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Pilot Comparison of Surface vs. Implanted EMG for Multifunctional Prosthesis Control

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***Abstract*—The classification accuracies of controllers utilizing EMG input from six surface and ten intramuscular recordings are compared. In addition, the effect of including autoregressive (AR) parameters into the input sets is examined. The average accuracies from four subjects are reported. It was observed that surface recordings based solely on amplitude data did not perform well (21.1% error) but adding AR coefficients increased this accuracy substantially (10.3%). The intramuscular recordings performed comparably to the surface recordings with AR coefficients using all ten (13.2%) and a smaller set of six (12.1%) channels of intramuscular data. The subset of six channels was selected using multinomial logistic regression. It was observed that adding the AR coefficients to the intramuscular recordings also produced an improvement in classification accuracy for the six (92.8%) and ten (93.7%) channel input sets. To our knowledge this is the first work in more than three decades that explores the use of intramuscular EMG for the control of upper-limb prostheses and this work demonstrates that it is possible to achieve a decrease in classification error of nearly 40% by using intramuscular recordings.**

I. Introduction

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 some groups using large numbers of surface electrodes [1-3] while others strove to use only a single EMG channel [4]. Attempts have been made to extract more information from the EMG signals by using time domain features [4], wavelet analysis [5-6] or creating autoregressive models [7-8]. Some have used statistical pattern recognition methods [9] while others have used neural networks [10] or fuzzy logic [11-12]. While much work has been done, all of these efforts have used surface EMG as the control signal and little effort has been placed into the use of intramuscular EMG signals.

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 is an implantable sensor that will allow for intramuscular EMGs to be chronically recorded directly from muscles in the forearm [13]. Recording directly from these muscles makes it possible to obtain more focal recordings and specifically allows for more reliable detection of the activity of the deep muscles of the forearm.

We hypothesize and hope to demonstrate that by utilizing these focal recordings it will be possible to substantially increase classification accuracies of multifunctional prosthesis controllers. If a substantial increase in classification accuracy is demonstrated, this will justify the invasiveness of using these devices. However, if it is shown that similar accuracies can be obtained from surface recordings then there is little justification for pursuing these devices from a prosthesis control perspective.

II. Methods

A. Protocol

The first objective of this work is to compare the ability of pattern recognition algorithms to correctly determine the intended movement of the user using either surface or intramuscular EMG. To this end both surface and intramuscular EMG data were collected from the forearm of each subject.

Previous work has shown high classification accuracies by utilizing an array of surface electrodes placed around the circumference of the forearm [6]. A circumferential array of surface electrodes represents an ideal geometry for implementation in a prosthesis. In addition, Davidge, et. al. [14] demonstrated that, while diminishing returns are observed above four electrodes, it is advantageous to utilize as many surface sites as possible in this array to maximize classification accuracy. Based on these observations we used an array of the maximum number of surface EMG channels available to us. Six surface channels were used because our EMG system has sixteen-channels and ten of these channels were already dedicated to the intramuscular recordings as a result of another experiment that was being run simultaneously.

Ten pairs of fine wire bipolar EMGs were recorded from 10 muscles in the forearm of four subjects. These pairs of wires were separated by approximately 13 mm, to mimic those signals that would be recorded by the IMES sensor. We feel as though these recordings will be representative of the recordings we will obtain with the IMES sensor because

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it has been shown in other recordings that while inter-electrode spacing effects the detection volume and signal frequency content, the electrode surface area has little effect on these parameters [15]. The muscles that were targeted were the 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). In addition, six surface electrodes were placed in an equally spaced array around the circumference of the forearm (Fig. 1). The electrodes were applied with the subject in a supinated position with the first electrode located one-third of the distance from the medial epicondyle of the humerus and the styloid process of the ulna. The other five electrodes were then spaced equally about the forearm. This electrode orientation was chosen to avoid placing an electrode over the ulna.

Verification of the location of the intramuscular electrodes was accomplished by instructing the user to perform a test movement that was obtained from a standard electromyography text [16]. Additionally, the test movements of the near neighbors were performed to ensure that EMG was being collected from the correct muscle.

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

EMG was collected as the subjects produced a series of contractions for each of the movements being investigated: hand close, hand open, pronation, supination, wrist extension and wrist flexion. 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 test the efficacy of the system.

