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Effects of Interelectrode Distance on the Robustness of Myoelectric Pattern Recognition Systems

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***Abstract*—Myoelectric pattern recognition control can potentially provide upper limb amputees with intuitive control of multiple prosthetic functions. However, the lack of robustness of myoelectric pattern recognition algorithms is a barrier for clinical implementation. One issue that can contribute to poor system performance is electrode shift, which is a change in the location of the electrodes with respect to the underlying muscles that occurs during donning and doffing and daily use. We investigated the effects of interelectrode distance and feature choice on system performance in the presence of electrode shift. Increasing the interelectrode distance from 2 cm to 4 cm significantly (p<0.01) improved classification accuracy in the presence of electrode shifts of up to 2 cm. In a controllability test, increasing the interelectrode distance from 2 cm to 4 cm improved the user's ability to control a virtual prosthesis in the presence of electrode shift. Use of an autoregressive feature set significantly (p<0.01) reduced sensitivity to electrode shift when compared to use of a traditional time-domain feature set.**

I. INTRODUCTION

ELECTROMYOGRAPHIC (EMG) signals have been used for decades to control prosthetic devices. In conventional EMG control systems, the amplitude of the EMG signal is mapped to an actuated degree of freedom [1]. This control scheme has gained widespread clinical acceptance, but is limited to control of one or two degrees of freedom, due to the limited independence of signal sources [2-4].

Pattern recognition for upper extremity prosthesis control has recently received considerable attention [5-8] but has not yet been clinically implemented. This control scheme has the potential to restore control of a greater number of degrees of freedom than conventional EMG control by combining information across multiple signal sources. Pattern recognition relies on the user to produce distinct, repeatable EMG signal patterns for each motion class [6], which is a reasonable requirement for experienced users. Lack of long-term robustness is a significant difficulty for clinical implementation. One major cause of system degradation is electrode shift, which has been shown to have a detrimental effect on myoelectric pattern recognition [9-11]. Electrodes are typically embedded in the prosthetic socket and may shift with respect to the underlying muscle as a user moves the limb and during prosthesis donning and doffing. Currently, the only strategies to deal with electrode shift are to train the system at the expected displacement locations [10] or to retrain the classifier entirely after electrode shift. The former requires a considerable amount of time and effort during training, since the electrodes have to be placed at the expected displacement locations, and the latter is a significant daily time burden on the user.

This study is part of an ongoing effort to increase the reliability of myoelectric pattern recognition systems in the presence of electrode shift [12]. Interelectrode distance (pole-to-pole spacing of a bipolar electrode pair) is an important property of the EMG signal detection interface. The typical clinical interelectrode distance is 2 cm; this value was selected in order to minimize muscle signal crosstalk [13]. The interelectrode distance affects the pickup volume of the EMG detection system [14] such that larger interelectrode distances yield greater pickup volumes. With a larger pickup volume, the chances for muscle signal crosstalk increase, but the relative magnitude of electrode shift relative to the electrode detection volume decreases, potentially reducing the effects of electrode shift. Also, the intramuscular cross-talk contributes relatively equally at shifted locations, thus providing a useful discriminatory signal when electrodes are shifted. In this study, we analyzed the effect of interelectrode distance on pattern recognition algorithms in the presence of electrode shift by measuring both classification error and online controllability as quantification metrics.

A number of studies have investigated feature extraction from myoelectric signals [11], [15], [16]. Time-domain (TD) features are computationally efficient to compute, but autoregressive (AR) features have been shown to be the most effective [16]. A combined time-domain and autoregressive feature set may perform slightly better [15]. In this study, we investigated each of these feature sets and their effect on classification error in the presence of electrode shift.

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II. METHODS

A. Data Collection

Surface EMG recordings were collected from seven non-amputee subjects for seven motion classes. Two control sites were used with one site on the forearm extensor muscles and one site on the forearm flexor muscles. At each control site, two surface Ag/AgCl EMG electrodes (Bio-Medical Instruments) were placed longitudinally in the direction of the underlying forearm muscle fibers forming two bipolar electrode channels.

