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A technique for optimizing electrode placement for electromyographic control of prostheses

Scott H. Walbran, S*tudent Member, IEEE*, Emilio P. Calius, G. Reg Dunlop *SMIEEE*, Iain A. Anderson

Abstract—**We present a technique that enables optimization of Electromyographic (EMG) electrode placement for grasp recognition. Previous works have shown that sophisticated control techniques for prosthetic devices are becoming available; however the issue of electrode placement has yet to be addressed. By processing a rich field of data, it is possible to determine which of the data sets will allow for greatest accuracy in prosthetic control.**

Data has been collected and processed from 128 sites on a human forearm while two different grasps were performed. Using two different feature extraction techniques – integral of absolute value and differential absolute value – the difference in means between performing each grasp type has been analyzed. This resulted in several regions around the wrist and the elbow that would be optimal for this particular setup. While the optimization process has been used here for discrimination between two particular grasps, it has the potential to extend to any desired actuation pattern.

I. Introduction

With the increasing sophistication in prosthetic devices there is a need for better intention recognition and control. One approach to controlling advanced prostheses is to use surface EMG signals as an input. EMG measures the electrical potential disturbance caused when an action potential from a motor neuron causes a muscle fiber group to depolarize. Given the large volume of tissue that depolarizes, this produces a disturbance that is measurable through a spatial filter – the skin.

EMG has been used as a control signal previously and it is generally limited to providing on/off control. While it has been shown that EMG can be used to identify different grasps that the hand can form [1-3], or to control single fingers [4], the issue has been the number and location of electrode sites on the forearm. Generally, the electrodes are placed by trained personnel; this is highly subjective [1].

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S. H. Walbran is with the Auckland Bioengineering Institute, Auckland, 1010, NZ (corresponding author to provide phone: 006493737599 extension 85067; fax: 006493677157; e-mail: s.walbran@auckland.ac.nz).

E. P. Calius is with Industrial Research Limited, Parnell, Auckland, NZ.

G.R.Dunlop is with the Department of Electrical and Computer Engineering, University of Auckland, Auckland 1010.

I. A. Anderson is with the Auckland Bioengineering Institute, Auckland, 1010, NZ

Electromyographic recordings can be either unipolar or bipolar. Unipolar recordings are taken with reference to a single point, meaning that amplification must occur at a remote site. Bipolar recordings are taken between two sites in close proximity, so while they have no single reference site, amplification can occur at the recording site, before noise becomes introduced into the system. Bipolar recordings have greatly reduced noise, which is advantageous for practical prosthetic systems.

Previous work by the authors has shown that electrode sites can be optimized in order to provide maximum accuracy control actuation [5]. This is based on identifying the sites that provide the greatest difference in signal strength from resting to activation. In this paper, we extend this to identify the optimal sites for grasp control, between different grasp types.

II. Methods

Data was collected from a rich field of sites over the right forearm of a subject using a custom-designed silicone armband with embedded electrodes. The electrodes were referenced to a point on the elbow (i.e. the recordings were unipolar) and were passed through a Universal Electrophysiological Mapping (UnEmap) system, developed by the Bioengineering Institute of the University of Auckland for the filtering, amplification, measurement and processing of biopotential signals [6].

With the silicone armband secured on the forearm, data was recorded from 128 sites while the subject repeatedly performed either a pinch grasp, or a cylindrical grasp. These two grasps were chosen as a subset of the possible grasps the human hand can make. The data recordings were performed at a sampling rate of 5kHz, with the anti-aliasing filter set at 1kHz and the gain at 88.

Bipolar recordings were estimated from unipolar recordings by taking spatial derivatives, i.e. the rate of change of surface potential recordings with respect to their location on the forearm. As some of the electrode sites did not record useable data (due to poor contacts) some data points could not be used for calculating spatial derivatives, with different grasp data sets having different electrode sites available. Channels that had rail-to-rail variances were discarded as having poor contacts.