B. Analysis

The EMG data was acquired at 1920 Hz using a Noraxon Telemyo 2400R (Phoenix, AZ). This data was then bandpass filtered between 20 and 500 Hz. For each channel, the root-mean-square (RMS) of 50 ms bins (96 samples/bin) of data was calculated. Additionally, it has been demonstrated that, when using surface EMG, it is possible to significantly increase classification accuracies by presenting a variety of signal features in addition to signal amplitude [4-8] to the pattern recognition system. For example, it has been demonstrated that including auto-regressive (AR) parameters substantially increases classification accuracies [7,8,12].

An auto-regressive model is a time series model in which the value at the current point can be predicted by several previous points in time each multiplied by a weighting coefficient and takes the form shown in (1):

$$x(t) = \sum_{i=1}^{N} a_i x(t-i) \tag{1}$$

where x is the EMG signal at time t, N is the autoregressive model order and a_i are the model coefficients. For each 50 ms window of data these models are created and the coefficients of these models are used as inputs to the pattern recognition algorithm.

The larger the autoregressive model the greater the computation time that is required to determine the AR coefficients and train the pattern recognition system. Therefore, the model should be kept as small as possible without sacrificing classification accuracy. Previous efforts have used 3rd or 4th order AR models [7,8,12]. Others have observed the best results from a 6th order model [17]. From our analysis of autoregressive models of different orders applied to the surface EMG we found that a 3rd order model gave us good results without being overly computationally cumbersome.

An additional aim of this work was to determine if the inclusion of additional signal parameters increases the classification accuracies that are achieved using intramuscular recordings. Therefore, 3rd order autoregressive models were constructed on each 50 ms window of data for both the surface and intramuscular recordings and the coefficients of these autoregressive models were added as features to the data sets.

The authors were curious if a smaller subset of intramuscular channels would provide similar classification accuracies when compared to the accuracy achieved using the entire set of ten intramuscular channels. The subset of intramuscular channels (note that data sets #5 and #6, listed below, do not use the entire set of 10 intramuscular channels) was determined by performing a multinomial logistic regression and removing the channels that produce the smallest ‘loss of fit’ when the regression was performed. The channels that were included in the smaller set of intramuscular analysis varied with each subject. It was found that six channels of intramuscular data performed as well as, and even slightly better than, the entire set of ten channels (figure 2).

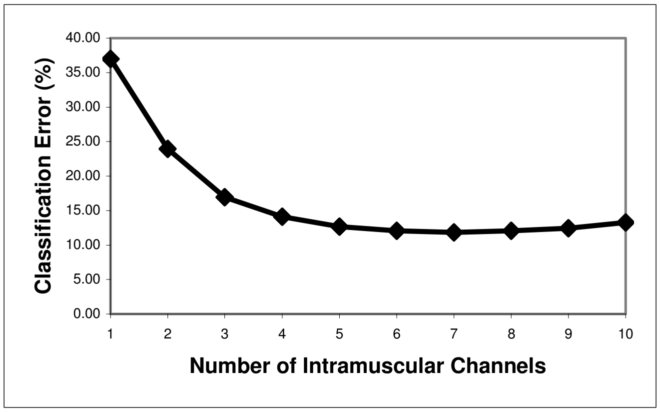

Fig. 2: Classification Error vs. Number of Intramuscular Channels. This shows that, for the six-class problem using RMS inputs only, using six channels of EMG is as accurate (and even slightly more so) as using ten EMG channels.

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

The accuracy of classification was determined by comparing the intended movement of the user to the output of the linear discriminant analysis (LDA) classifier. Unlike other attempts at multifunctional classification, this particular protocol also attempts to classify the state of 'off' and all data points in the transitory states (from rest to a steady state contraction and from the steady state contraction back to rest), which may decrease the relative accuracies if these efforts are compared to previous work.

III. RESULTS

The classification accuracies that resulted from the six input sets described above are shown in Figure 3 and summarized in Table 1. 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%).

TABLE I
CLASSIFICATION ACCURACIES

Input Data Set	Classification Error(Accuracy)
6 Surface: RMS Only	21.1% (78.9)
6 Surface: RMS + AR	10.1% (89.9)
10 Intramuscular: RMS Only	13.3% (86.7)
10 Intramuscular: RMS + AR	6.3% (93.7)
6 Intramuscular: RMS Only	12.1% (87.9)
6 Intramuscular: RMS + AR	7.2% (92.8)

Classification error (and accuracy) from the six input sets. Each of these inputs was placed through a linear discriminant analyzer and the movement that was selected by the pattern recognition system was compared to the user's intended motion. The input data sets were either constructed from the surface or the intramuscular data and contained either magnitude information or magnitude information along with AR parameters.

