Published in final edited form as:

IEEE Trans Biomed Eng. 2011 September ; 58(9): 2537–2544. doi:10.1109/TBME.2011.2159216.

The Effects of Electrode Size and Orientation on the Sensitivity of Myoelectric Pattern Recognition Systems to Electrode Shift

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Abstract

Myoelectric pattern recognition systems for prosthesis control are often studied in controlled laboratory settings, but obstacles remain to be addressed before they are clinically viable. One important obstacle is the difficulty of maintaining system usability with socket misalignment. Misalignment inevitably occurs during prosthesis donning and doffing, producing a shift in electrode contact locations. We investigated how the size of the electrode detection surface and placement of electrode poles (electrode orientation) affected system robustness with electrode shift. Electrodes oriented parallel to muscle fibers outperformed electrodes oriented perpendicular to muscle fibers in both shift and no-shift conditions ($p < 0.01$). Another finding was the significant difference ($p < 0.01$) in performance for the direction of electrode shift. Shifts perpendicular to the muscle fibers reduced classification accuracy and real-time controllability much more than shifts parallel to the muscle fibers. Increasing the size of the electrode detection surface was found to help reduce classification accuracy sensitivity to electrode shifts in a direction perpendicular to the muscle fibers but did not improve the real-time controllability of the pattern recognition system. One clinically important result was that a combination of longitudinal and transverse electrodes yielded high controllability with and without electrode shift using only four physical electrode pole locations.

Index Terms

Electrode Shift; Electromyography (EMG); Pattern Recognition; Virtual reality prosthesis control

I. Introduction

Amputation is a major cause of disability throughout the world, yet commercially available myoelectric prostheses provide only limited functionality to amputees. In a typical clinical setup, EMG signals are detected by bipolar electrodes oriented parallel to muscle fibers, and the magnitude [1] or slope [2] of the detected EMG signal is used to control the prosthesis. This type of control scheme has received widespread clinical acceptance but provides limited functionality. Typically, only one or two degrees of freedom (DOF) can be controlled through electromyographic (EMG) control sites and mechanical switches [3–5]. At least one, and sometimes two, independent EMG control sites are required for each DOF. This limitation is especially troublesome for higher level amputees because fewer remaining control sites are available and more functionality needs to be restored.

Pattern recognition of EMG signals for myoelectric control is an active area of research that can potentially restore greater functionality than conventional control techniques. It is based on the premise that amputees can voluntarily activate repeatable and distinct EMG signal patterns for each class of motion. These signal patterns can then be mapped to physiologically appropriate prosthesis commands. The pattern recognition procedure can be broken down into three broad steps [3]: (1) signal detection, (2) signal representation, and (3) signal classification.

Signal representation (step 2) and signal classification (step 3) have been investigated in detail in a large number of studies [6–18]. Many combinations of feature sets and classifiers can be used to effectively represent multi-channel EMG signal patterns. One such computationally efficient combination is time-domain (TD) features classified by a linear discriminant analysis (LDA). This specific pattern recognition scheme has been described in detail [19], has been shown to yield efficient and effective real-time control [20, 21]. In this paper, classification using LDA is compared to a non-linear, artificial neural network that has been used in previous myoelectric pattern recognition studies [6, 11, 13, 22].

Although promising results have been demonstrated in laboratory settings, pattern recognition has yet to receive widespread clinical application. One barrier to clinical acceptance is concern over long-term system robustness. Over days or weeks of use, misalignment of the socket with respect to the residual limb may cause a change in electrode recording locations. These electrode shifts are likely to occur each time the user dons the device.