Training and testing data were initially recorded at the nonshifted electrode locations for three interelectrode distances. Data were recorded for seven motion classes: wrist flexion, wrist extension, hand open, hand close, forearm pronation, forearm supination, and a relaxed (or *no motion*) class with two repetitions each per trial in random order. Subjects performed isometric contractions for 4 s, producing a total of 16 s of training data and 16 s of testing data at each of the three nonshifted locations.

Data on each side of the arm were collected at nine different electrode configurations. The three interelectrode distances tested were 2 cm, 3 cm, and 4 cm. These distances were created by moving the distal electrode of each bipolar pair (Fig. 1). Electrode shifts were performed in a direction perpendicular to the underlying muscle fibers (clockwise from the user's perspective) at distances of 1 and 2 cm (see Fig. 1). Shifts were only tested in the perpendicular direction because previous research indicated that this had the greatest effect on pattern recognition performance [12]. Testing data were collected at all three electrode interelectrode distances for the no-shift, 1 cm shift, and 2 cm shift conditions. The order of collection across these configurations was randomized for each subject.

The Target Achievement Control (TAC) test was used to assess controllability. This test prompts the user to move a virtual hand to designated postures and gives real-time visual feedback of the virtual arm's position. Full descriptions of this test are provided elsewhere [17], [18]. In this study, each prompted posture required the user to perform only one motion class, but all seven classes were active at all times. Subjects were therefore forced to correct for any extraneous movements in order to reach the target posture. Each target posture required subjects to move the virtual prosthesis through 75 degrees of motion into a target zone. Once there, the virtual hand changed color and subjects had to dwell within the target zone for 2 s to complete a trial. Performance was measured in terms of completion rate (the percentage of trials successfully completed) and completion time (the average time across all motions to complete a trial). One test consisted of 12 trials in which each of the six motion classes was completed twice. One TAC test was performed with electrodes arranged at four orientations: no shift and 2 cm shift with both the 2 cm and 4 cm interelectrode distances. Only four of the nine locations were tested for controllability due to long experimental times.

B. EMG Signal Processing

EMG signals were preprocessed by amplification (~2000x) and high-pass filtering (20 Hz cutoff frequency). Data were segmented into 250 ms windows with 50 ms of overlap [17]. TD and AR features were extracted from the EMG signals. The TD feature set included mean absolute value, zero crossings, slope sign changes, and waveform length. The AR feature set included the mean absolute value and the six coefficients of a 6^{th} order autoregressive model, which was selected based on previous related work [15]. Linear discriminant analysis was used for feature classification because of its computational efficiency and comparable performance to other classification techniques [16].

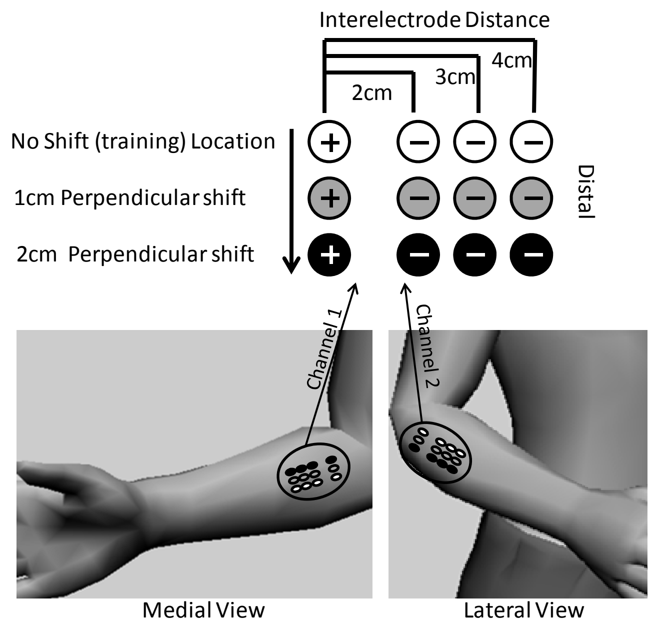

Fig. 1. Shift and training locations of electrodes for two channels. Electrodes were shifted during the experiment such that the proximal electrode (left column in figure indicated by + signs) moved only perpendicularly through three locations (no shift, 1cm, and 2cm). The distal electrode was moved distally for larger interelectrode distances and perpendicularly for shifted locations through nine locations (each location is indicated by a – sign for each electrode). Channel 1 was located on the flexor muscles, and channel 2 was located on the extensor muscles with the same electrode placements as those shown.