Signal processing was performed using a 4-step process. First the electrical mains noise was removed from the signal using a 3rd order Butterworth digital filter and matched filtering was performed. Features were then extracted to act as representative quantities for the signal, and finally a set of representative data points were chosen for comparison to be made between data sets. The cut-off frequencies for the digital band-stop filter were set at 45Hz and 55Hz. This ensured removal of the 50Hz mains noise without significant attenuation of the desired signal.

Matched filtering was performed by convolving the original signal with a time-reversed known action potential (AP) signal. This known AP signal was derived from the average of a series of action potentials detected using an automatic detection algorithm. The data used to find the AP was then cross correlated with the found AP, and was run through the automated detection algorithm again. This process was repeated until the action potential to be used as a template had converged to the result shown in Fig. 1. Matched filtering was then performed on the data from each channel. An example data set is shown in Fig. 2, along with the result of the matched filtering of that data set.

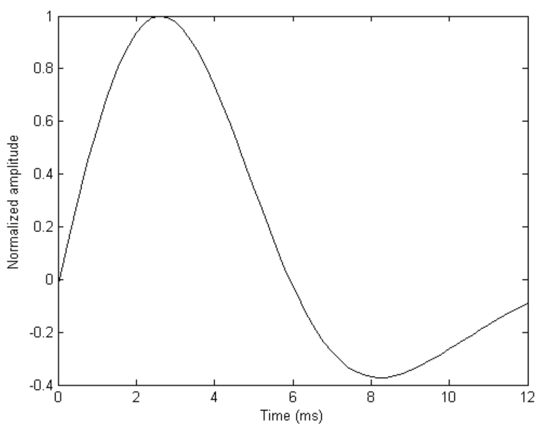
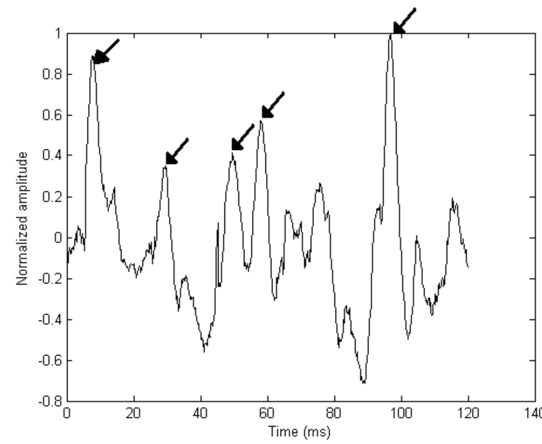


Fig. 1. Averaged, filtered action potential after iterative cross correlation.

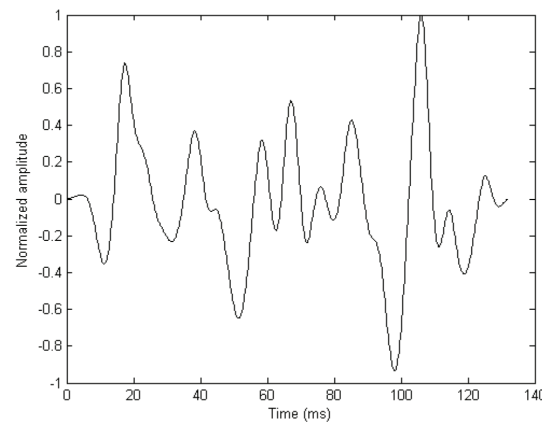
Two feature extraction techniques were used in order to gain different representations of the data.

The first feature extraction method, referred to as integral of absolute value (IAV) is:

1. Take the absolute value of the data.
2. For each time step, numerically calculate the definite integral of the data over 50ms either side of the current point.



(a)



(b)

Fig. 2. (a): Raw signal. Arrows indicate action potentials that are to be extracted. (b): Signal after matched filtering, note that the areas marked in (a) have become prominent.

