INVESTIGATING CLASSIFICATION PARAMETERS FOR CONTINUOUS MYOELECTRICALLY CONTROLLED PROSTHESES

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I. INTRODUCTION

During the contraction of skeletal muscle, there is an associated movement ions in the individual muscle fibres. This electrical activity can be recorded using the surface electrodes located above the muscles of interest. The resultant signal is the sum of the muscle fibre action potentials in the vicinity of the electrodes, termed the myoelectric signal (MES). MESs are used in a variety of applications including prosthetic control, monitoring muscle fatigue, and automatic speech recognition (ASR) systems. The research done thus far in the prosthetic application of MESs employs different classification techniques based on different feature extraction and classification algorithms.

The purpose of this research is to address the following questions:

1. Assuming we are using autoregression (AR) coefficients as signal features, what effect does the AR model order have on the MES classification accuracy?
2. How many numbers of channels are required to maintain a high degree of classification accuracy?

To answer these questions, a series of experiments were performed to collect and process the MESs using different AR coefficients as signal features, computed using different AR model orders and different sets of MES channels.

II. METHODS

A. Data Collection

Data were collected in accordance with guidelines established by the Tri-council policy [1]. Eight channels of surface MES were collected from the right arm (Figure 1) using Duo-trode Ag-AgCl electrodes (Myotronics, 6140). Two of these electrodes (electrodes #1 and #2) were placed at a location one third of the forearm length from the wrist to the elbow. Five electrodes (electrodes #3 to #7) were placed at a location one third of the forearm length from the elbow to the wrist, with an equal spacing around the forearm. The eighth electrode was placed on the bicep muscle of the upper arm. An Ag-AgCl Red-Dot electrode (3M, 2237) was placed on the wrist to provide a common ground reference. These signals were fed through wide band, high gain AC amplifiers (Model 15, Grass Telefactor), with the variable gain set at 1000 and bandwidth set at 1 Hz to 1 kHz. Signals were sampled at 3 kHz using an analog-to-digital converter board (National Instruments, PCI-6071E). MES data were later downsampled to 1 kHz and processed off-line using Matlab.

Data were collected from the right arm of thirty normally limbed subjects (twelve males and eighteen females). Each subject underwent four sessions, with one to two days' separation between sessions. Each session consisted of six trials. Seven distinct limb motions were used: hand open, hand close, supination, pronation, wrist flexion, wrist extension, and rest. Within each trial, subjects held each limb motion, four times, for a duration of three seconds. The order of these limb motions was randomized. A five-second rest period was introduced at the start and end of each trial to avoid data being cutoff while collecting the data, making each trial 94 seconds in length. These five-second rest periods were removed before data processing. The elbow was sustained at 90-degree flexion during the trials and a rest period approximately one minute was provided between each trial. Electrode placements were marked by permanent markers to ensure the consistency of recording sites throughout all the sessions. The electrode placements were documented by taking digital pictures (one ventral, one dorsal, and two lateral views) during the first session.

B. Training and testing

MES data were manually labeled with their associated limb motion by indexing the data files at the motion transitions. Classification of the MES was done in two steps: training and testing. The processing was done on the fourth session, as this session should have the least amount of variability and the majority of any learning effects. Data from the first two trials were used for training and remaining data from the last four trials were used for testing. Overlapping observations

Note: The MES data for subject 5 did not show any muscle activity for supination and hence repeated all four sessions. This subject improved the classification accuracy from 81.66% to 92.27% for session 4.

windows of 256 ms, with 32 ms spacing were used. Data from each window were parameterized using AR coefficients and classification was done by using linear discriminant analysis. In [2], it was noted that majority of classification errors occur in the transitory periods between limb motions. These errors are quite evident from the fact that the MES is in an undetermined state during contractions. To account for transitory periods, 256 ms of data before the start and at the end of each limb motion were removed from the training as well as testing set.

Majority vote post-processing was used to help eliminate spurious misclassifications. Using a similar approach as in [3], a majority vote was implemented using the current elementary decision and the preceding eight elementary decisions. The classification accuracy (CA) results presented in this paper are based on majority vote, excluding transition periods.

To study the effect of AR model order, the AR order was varied from 1 to 14 in steps of 1 and corresponding CA was calculated. The optimal result from this study was used as the feature set in the analysis of the effect of number of channels on the CA. Data used for classification was varied from 8 down to 1 different combinations of channels, eliminating channels in steps of 1, and corresponding CA was calculated. During each iteration, the channel that had least effect on the CA after elimination was removed before the start of the following iteration.