Many feature sets have been used in the literature to classify myoelectric signals. TD features were used for controllability testing due to the ease of implementation in real-time systems. However, other feature sets such as AR features may improve the robustness of pattern recognition systems and were investigated here offline.

III. RESULTS

A. A Comparison of Interelectrode Distances

The performance of three interelectrode distances was compared in terms of classification error using TD features. In all cases, classification error rose with greater shift distance ($p<0.01$). At all three test locations—no shift, 1 cm shift, and 2 cm shift—larger interelectrode distance decreased classification error (Fig. 2). Based on a post-hoc Bonferronni test, the 4 cm interelectrode distance performed better overall than the 3 cm ($p<0.05$) and 2 cm ($p<0.01$) interelectrode distances. The 2 cm and 3 cm groups were not statistically different ($p = 0.329$) in this study.

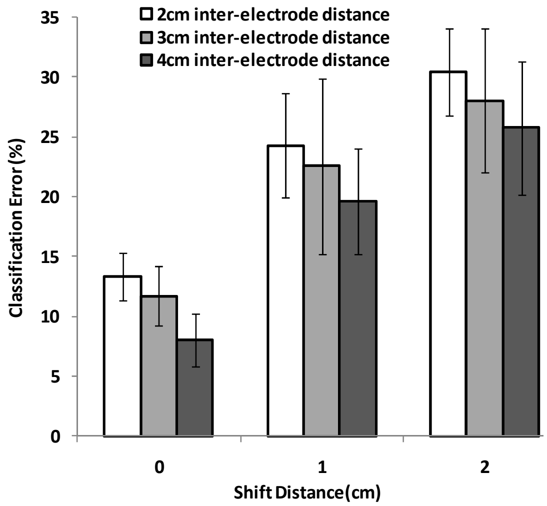

Fig. 2. Effect of interelectrode distance on classification error using TD features. Classification errors were averaged over seven subjects. A shift distance of 0 corresponds to classification error at the training location. Error bars show +/- 1 SEM.

For the controllability tests, interelectrode distance made little impact in the absence of electrode shift: completion rates and completion times were nearly the same for 2 cm and 4 cm electrode spacing at the no shift location (Fig. 3). At the 2 cm shift location, completion rates were 20% higher (Fig. 3a), and completion times were over 2 s faster (Fig. 3b) with 4 cm interelectrode distance compared to 2 cm interelectrode distance.

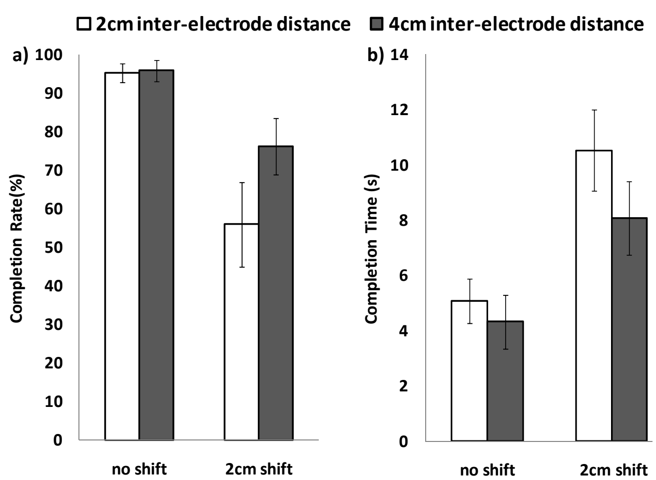

Fig. 3. Effect of interelectrode distance on system controllability in the presence of electrode shift. TAC test completion rates (a) and completion times (b) for tests conducted with electrodes at the no shift and 2 cm shift locations for interelectrode distances of 2 cm and 4 cm using TD features. Results are averaged over seven subjects with one outlier at the no shift location removed. Error bars show +/- 1 SEM.