The effect of electrode shift on myoelectric pattern recognition has been previously studied with mixed results [6, 23, 24]. Hudgins et al. [6] used an untraditional electrode orientation in which one electrode pole was placed on the biceps and the other on the triceps. Using only this widely-spaced EMG channel, they found that electrode shifts in any direction had very little effect on pattern recognition accuracy. Hargrove et al. [23] found different results using five electrodes oriented parallel to the muscle fibers. The pattern recognition system trained with traditional electrode orientations was very sensitive to electrode displacement in all directions as measured by a reduction in classification accuracy. Hargrove suggested that the Hudgin's widely-spaced transverse electrode pair contained a more global measure of

EMG activity due to the larger pickup area than that of the longitudinal electrode orientation. The magnitude of electrode shift relative to the magnitude of the pickup area was larger for the longitudinal orientation, potentially explaining the decrease in classification accuracy with electrode shift. Hargrove demonstrated that the effect of electrode shift can be mitigated by training at all expected displacement locations [24]. However, this is an inconvenient solution which requires a considerable amount of time and effort since the electrodes have to be moved to expected displacement locations during training.

In this study, we investigated two parameter changes in signal detection (step 1) to reduce misclassifications associated with electrode shift. We investigated how the placement of electrode poles (transversely versus longitudinally oriented electrode pairs) affected offline classification error and online controllability score in the presence of shift. In this study, we refer to transverse electrodes as consisting of a bipolar electrode pair with one pole on a flexor muscle group and another pole on an extensor muscle group. Our results demonstrated that the transverse orientation was more sensitive to shift than the longitudinal orientation. We also investigated how the size of the electrode detection surface affected myoelectric pattern recognition degradation due to shift. Increasing electrode size reduced classification accuracy sensitivity to electrode shift but made the pattern recognition system less controllable at the non-shifted location.

II. BACKGROUND

The origin of the EMG signal is the depolarization and repolarization of the muscle fiber cell membrane during a contraction. This change causes ionic currents to circulate, creating measurable action potentials in the body [25]. Surface EMG signals are stochastic in nature and are comprised of the spatiotemporal supposition of the motor unit action potentials. These action potentials reside within the electrode pick-up area, and the detected voltage is the summation of individual motor unit action potentials [26]. The pick-up area of a bipolar EMG channel is determined by the size of the electrode detection surface and pole spacing distance.

The placement of the recording electrodes significantly affects the surface EMG waveform [27]. This effect is most important in relation to the underlying innervations zones which can produce artifact in EMG recordings during dynamic contractions [28]. The location of recording electrodes in relation to the innervation zones also affects features of the EMG signal, especially the frequency characteristics [29, 30]. One study has mapped the innervation zones of the forearm muscles [31], demonstrating the difficulty of targeting electrode positions near innervation zones corresponding to specific muscles. However, the targeting of specific muscles for pattern recognition control to achieve greater signal independence has been shown to make no improvements over simply evenly spacing electrodes around the forearm [18].

According to SENIAM (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) guidelines [32], bipolar electrodes should be oriented longitudinally with muscle fibers. The recommended size is a 10 mm diameter electrode. This size is small enough to

avoid most of the crosstalk from surrounding muscles while still large enough to pick up from a pool of motor units. The recommended electrode spacing is a distance of 2 cm between the centers of the electrode poles. These guidelines are followed whenever practical for conventional myoelectric control which relies on selective measurements from individual muscles.

The SENIAM guidelines may not be optimal for pattern recognition based control schemes. Contributions from other muscles that are recorded are typically undesirable in conventional control schemes. However, this inter-muscular crosstalk may add useful discriminatory information that can be extracted in pattern recognition control schemes [13, 33]. The global activity of a muscle group can be recorded by having large electrode sizes as this decreases muscle selectivity [27]. For larger detection surfaces, the electrode shift relative to the electrode pickup becomes smaller; and thus may reduce the effects of electrode shift.

