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SURFACE VS. IMPLANTED EMG FOR MULTIFUNCTIONAL PROSTHESIS CONTROL: PILOT RESULTS

Todd R. Farrell[1], Richard F. Weir[1-3]
[1]Department of Biomedical Engineering, McCormick School of Engineering and Applied Science, Northwestern University, Evanston, IL
[2]Jesse Brown VA Medical Center, Department of Veterans Affairs, Chicago, IL
[3]Department of Physical Medicine and Rehabilitation, Feinberg School of Medicine, Northwestern University, Chicago, IL

INTRODUCTION

It has been hypothesized that, due to the potential to both provide a larger number of independent control sites and selectively record from forearm muscles (in particular the deep muscles), intramuscular EMG should be advantageous for multifunctional prosthesis control [1].

The use of surface electromyograms (EMG) to control a multiple degree-of-freedom prosthesis has been investigated for several decades. A variety of approaches have been employed with groups using different numbers of input channels [2-3], feature extraction methods [3-6] and pattern recognition algorithms [3,7-8]. While much work has been done, all of these efforts have used surface EMG as the control signal. Only a single preliminary study was found that acquired intramuscular EMG for prosthesis control [9].

Admittedly, the technology has not existed for chronic intramuscular recordings to be clinically feasible for prosthetic use. The Implantable Myoelectric Sensor (IMES) that is being developed at the Northwestern University Prosthetic Research Laboratory will make chronic intramuscular recordings clinically feasible [10].

We hypothesize and hope to demonstrate that by utilizing intramuscular EMG it will be possible to substantially increase classification accuracies of multifunctional prosthesis controllers (i.e., increase the percentage of the time that the controller can correctly predict the intended movement of the user). If a substantial increase in classification accuracy is demonstrated, this will justify the invasiveness of using these devices. However, if similar accuracies can be obtained from surface recordings then there will be little justification for pursuing these devices for transradial prosthesis control purposes.

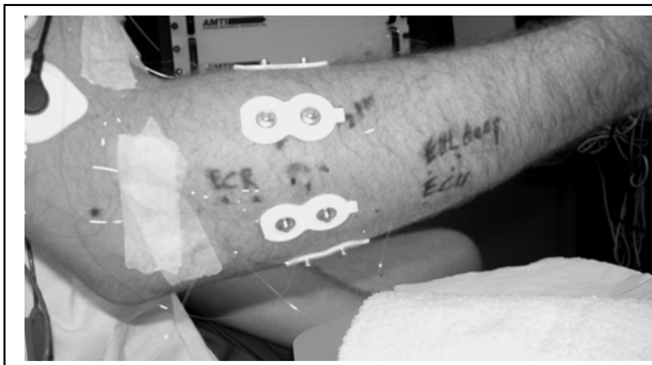

Figure 1 - A photograph of the location of the surface electrodes and fine wire insertion sites. The writing on the forearm indicates preliminary markings to assist in locating the fine-wire sites.

METHODS

Protocol

Both surface and intramuscular EMG data were collected from the forearm of four subjects. Six surface electrodes were placed in

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an equally spaced array around the circumference of the forearm (Fig. 1). Additionally, ten pairs of fine wire bipolar EMGs were recorded from 10 muscles of the forearm: extensor carpi radialis (ECR), extensor carpi ulnaris (ECU), extensor digitorum communis (EDC), extensor pollicis longus (EPL), flexor carpi radialis (FCR), flexor carpi ulnaris (FCU), flexor digitorum superficialis (FDS), flexor pollicis longus (FPL), pronator teres (PRON), and supinator (SUP). Verification of the location of the intramuscular electrodes was accomplished by instructing the user to perform a test movement that was indicated by a standard electromyography text [11]. Additionally, the test movements of the neighboring muscles were performed to ensure that EMG was being collected from the correct muscle. The intramuscular electrodes were separated by approximately 13 mm to mimic the recordings we would expect from the IMES sensor.

EMG was collected as the subjects performed a series of contractions corresponding to the six movements that can be produced using commercially available prosthetic components: hand close, hand open, pronation, supination, wrist extension, and wrist flexion (figure 2). For each trial the subject would produce four five-second contractions of the same movement, each time starting from and returning to rest. Four of these trials were collected for each movement with two trials used as training data for the pattern recognition system and the other two used to determine classification accuracies.

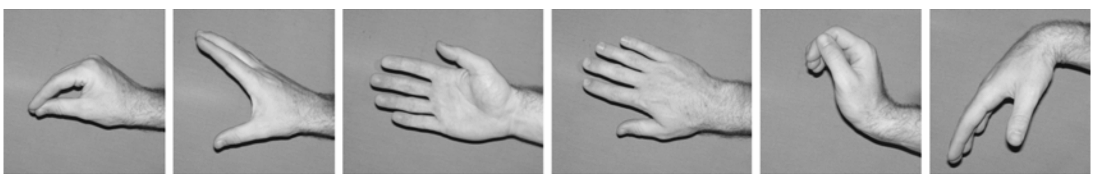

Figure 2 - Photographs of the six movement classes used in the pilot experiments: Hand Close, Hand Open, Pronation, Supination, Wrist Flexionand Wrist Extension.