The second feature extraction method, referred to as differential absolute value (DAV) is:

1. Take the absolute value of the data.
2. Using a windowing technique, find the peak value within each 11ms window of data. The 11ms window interval is based on the length of the result of cross correlating the known action potential with itself.
3. Low pass filter the data.
4. Numerically calculate the derivative of this data set.

From these extracted features, the spatial gradients in the circumferential and longitudinal forearm directions were calculated, using a simple 2-point approximation. To counter the loss of information at some sites due to poor electrode contacts the remaining data was interpolated to form a complete surface over the arm.

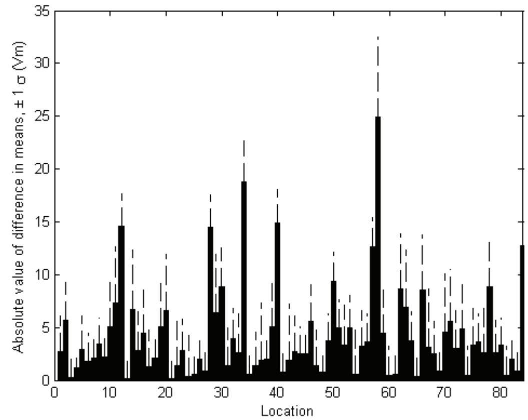


Fig. 3. Circumferential derivatives, using feature IAV

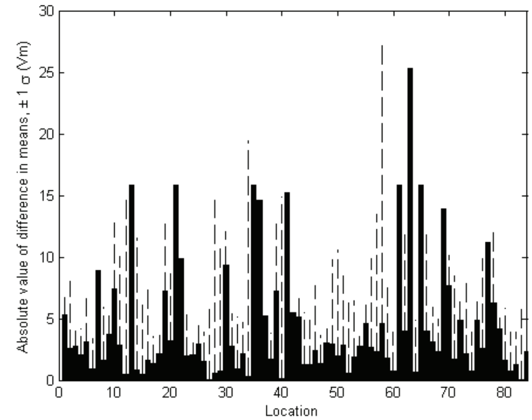


Fig. 4. Longitudinal derivatives, using feature IAV

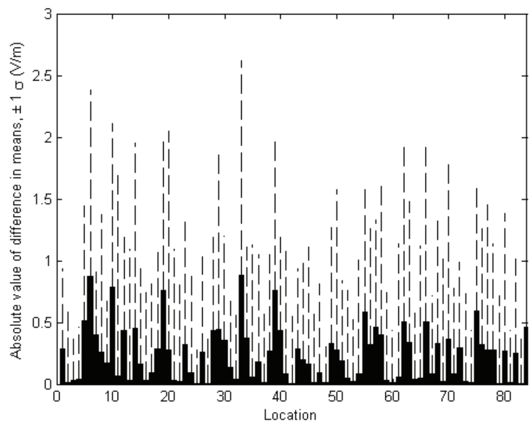


Fig. 5. Circumferential derivatives, using feature DAV

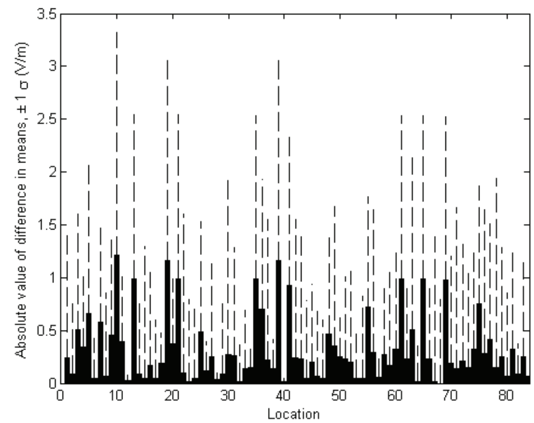


Fig.6. Longitudinal derivatives, using feature DAV

Finally, a series of representative time points were chosen for each grasp type, and the feature extraction method and derivative direction were computed. The difference of means infers the change in electrical activity when performing one grasp type as opposed to another. The difference of means between grasp types were calculated. The points where this difference was found to be highest were taken as the optimal electrode sites for this differentiating between the two grasps.