III. METHODS

Seven healthy subjects (three males and four females, mean age of 29 years $\pm$ 3 years) completed the experiment that had been approved by the Northwestern University Institutional Review Board. Based on preliminary work, seven subjects were selected using a power analysis with a difference of means of 5% classification error. Two control sites were located for each subject on the forearm through palpation during wrist flexion and extension test contractions. Reusable, self-adhesive carbon electrodes from National Medical Alliance were used for this experiment. Two of these surface electrodes (square shaped with a 1 cm² surface area) were placed longitudinally along both the flexor and extensor muscles with an inter-electrode distance of 4 cm. A ground electrode was placed on a bony region on the elbow and away from the muscles of interest. Four differential EMG channels were formed from the four electrodes (Fig. 1): one longitudinal pair along the forearm extensor muscle group, one longitudinal pair along the forearm flexor muscle, one transverse pair consisting of the proximal flexor pole and the proximal extensor pole, and one transverse pair consisting of the distal flexor pole and the distal extensor pole. The data were amplified by a factor of 800x using research electrodes purchased from Liberating Technologies, Inc. A second gain stage multiplied the signal amplitude by an additional 6x, yielding approximately a 2400x total gain. Data were digitally sampled at 1000 Hz using a 16 bit A/D converter and high pass filtered at 20 Hz using a 3rd order Butterworth filter to reduce motion artifact.

Training data were recorded at this non-shifted electrode location. Internally developed computer software called Control Algorithms for Prosthetics (CAPS) [20] was used to prompt each user to perform two repetitions of the following seven different motion classes: wrist flexion, wrist extension, forearm pronation, forearm supination, hand open, hand close and a relaxed or no motion class in a random order. Subjects held the contractions for 4 s and were instructed to make repeatable, constant-force contractions to the best of their ability. Four sets of data were collected, two for training and two for testing, yielding a total of eight repetitions of each of the seven motion classes.

Three separate pattern recognition classifiers were trained using different combinations of the four recorded channels. One classifier was trained with the two longitudinal channels, the second was trained with the two transverse channels, and the third was trained with both two longitudinal and two transverse channels. In each case, data pre-processing consisted of segmenting the data into 250 ms windows with 50 ms overlap [19, 34]. An LDA classifier was trained using time-domain features including mean absolute value, zero crossings, slope sign changes, and waveform length [6]. The classifier was trained using 16 s of data from each class and tested using a different 16 s of data from each class. This combination of classifier and feature set has been used extensively in real-time myoelectric control experiments [19, 20, 35].

The performance of the LDA classifier was compared to a multilayer perceptron (MLP) neural network. For this comparison, all four recording channels were used along with time domain features. A similar approach to Oskoei and Hu [22] was used to train the MLP. A feed-forward back propagation network was trained and adjusted on a per subject basis. A variable number of nodes in the single hidden layer were tested: 4, 6, 8, 10, 12, 15, and 20. Due to the problem of convergence to local minima, the neural network was trained and tested 25 times for each number of nodes in the hidden layer for each subject (a total of 175 test networks per subject). The best MLP classifier was selected for each subject as the one that minimized classification error at the no shift location.

We collected testing data from five different locations for each user. These five locations included the non-shifted location, 1 cm and 2 cm shifts parallel to the muscle fibers and distal to the elbow joint, and 1 cm and 2 cm shifts perpendicular to the underlying muscle fibers. For each testing location, all four electrodes were taken off and placed at the new location. The same amount of testing data was collected as training data at the non-shifted location and used to calculate offline classification error. Additionally, the Target Achievement Control (TAC) Test [34] was conducted at the training location and both of the 2 cm shift locations. The TAC Test prompted the user to move a virtual limb to one of six predetermined target postures. Real-time performance was measured in terms of user completion rate which is the percentage of trials the user successfully completed.

The entire experimental procedure for each subject was repeated for each electrode size using the same set of electrodes (trimmed to the proper size each time). Three different square detection surface sizes were tested including 9 cm² (3 cm x 3 cm), 4 cm² (2 cm x 2 cm) and 1 cm² (1 cm x 1 cm).