B. Feature Set Comparisons

Classification performance resulting from use of AR and TDAR feature sets was compared to use of the TD feature set for both the 2 cm and 4 cm interelectrode distances (Fig. 4). Use of TDAR features resulted in the lowest classification error, use of AR features resulted in the next lowest classification error, and use of TD features resulted in the highest error for both 2 cm and 4 cm interelectrode distances at no shift, 1 cm shift, and 2 cm shift locations. Also, the 4 cm interelectrode distance performed better than the 2 cm interelectrode distance regardless of feature choice. Based on a post-hoc Bonferronni test, the AR and TDAR feature groups performed significantly ($p<0.05$) better than the TD feature set.

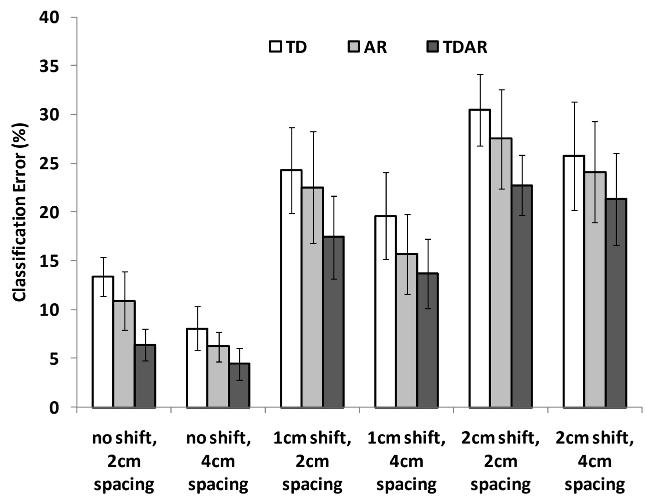

Fig. 4. Effect of feature set on classification error. Time domain (TD), autoregressive (AR) and a combination of time domain and autoregressive (TDAR) features were compared for 2 cm and 4 cm interelectrode distances (spacing). Results are an average of 7 subjects. Error bars show +/- 1 SEM.

IV. DISCUSSION

Electrode shift significantly degrades pattern recognition system performance, as demonstrated by real-time controllability tests and classification error. A shift of 2 cm was considered to be a worst-case scenario in practical use. With the standard interelectrode spacing of 2 cm, this shift degraded a classifier with high controllability (>90% completion rates) to one with low controllability (<60% completion rate). These results demonstrate the clear need for strategies to increase the robustness of pattern recognition interfaces to electrode displacement.

Increasing the interelectrode distance resulted in a larger pick-up volume and helped to improve the robustness of the system to electrode shift as measured by both classification error and real-time controllability. Therefore, we recommend using larger interelectrode distances up to 4 cm.

The selection of EMG feature set also affects the robustness of the pattern recognition system. Use of AR and TDAR feature sets significantly improved the pattern recognition system in the presence and absence of electrode shift. The average decrease in classification error resulting from use of TDAR features as opposed to TD features was

5.9% on average across all testing conditions.

The most robust classifier in this study resulted from use of TDAR features and a 4 cm interelectrode distance. These two properties of the EMG signal detection system decreased classification error both independently and cumulatively, as demonstrated in Fig. 4.

One notable limitation of this study was that only two EMG channels were recorded—a low number compared to other myoelectric pattern recognition studies. Future work will focus on the effect of the number of channels and specific electrode configurations to increase system robustness in the face of electrode shift. The interaction between these two properties and the interelectrode distance and feature sets presented in this study will also be addressed.

Overall we have found that electrode shift significantly decreases the robustness of pattern recognition in terms of both classification error (Figs. 2 and 4) and controllability (Fig. 3). However, based on the results presented in this paper, we recommend utilizing wider interelectrode distances combined with TDAR features to increase robustness of pattern recognition systems to electrode shift.

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