III. Results And Discussion

Statistical analysis of the data was carried out using R for Windows version 2.8.1. The Levene equal-variance test was used to check for equal variance between each grasp type, and in all cases there was extremely strong evidence that the variances were not equal. Using either feature, with derivatives taken in either direction did not change this result. As a result, the data was transformed. However after using a logarithmic transform, the data still did not have equal variance. As a result, 2-way Anova could not be performed. The final results are presented as the difference of means between grasp types.

The absolute value of difference in means for each location has been plotted in figures 3-6. The solid lines on these figures represent the differences in means, while the dashed lines represent difference in means + 1 standard deviation. Each location refers to a specific point in the arm, starting from a point just distal to the elbow (location 1) and heading to a point just proximal to the head of the ulna (location 6). The locations then move around the posterior surface of the forearm (counter-clockwise), such that locations 15-16 are in the middle of the extensor compartment, locations 32-33 are halfway along the radius bone, and locations 54-55 are in the middle of the flexor compartment. This means that in general, a location with a higher number will be further counter-clockwise from the ulna.

Some observations can be made from these Figures Firstly, the standard deviation of the difference of the means for feature DAV is generally much larger than for feature IAV. This indicates that measurement scatter will be higher for DAV and therefore this feature may not provide the best inter-grasp discrimination. Secondly, there are certain locations for each direction of derivatives that show reasonable difference in mean values for IAV.

In order to understand the physical representation of these results, the locations have been mapped back onto the geometry of the arm in Fig. 7. Superimposed onto the geometry are markers corresponding to the results in each of Fig. 3-6. The relative sizes of the markers indicate the strength of the difference of means.

From this Figure, we can see that regions around the wrist would be best for using circumferential derivatives (circles and squares), while regions around the elbow would be best for using longitudinal derivatives (triangles left and right).

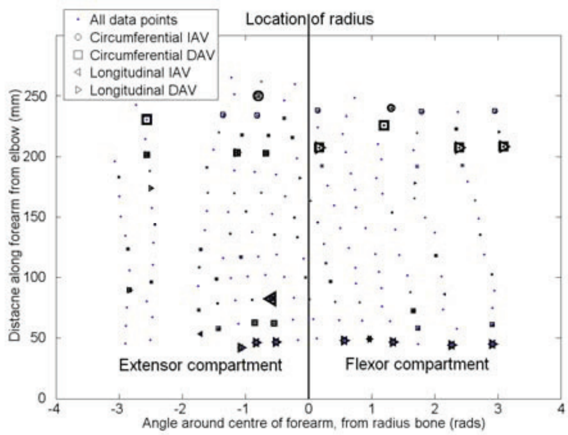


Fig. 7. Difference in means for each of IAV and DAV, both circumferential and longitudinal. The relative sizes of the markers indicate the strength of the difference of means.

The wrist is the only place in the forearm where the thumb muscles are close to the surface of the skin [7]. As the thumb is responsible for a majority of the grasp forming, it is likely that there would be points in this region that would show large changes when a grasp type is changed. This is seen in the circumferential derivative data; however it is surprising to find that for longitudinal derivatives the majority of the useful sites are found closer to the elbow. Given that muscles in the forearm run approximately longitudinally [7], these derivatives would be expected to represent action potentials running the length of the muscle fiber [8]. This could represent a region where rotator muscles run, or it is possible that there are subject specific characteristics with the subject. Without further data, no conclusions can be drawn from the longitudinal derivatives.

IV. Conclusion

This work demonstrates the capability of a system to optimize electrode placement in order to distinguish between pre-defined actuation patterns. Though only limited data sets are presented here, this system has the potential to extend to any user-designed actuation pattern. To this end, current and future work involves repetition of the experiments presented, along with identification of optimal electrode placement for other grasp types.

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