Differences in offline performance were analyzed with a General Linear Model (GLM) using classification error as the response variable and subject as a random factor. Shift distance, shift direction, electrode size and electrode orientation were input as fixed factors. Additional post-hoc comparisons with a Bonferroni correction were analyzed for each statistically significant factor of interest. The Gaussian distribution assumption was justified based on a normal probability plot of the residuals. A secondary investigation conducted in this experiment was determining the effect of classification accuracy on controllability. This was done through a linear regression model and differences in online performance were analyzed using a second General Linear Model using completion rate as a response variable,

classification accuracy as a covariate and subject as a random factor. Testing location, electrode size and electrode orientation were input as fixed factors.

IV. RESULTS

A. Analysis 1: A Comparison of Longitudinal versus Transverse Channel Orientation

The performance of the two longitudinal channels was compared to the two transverse channels in terms of classification error.

In all cases, electrode shift increased classification errors (Fig. 2). Classification error was reduced for the longitudinal channels compared to the transverse channels at all test locations. These two electrode orientations were significantly different (GLM: $p < 0.01$). The direction of electrode shift was found to be a significant factor (GLM: $p < 0.01$) with perpendicular shifts resulting in higher classification errors compared to parallel shifts.

TAC Test completion rates with the longitudinal electrode orientation were 95% (S.E.: 6.6%) with no shift, 70% (S.E.: 15%) with 2 cm parallel shift and a 42% (S.E.: 13%) with a 2 cm perpendicular shift. Similar to classification error, the decrease in controllability was larger with perpendicular shifts compared to parallel shifts across all subjects.

B. Analysis 2: Combined Effect of Transverse and Longitudinal Channels

The results for combining both longitudinal and transverse channels are displayed in Fig. 3. The use of both types of channels in the pattern recognition scheme significantly decreased classification error at all five locations (GLM: $p < 0.01$) in comparison to using only the longitudinal or only the transverse channels. The controllability test also demonstrated improved performance. TAC Test completion rates with the combined configuration were 98% (S.E.: 2.4%) with no shift, 96% (S.E.: 3.6%) with 2 cm parallel shift and a 67% (S.E.: 12%) with a 2 cm perpendicular shift. Notably, a shift of 2 cm parallel to muscle had little effect on controllability scores, while a shift of 2 cm perpendicular to muscle had a sizeable drop in controllability and an increase in classification error.

The results for the MLP classifier are also displayed in Fig. 3. These demonstrate that a non-linear classifier such as a MLP does not outperform a LDA. The MLP did not generalize as well as the LDA at any of the shift locations.

C. Analysis 3: Electrode Size results

The results for the effects of the three electrode sizes tested are displayed in Fig. 4. Based on classification error, the larger sized electrodes performed worse at the non-shifted location and with parallel shifts (Fig. 4a), but there were no statistically significant differences between sizes with parallel shifts. The results of the General Linear Model indicated that there was an interaction between electrode size and shift direction ($p < 0.01$). Post-hoc comparisons between sizes showed that the largest size electrode was less sensitive to perpendicular shifts ($p < 0.05$) than the smaller sized electrodes (Fig. 4b).

At the non-shifted location, fewer trials of the TAC test were successfully completed using the largest size electrodes (Fig. 5). Completion rates for the largest size electrodes did not

further decrease at either the 2 cm parallel or 2 cm perpendicular shift locations compared to the non-shifted location. The medium size electrode performed well at the no-shift location and 2cm parallel shift locations (>80% completion rates), but the completion rate dropped to approximately 45% at a 2cm perpendicular shift. The small size electrode performed well at the training location (>90% completion rate), but completion rates dropped to 70% with a 2cm parallel shift and 44% at a 2cm perpendicular shift.