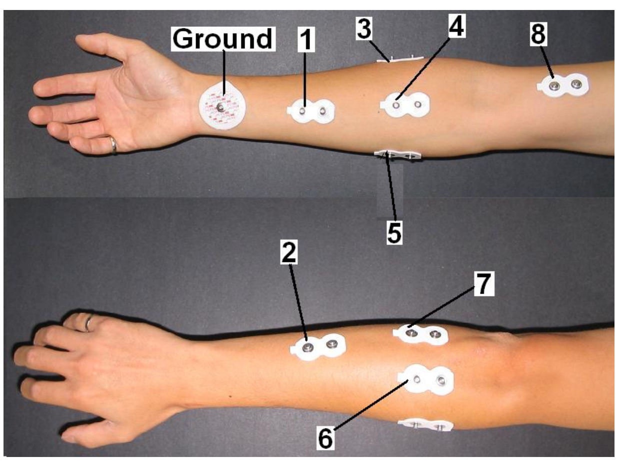

Figure 1 Electrode placements on the right arm

III. RESULTS

A. Effect of autoregression order

The effect of the AR order on the CA is shown in the Figure 2. There is a 9.26% increase in the CA when the AR model order is changed from 1 to 2, followed by an increase of about 1.20% as the order is increased to 3. As the order is changed from 3 to 14, there does not appear to be drastic variation in CA. From 3 to 7, there is a total increase of 1.19%, beyond which there is a decrease in CA by 0.24% on average for each step increase in the AR order. Though there are not any dramatic fluctuations, the AR order 7 is noted as the optimal point with the highest CA of 92.64%.

The AR order 7 is chosen as the feature set in the further study of the effect of channel placements.

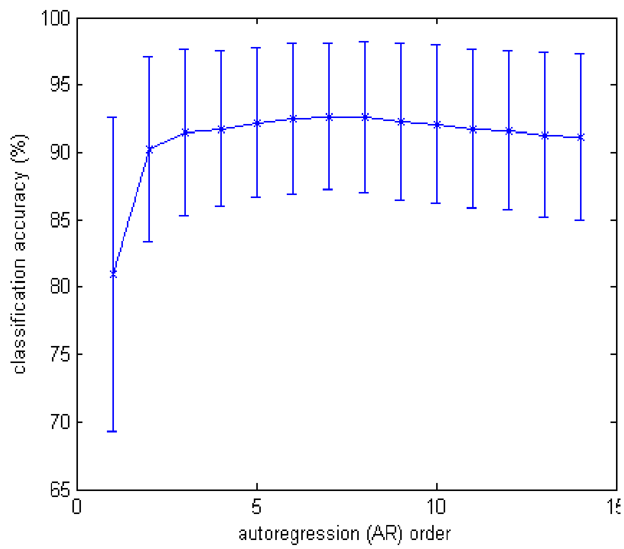

Figure 2: Effect of autoregression (AR) order on the classification accuracy (average with one standard deviation)

B. Effect of number of channels

The effect of number of channels on CA is shown in the Figure 3. The CA increases as the number of channels increases from 1 to 7 and decreases slightly by 0.22% for eight channels. The CA jumps drastically by 17.31% when the number of channels is increased from 1 to 2 and by 4.20% from 2 to 3. The CA further increases almost linearly by 1.13% on average for each increase in the number of channels over the range 3 to 6. For 7 channels the CA further increases by a small amount of 0.35% and decreases for 8 channels by 0.22%. This indicates that 7 is the optimum point after which any increase in the number of channels of data has adverse effect of the CA. The one channel that causes this decrease in the CA is channel #1.

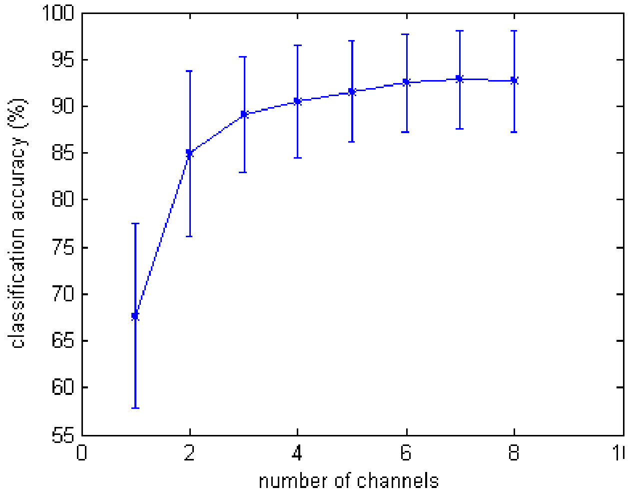

Figure 3: Effect of number of channels on the classification accuracy (average with one standard deviation)

IV. DISCUSSION

A. Primary Limb Motion(s):

The effect of channel elimination was studied in eight iterations, eliminating one channel in each iteration (Grid 1). In the first iteration channel #5 is the most important while channel #1 is the least important. The channel which had the least impact on CA after elimination was taken out before the following iteration, thus reducing the channel set by one. During the first iteration, channel #1 had the least effect on CA after elimination and was removed before second iteration. The order in which channels were eliminated is #1, #2, #4, #7, #8, #6, and #5. Empirically, it was found that channel #1 is the least important and channel #3 is the most important input. Though the order of importance varies between iterations, channels #3, #5, #6 and #8 were consistently the first four important channels, which give considerably high CA of 90.48%.