Analysis

It has been demonstrated that extracting signal features in addition to EMG amplitude from the recorded signals substantially increases the classification accuracy of prosthesis controllers [3-6,8,12-13]. Therefore, an autoregressive (AR) model was created and the root-mean-square (RMS) of each channel was calculated for each 50 ms bin of data. AR parameters have been used repeatedly in previous research [6,12-13] and have been found by the group at the University of New Brunswick to outperform other signal features for myoelectric control. In this study we used a 3rd order model.

Six sets of input data were created for analysis:

1. 6 surface channels: RMS only
2. 6 surface channels: RMS + 3rd order AR
3. 10 intramuscular channels: RMS only
4. 10 intramuscular channels: RMS + 3rd order AR
5. 6 intramuscular channels: RMS only
6. 6 intramuscular channels: RMS + 3rd order AR

Note: The subsets of six intramuscular channels used in input sets #5 and #6 were selected using multinomial logistic regression.

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The classification accuracy was determined by comparing the intended movement of the user to the output of a linear discriminant analysis (LDA) classifier.

RESULTS

The classification accuracies that resulted from the six input sets described above are shown in Figure 3. When utilizing only EMG amplitude the surface data produced the largest amount of error of any data set (21.1%). Adding AR coefficients to the input data set decreased the classification error by more than half (10.3%).

When compared to the surface with AR data set the intramuscular data had slightly larger error rates when using only signal amplitude with all 10 channels (13.3%) and 6 channels (12.1%). It was also demonstrated that the use of the AR parameters again reduced the error substantially when applied to the intramuscular input sets of 10 (6.3%) and 6 (7.2%) channels.

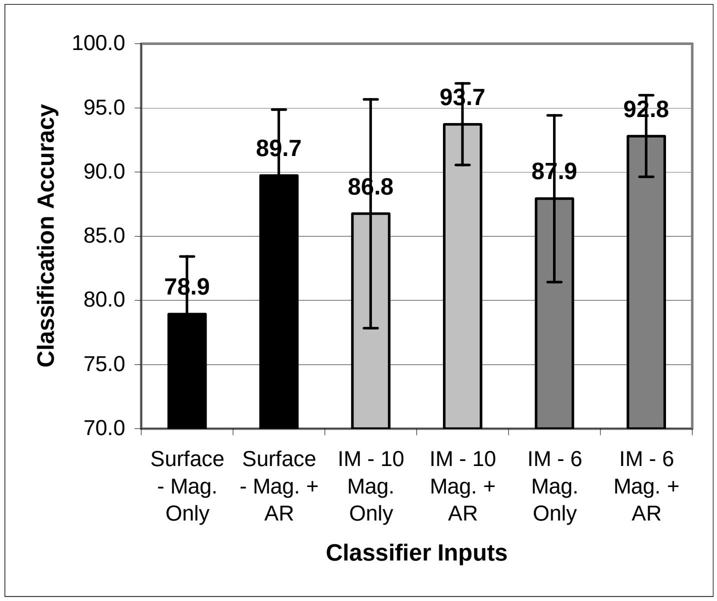

Figure 3 – Classification accuracies resulting from surface and intramuscular EMG. The surface recordings are shown in black, the full set of 10 intramuscular recordings are shown in light gray and a subset of six of the ten intramuscular channels chosen via multinomial logistic regression are shown in dark gray. The left column of each pair shows classification accuracies when only EMG amplitude is used and the right column show classification accuracies from using autoregressive coefficients in addition to EMG amplitude.

DISCUSSION

The increased accuracy that is seen by implanting the electrodes is encouraging. However, these results are based on a comparison of non-targeted surface channels to targeted intramuscular channels and to achieve a truly fair comparison of surface vs. intramuscular EMG we feel we need to target both recordings. In the near future we will be able to compare targeted surface recordings with the targeted intramuscular data.

It was also interesting to note the considerable improvement that is achieved by adding the auto-regressive parameters to each input set. The classifier error was reduced by more than half in two instances with the error being decreased by 51.7% for the surface inputs and 52.8% for the 10 channel intramuscular inputs.

The final observation is the ability of a smaller number of intramuscular channels to perform as well as the 10-channel set for this set of tasks. This indicates that it is only necessary to record from a subset of forearm muscles to maximize classification accuracy for this six-class problem. The muscles that were contained in these six-channel subsets were not consistent for each subject however when a fixed subset of six channels was used for all subjects it performed comparably (91.0 %) to the sets that were customized for each subject (92.8%).

FUTURE WORK

We are in the process of performing additional experiments in which surface and intramuscular EMG are collected from both targeted and untargeted sites on the forearm. We also plan to investigate the use of multinomial logistic regression for pattern recognition purposes as well as to increase the number of classifier output classes to make the classification problem more difficult.

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