 depict the detected contraction vectors and the corresponding average fidelities for intact subjects 1 and 2 respectively.

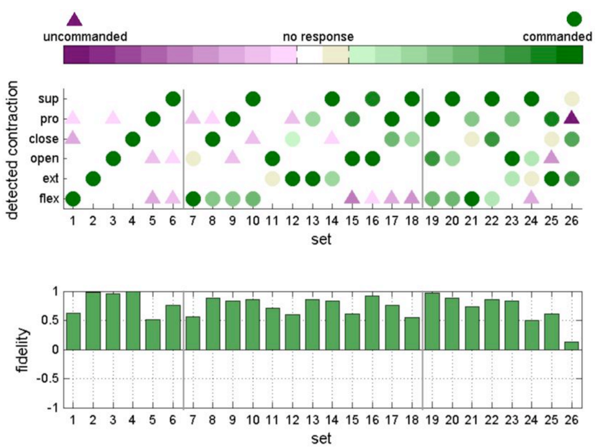

Fig. 4. Averaged contraction vectors and corresponding fidelities for intact subject 1 with isometric contractions.

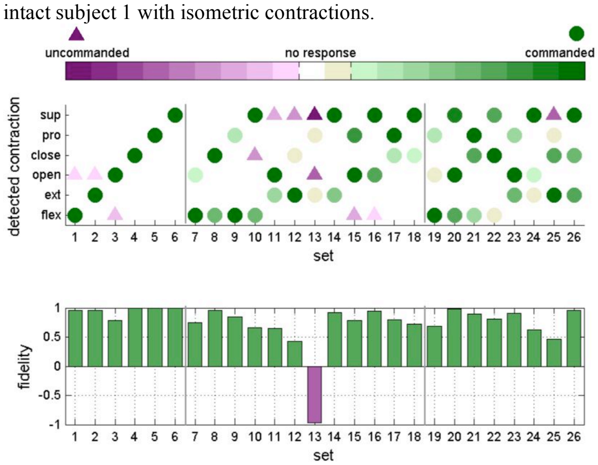

Fig. 5. Averaged contraction vectors and corresponding fidelities for intact subject 2 with isometric contractions.

With the average fidelity of around 0.75 for both subjects, isometric contractions provided reliable proportional multi-axis control for nearly all permutations of contractions. Much of the error may have come from the subjects' lack of ability to match the requested contractions in a balanced proportion, especially given the absence of proprioceptive feedback. It may also be possible that opposing muscles may be recruited in some contractions.

B. Unconstrained contractions

Figures 6 and 7 depict the results of the same experiment on the same two intact subjects with the forearm unconstrained during the contractions. The average fidelity is 0.54 and 0.55 now and the number of misclassified contractions is higher.

Notice that the all contractions that exclude pronation and supination exhibit high fidelities. This may be explained by large lateral displacement of muscles during pronation and supination, as well as the minimal distance between pronator and supinator muscles.

Indeed, excluding these contractions from the calculation in a subsequent experiment produced average fidelities of 0.77 and 0.81.

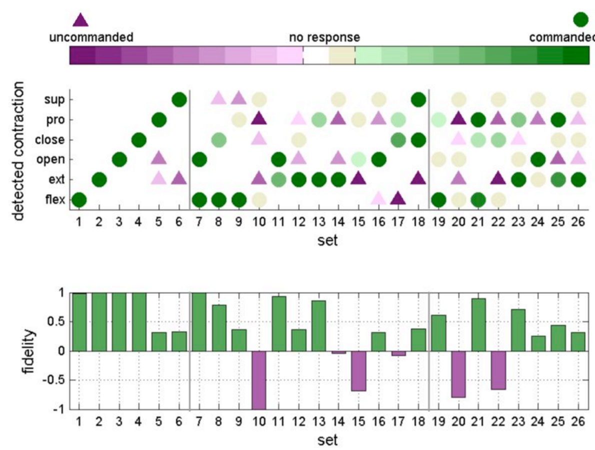

Fig. 6. Averaged contraction vectors and corresponding fidelities for intact subject 1 with unconstrained contractions.

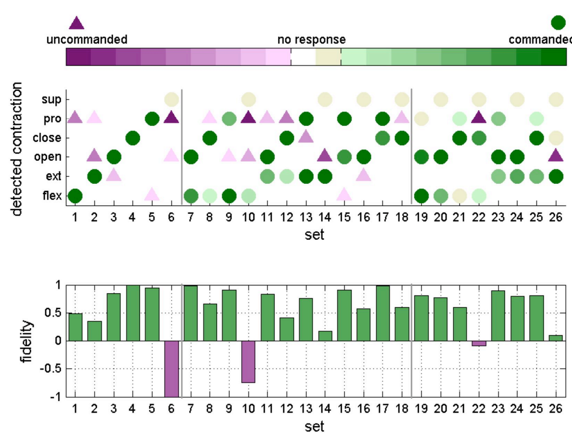

Fig. 7. Averaged contraction vectors and corresponding fidelities for intact subject 2 with unconstrained contractions.

C. Subject with transradial amputation

Figure 8 depicts the results from the subject with transradial amputation with unrestrained motion of the residual limb. The average fidelity was 0.59, placing these results between the isometric and unconstrained contractions from the two intact subjects.

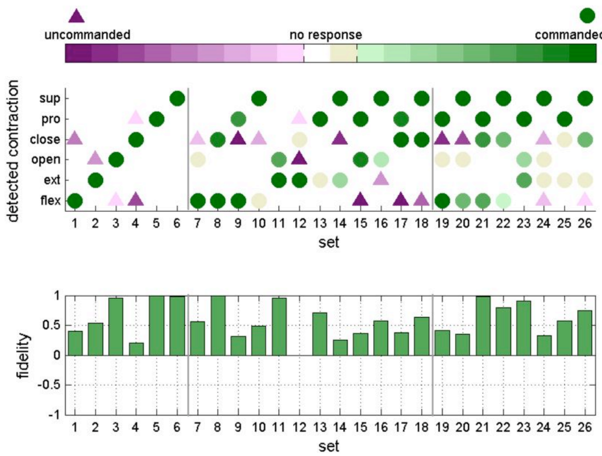

Fig. 8. Averaged contraction vectors and corresponding fidelities for the subject with transradial amputation.

The results indicate a high degree of control of the single contractions separately and in various combinations. Despite the subject's reported struggle to visualize and reproduce contractions that had not been exercised for several years and despite the lack of any visual feedback of the contractions and muscle fatigue, even the more complex triple contractions were performed with accuracy comparable to that of intact subjects in the first trial.

IV. Discussion and Future Work

Preliminary results collected from three subjects, including one with transradial amputation, indicate that multi-electrode surface EMG provides sufficient independent sources for multi-axis proportional control to enable a simple technique based on spatial distributions of surface EMG energies to control the motion of a prosthetic limb.

The quality of the study may be further improved by allowing the subject to receive real-time visual feedback of actuated movements using a virtual or a physical prosthesis.

Furthermore, the signal projection matrices resulting from a multi-electrode study described here may be adapted to assess the presence of residual neurological function and determine the optimal placement of a reduced set of electrodes.

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