D. Investigation of the Effect of Classification Error on Controllability

The effect of classification error on controllability is displayed in Fig. 6. Based on a linear fit of the data, an R^2 value of 0.53 was found which demonstrates a correlation between the variables. A 3% increase in classification error corresponded to approximately a 2% decrease in completion rate scores. A trend is observed that low classification errors (<10%) led to high controllability scores across users and high classification errors (>35%) led to low controllability scores. Primarily, the intermediate scores (between 10–35% classification error) resulted in highly variable controllability scores. We believe that some subjects are able to adapt their contraction patterns in these intermediate classification error ranges to maintain control the prosthesis. The General Linear Model for completion rates found that classification accuracy was a highly significant covariate of completion rate ($p<0.01$). Also subject ($p<0.01$) and electrode orientation ($p<0.05$) were found to be significant.

V. DISCUSSION

The longitudinally oriented channels had lower classification errors compared to the transverse channels in all conditions (Fig. 2). The longitudinal channels recorded from two separate muscle groups each of which provided distinct information. There was likely redundant information between channels T1 and T2 because each channel contained a pole on the flexor group and the extensor group. We expected the transverse channels to be less sensitive to shift than what was found in this study. The longitudinal channels had a similar sensitivity to previous studies [24], but the transverse channels were more sensitive [6]. This may be because the small muscles of the forearm are closely spaced amongst each other; and therefore, even a small shift of up to 2cm may have changed the muscle which one or more of the electrode poles were recording EMG signals. The discriminatory information added by the transverse channels was complementary to the information contained in the longitudinal channels; the total classification error was lower when all four channels were used in the pattern recognition system (Fig. 3). The four channel system remained sensitive to electrode shift; however, at shifts of 1 cm, the classification error was very similar to the longitudinal channels only without any electrode shift. Based on this study, the addition of transverse channels may be useful for pattern recognition systems, but further work needs to be performed to quantify the addition of transverse channels compared to additional longitudinal channels.

All electrode shifts significantly increased classification error, but perpendicular electrode shifts increased classification error more than parallel shifts for all electrode sizes and configurations. The same trend was also found to apply to TAC Tests results; shifts in either direction reduced motion completion rate but shifts in the perpendicular direction had more of an impact. These results can be explained by considering that action potentials travel

along the muscle. Shifts parallel to the muscle fibers will sample the same muscle fibers but at different locations. The signals remain similar so long as the electrodes do not shift across the innervation zone. In contrast, shifts perpendicular to the muscle fiber result in a sampling of different motor units and likely yield different interference patterns. Consequently, the muscle activation patterns recorded from parallel shifts are much more similar than those recorded from perpendicular shifts, which enables the classifier to better discriminate classes with a parallel shift.

Previous studies have shown that there is little difference in terms of classification error between different types of classifiers for myoelectric pattern recognition [13, 22, 36]. Often, the choice of classifier has made no difference in terms of classification error, and we found a similar result in this study with no electrode shift. However, with electrode shift we found that the MLP did not generalize as well, indicating that a MLP classifier may not be as robust to the changes that occur to the myoelectric signal when electrodes are misaligned compared to an LDA classifier unless some form of online adaptation was incorporated into the control system design.

This experiment found that large electrode sizes are significantly ($p < 0.05$) less sensitive to electrode shift in the direction perpendicular to muscles. These results are likely because even with a 2 cm shift, the largest sized electrode was still recording from a portion of the skin's area from the non-shifted location. One-third of the area (3cm^2) of the largest electrode still covered the area that the classifier had originally been trained at. In contrast, at a 2 cm shift, the medium and small sized electrodes were no longer sampling from any of the non-shifted location's area. Large electrodes yield a system that is slightly, but not statistically significant, less accurate (Fig. 4) and less controllable (Fig. 5) at the non-shifted location. This likely occurred because larger electrodes detect less selective signals, and this loss in selectivity decreased the ability of the classifier to discriminate motion classes. Given this tradeoff we do not recommend using a large sized detection surface because the sacrifice in controllability at the non-shifted locations outweighs the benefit of maintaining the controllability at large shift locations which would unlikely be encountered during normal operation.