5	5	5	5	5	5	3	3
3	3	6	6	6	3	5	
6	6	3	3	3	6		
8	8	7	8	8			
7	4	8	7				
2	7	4					
4	2						
1							

Grid 1: The order of channel elimination

Table 1 summarizes target muscle(s) and limb motion(s) associated with each channel determined by human physiology of limb movement [4]. It should be noted that none of the target muscles have a primary role in hand close or pronation. All muscles in the given table run along the forearm length, except channel #8, which runs along the upper arm length. A muscle is fleshy at the center and tapers at the ends. Channels #1 and #2 are placed at the ends of the muscles and channels #4 and #7 are placed in between the two muscles. All these four muscles are eliminated in the first four iterations of channel elimination process. Channels #3, #5, #6 and #8, which are placed on the fleshy part of the muscles, are found to be most effective control input. It is interesting to note that the two electrode sites closest to the hand (channel #1 and channel #2) were the least important channels, despite the limb motions being primarily hand and wrist motions. It appears that channel placement at the center of the muscle is more important, perhaps as it produces a signal that is more consistent and higher in amplitude.

Channel #	Muscle(s)	Limb motion(s)
1	Flexor carpi radialis	Wrist flexion
2	Extensor carpi ulnaris	Wrist extension
3	Brachioradialis	Wrist flexion
4	In between brachioradialis and flexor carpi radialis	Wrist flexion
5	Flexor carpi ulnaris	Wrist flexion
6	Extensor digitorum	Wrist extension, Hand open
7	In between extensor carpi ulnaris and flexor carpi ulnaris	Wrist flexion, Wrist extension
8	Biceps	Supination

Table 1: Primary Limb Motion(s)

B. Effect of AR order and number of channels:

There is a common ground that ties both the AR order and number of channels. Increasing the AR order or the number of channels has an adverse effect on CA beyond a particular optimal point; for the data in this study, the optimal AR model order was 7 and the optimal number of channels was 7 as well. Increasing AR order or number of channels provides additional information to the classification system and should theoretically increase CA, or at least not be a detriment to the system; however, this theory fails in practice, because the introduction of additional information also increases the variability of training data. Beyond a certain point, the additional information will provide little redundant information, which would require additional training data to reduce the effects of the training data variability necessary to make this non-redundant information useful. The potential increase is CA may be outweighed by the increase required in training data and hence training time.

Figure 4 shows distribution of the number of subjects over different CA ranges (AR order 7 with 7 channels of data). All the subjects show the CA above 75% and there is a large majority of the subjects (just over 75%) that have a CA above 90%. As noted earlier, the MES data for subject 5 did not show any muscle activity for supination and hence repeated all four sessions. This subject improved CA from 81.66% to 92.27% for session 4. There is a high probability of subjects with a CA lower than 90% significantly improving by having subjects undertake more training to learn to perform limb motions with increased consistency.

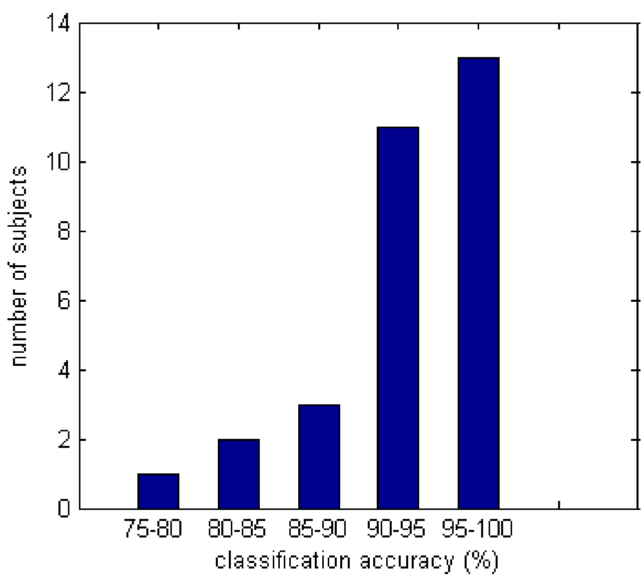

Figure 4: Distribution of subjects over classification accuracy

IV. CONCLUSION

A high degree of classification accuracy (92.64%) is obtained using autoregression (AR) as the feature set at the AR order 7, using all eight channels. This is an optimal value after which any increase in the AR order decrease the classification accuracy.

Increasing number of channels increases the classification accuracy up to a certain point. The highest classification accuracy of 92.84% is found at 7 channels. Increasing the number of channels beyond 7 decreases the classification accuracy, albeit a small amount (0.22%). It is also important to note that even with only four channels of MES, classification accuracy is excess of 90% is still possible.

This dataset establishes a good database that will enable comparisons of other signal features such as root mean square and waveform length transform. Collecting data across multiple sessions and trials also enables the investigation of inter and intra-test variability to further improve the classification accuracy for myoelectrically controlled prostheses.

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