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.

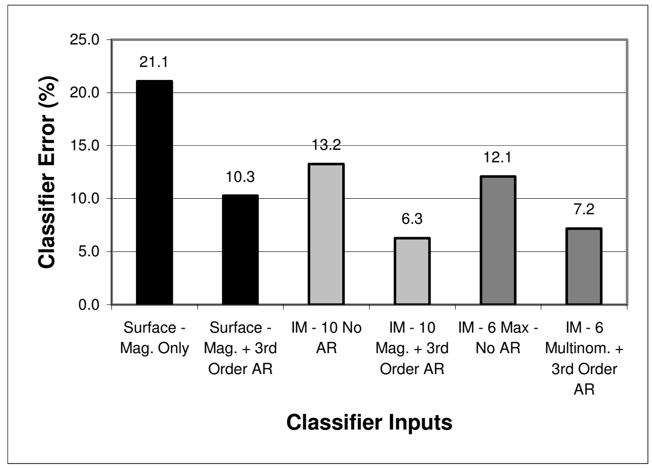

Fig. 2: Classification error of the six input sets. Note that adding the auto-regressive parameters decreases the classification error for all data sets (columns 1+2, 3+4, 5+6). Also note that by using a smaller subset of intramuscular channels it is still possible to achieve the similar classification accuracy (columns 3+5, 4+6).

IV. DISCUSSION

A. Data Interpretation

The data offers three interesting observations. The first is the considerable improvement that is achieved by adding the auto-regressive parameters to each input set. The classifier error was cut in half in two instances with the error being reduced by 51.7% for the surface inputs and 52.8% for the 10 channel intramuscular inputs. The second observation is that it is possible to substantially reduce the classification error by acquiring the EMG intramuscularly. 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.

The observation that the classification accuracy of the surface and intramuscular signals is improved by adding more complex features is logical. There is more information contained in EMG recordings than simply the signal amplitude. For example, the frequency information that is captured in the AR coefficients will be useful for determining the activity of neighboring muscles.

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. In the near future we hope to be able to compare targeted surface recordings with the targeted intramuscular data.

The similar performance of smaller subsets of intramuscular channels was expected since each channel of EMG was not entirely independent due to crosstalk. In the future we plan to investigate this relationship with a more difficult control problem, i.e. control of a greater number of degrees of freedom.

It is also interesting to note that the intramuscular EMG without any additional features performed approximately as well as the surface EMG with the AR coefficients. Calculating the AR parameters involves considerable processing time and being able to avoid the use of AR, or other signal processing techniques, is advantageous from a real-time prosthetics control perspective.

B. Protocol

For a truly fair comparison of the capabilities of the surface and intramuscular recordings it would be ideal to record from targeted intramuscular sites and, at the same time, record from targeted surface electrodes placed directly above the intramuscular sites. However, we are not able to do this because the fine wire electrodes would have to pass through the surface electrodes, which is not possible with our EMG system.

The implantation of the fine wire electrodes is uncomfortable and thus may alter the contractions that are made by the subject. Therefore, it would also be ideal to obtain surface recordings from the same contractions that are produced when the intramuscular data is collected. Therefore we used the non-targeted six-channel array approach described here.

V. FUTURE WORK

After the preliminary work that was presented here it was concluded that it would be advantageous to run additional experiments in which surface EMG was collected from ten targeted sites on the forearm located at the sites of the fine wire insertions. It is possible that the contractions may differ slightly without the presence of the fine wires however, since the intramuscular sites were targeted, a fair comparison would not be possible if we did not also target the surface electrodes. A majority of the muscles of the forearm are located superficially and therefore it should be possible to target a considerable number of these muscles with surface electrodes.

VI. CONCLUSION

Intramuscular and surface EMG data has been collected and preliminary analysis performed on four normal subjects. The analysis shows that adding auto-regressive model coefficients to the input set to a LDA classifier increases the ability of the classifier to accurately predict the subjects intended movement when the surface and intramuscular EMG data is used. At this point only non-site-specific surface EMG recordings have been obtained and this prevents any firm conclusions from being drawn regarding the abilities of classifiers that use intramuscular versus surface EMG inputs. Future experiments will target the surface EMG sites and allow for a comparison of the classification accuracies of the two approaches.

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