One confounding factor in this experiment was the large inter-electrode spacing. The inter-electrode spacing was set at 4 cm for all sizes which is larger than spacing normally used in EMG studies. We wanted to keep the inter-electrode spacing between all sizes consistent, and we needed 4 cm to ensure that the largest electrodes did not overlap. The larger spacing may have decreased the system's sensitivity to electrode shift because larger spacing has a wider pick-up area. A future experiment will quantify the effects of the inter-electrode spacing.

There were a number of limitations to this study that are important. One limitation was that this experiment was performed only on forearm muscles of healthy subjects. We believe the trends demonstrated in this experiment are likely relevant to amputee subjects assuming that the subject has sufficient residual muscles over which to place the electrodes of the sizes and orientations (i.e. longitudinal) analyzed in this study. Future research on amputee subjects is needed to verify these findings. Also, these results are likely relevant to other agonist/

antagonist muscles pairs (such as the biceps/triceps) because the electrode detection interface (such as parameters for size and electrode orientation) determines the nature of the EMG signals i.e. global or selective. This in turn contributes heavily to the sensitivity of the system to electrode shift, irrespective of which muscle groups are used for recording. Another limitation of this study was the virtual test. Virtual tests are useful because physical arm prostheses are not required. Such physical prostheses are expensive, limited in degree of freedom functionality, and there are no commercially available prostheses that can do pattern recognition. Conversely, the virtual test was limited because it does not model the physics, nor provide 3-D visualization of the environment both of which are important factors when using these devices clinically. A further limitation was that the effects of using only transverse channels was not tested with a controllability test due to experimental time restraints.

The probability density function of electrode shifts in clinical practice is not documented; however, skilled prosthetists create well fitting sockets that maintain consistent electrode placements. The 2 cm shift location tested in this experiment represents one of the worst possible shift conditions and may not be encountered during use. A shift of 1 cm (also tested in this experiment) or less is much more likely in clinical situations using modern fitting methods. Therefore, the controllability results demonstrated in this experiment at the 2 cm shift location are worse than what we would expect in a clinical situation and these shift locations were selected to demonstrate the loss in controllability due to electrode shift. Based on the relationship we found between classification error and controllability, and the classification error at 1 cm shifted locations, we expect controllability with smaller shifts encountered in practice to be considerably better than the controllability results at 2 cm.

Four channels were measured in this study from four poles (see Fig. 1) in order to compare longitudinal to transverse channel orientations. This is unusual in that four channels are typically recorded from eight poles. The performance of combining all four channels into one classifier was readily analyzed with this experimental setup. The system using four channels had very low classification error at the no shift location, and was resilient to electrode shift with parallel shift up to 2 cm and perpendicular shift up to 1 cm. This was a key finding in that more useful classification information can be recorded from the same pole locations, which decreases the physical number of electrodes necessary for myoelectric pattern recognition control. This is important for clinical robustness in terms of system maintenance and that fewer components are necessary.

This study used only a small number of recording channels. There is a growing interest in multichannel recording and interpretation within the field. However, there are advantages to studies that consider using a small number of channels and pole locations for myoelectric pattern recognition based control. First, signal processing must be implemented on a microcontroller in real time and occur on the order of milliseconds for adequate control, which is more easily accomplished using few channels rather than a large electrode array. Also, the poles must be incorporated into a prosthetic socket device which is a nontrivial task that becomes very difficult as more pole locations are included. Finally, in a study using a multichannel electrode array [37], it was found that bipolar electrodes compare closely in terms of classification accuracy with double differential electrode configurations and higher

order spatial filter electrode configurations. Also, since the higher order spatial filters record more selective EMG activity, then it is likely that these configurations would be more sensitive to electrode shift.

Many previous pattern recognition studies have looked at classification accuracy as the sole metric in analyzing a pattern recognition system. Recent efforts have also stressed relating classification error to real-time controllability [12, 20, 21, 34]. We found that the controllability scores of the TAC test were significantly ($p < 0.01$) correlated to the offline calculation of classification error which suggests that offline classification error is one important metric for describing the effectiveness of a given classifier.

VI. CONCLUSIONS

This research analyzed electrode interface parameters in terms of their robustness to electrode shift using myoelectric pattern recognition systems. We found that transverse oriented electrodes performed worse than longitudinal oriented electrodes both with and without shift. However, the transverse channels added complementary information to the longitudinal channels which improved classification errors. This is useful clinically because the same two electrode locations can provide sufficient control information at the non-shifted location using the four channels and also significantly more robust to electrode shift. Another finding of this research was that larger electrodes had the effect of reducing sensitivity to electrode shift, but are not necessarily advantageous for myoelectric pattern recognition systems due to the deleterious effects at the no-shift location. While the result may be intuitive, this was the first study to find that electrode shifts perpendicular to muscle fibers were far more damaging than parallel shifts to pattern recognition systems. Shifts up to 2cm were tested in this study, which are larger than expected in clinical situations; and therefore, the sharp decreases in controllability seen in this experiment are unlikely to be as severe in practice. Designs that utilize the suggested electrode interface parameters may be utilized to allow for greater controllability in situations that involve changing myoelectric signals such as electrode shift [35]. Finally, we have demonstrated that classification accuracy is correlated to controllability. This research found that systems with classification errors less than approximately 10% yield controllable systems whereas systems with classification errors greater than approximately 35% yield systems which are not controllable as measured through a TAC test.

Acknowledgments

This work was supported in part by the NIH under Grant R01-HD-05-8000 and this research was made with Government support under and awarded by DoD, Air Force Office of Scientific Research, National Defense Science and Engineering Graduate (NDSEG) Fellowship, 32 CFR 168a. A.J. Young was supported by NSF and NDSEG Graduate Research Fellowships.

The authors would like to acknowledge Ann Simon and Aimee Schultz for helping to revise and edit the manuscript.

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Four Bipolar Channels

Fig. 1. Diagram representing electrode setup. Channels L1 and L2 are the longitudinally oriented electrodes. Channels T1 and T2 are the transverse electrodes.

Fig. 2.

Effect of electrode orientation on classification error for the smallest-sized electrode (1 cm x 1 cm). Classification errors were averaged over seven subjects for the longitudinal (L) and transverse (T) electrode orientations. For each orientation, separate lines are shown for both directions of shift: parallel to muscle fibers (||) and perpendicular (⊥) to muscle fibers. A shift distance of 0 corresponds to testing at the no-shift location. Error bars show one standard error of the mean. Similar trends were seen for the other two electrode sizes.

Fig. 3.

Effect of combining transverse and longitudinal channels (L+T) on classification error for the smallest-sized electrode using LDA and MLP classifiers. Separate lines are shown for both directions of shift: parallel (||) to muscle fibers and perpendicular ($\perp$) to muscle fibers. Error bars show one standard error of the mean. Similar trends were seen for the other two electrode sizes.

Fig. 4. Effect of electrode size on classification error for a) parallel shift and b) perpendicular shift. Error bars show one standard error of the mean. A shift distance of 0 cm corresponds to testing at the no-shift location.

Fig. 5.

Effect of electrode size on TAC Test completion rates. Only the two longitudinal oriented electrodes were used to generate these results but the same trends hold for the four channel configuration. One outlier was removed at the training location for the largest sized electrode. Error bars show one standard error of the mean.

Fig. 6.

Effect of classification accuracy on controllability scores. Results for all three sizes and two electrode configurations are included. Darker points were TAC tests conducted using four channels; while hollow points were TAC tests conducted using two longitudinal channels. One outlier point was excluded.