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Optimal Electrode Configurations for Finger Movement Classification using EMG

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***Abstract*—The myoelectric signal has played a major role in the development of prosthesis control technology. A myoelectric classification system has the ability to determine a prosthesis user's intent based solely on his or her muscle activity, thereby allowing for more intuitive prosthetic control. Much work has been done on the recognition of upper arm and gross hand movement tasks, but it was not until accuracy levels approached 100% [3] that more attention was given to specific finger movements. In this study, the effect of electrode array size and arrangement on classification accuracy is investigated for a four-finger typing task. This follows from previous work [1] in which the classification system itself was optimized. Unique advantages were found using array sizes of three and seven electrodes; classification accuracy of 92.7±3.9% was found in the latter case across twelve subjects.**

I. Introduction

Integral to the effective control of a powered prosthesis is the movement classification system, which translates a user's intent into a desired prosthetic motion. The myoelectric signal, or electromyogram (EMG), has often been used to communicate user intent with average classification accuracy across multiple subjects of up to 98% for four transient gross hand and arm movements [3], 93% for four transient single-finger movements [1], and 98% for twelve sustained single- and multiple-finger movements [2]. The operation of a classification system generally involves movement detection (e.g., detecting movement onset from the EMG signal), extraction of a set of features from the signal (e.g., RMS averages), sometimes a reduction in the dimensionality of the feature set, and finally classification of the feature set using a classifier, such as the linear discriminant analysis (LDA) classifier.

For movement classification, myoelectric signals are most commonly collected using one or more electrodes placed on the skin surface; the electrodes are placed either with reference to particular muscles [4]–[6] or equidistantly over an area of interest [1], [3]. The importance of the electrode configuration lies in its effect on classification accuracy, and in its contribution to prosthesis production cost and computational load based on the number of electrodes used.

Much research has been done on EMG-based classification systems for gross hand and arm movements, such as flexion at the elbow or closing of the hand; more dexterous finger movements have received significantly less attention until recently. Finger movement classification systems using one [4], [6], two [6], four [5], eight [1], and 32 [2] electrodes have been tested. The effect of electrode configuration on classification accuracy can not be clearly deduced through comparison of these studies because of significant differences in the study details: most notably, the number of movements classified, the movement types and durations, the classification systems used, the number of subjects, and the data set sizes.

This study investigates the effect of different electrode array sizes and arrangements on finger movement classification accuracy. This is done with two goals in mind: firstly, to determine those configurations—and more generally, array sizes—that yield the highest classification performance, and secondly, to determine whether an upper limit exists above which additional electrodes offer no advantage, and therefore contribute only to production cost and computational load. A configuration that yields a high classification accuracy while using few electrodes would have a very useful application in prosthetic control.

II. Methods

Twelve healthy subjects (age: 24.7±2.5 years, height: 175±9 cm, weight: 73±11 kg, ten right- and two left-handed, six male and six female, no limb deficiencies) volunteered for this study. The study was approved by the Health Sciences Research Ethics Board of Queen's University. All subjects provided informed consent prior to their participation in the study.

After cleaning the skin with isopropyl alcohol, eight electrodes (Delsys DE-2.1) were placed around each subject's forearm at approximately one third of the forearm length from the head of the *radius*; the first electrode was placed just superior to the *ulna* and distances between adjacent electrodes were approximately equal, as shown in Figure 1. A reference electrode was placed over the *manubrium* for subjects 1–3 and over the midpoint of the *right clavicle* for subjects 4–12; the position was changed to reduce noise.

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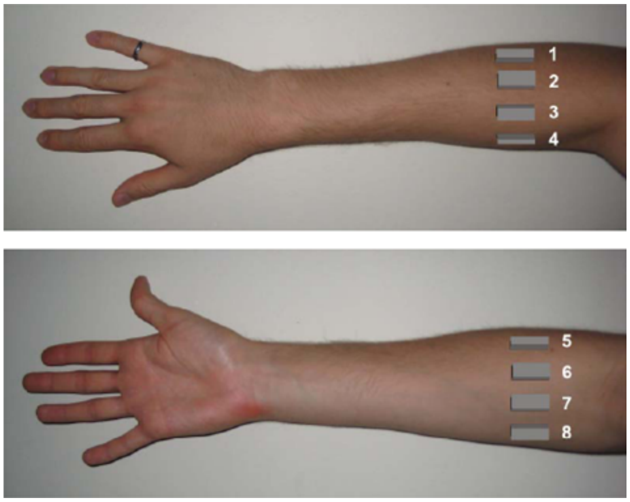

Fig. 1. Illustration of electrode placement on the posterior surface (top) and anterior surface (bottom) of the forearm

Myoelectric signals collected from the electrodes were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software (version 3.1.0.5).

Subjects performed four different exercises, two trials each, on a standard keyboard using their right hand. All exercises involved 20 instances of four different keypress motions: j with the second digit, k with the third digit, l with the fourth digit, and *;* with the fifth digit. Each of the four exercises required the keystrokes to be typed in a unique fashion:

- Exercise 1: ordered keystrokes paced at 1 per second,
- Exercise 2: ordered keystrokes, freely paced,
- Exercise 3: non-ordered keystrokes paced at 1 per second,
- Exercise 4: non-ordered keystrokes, freely paced,

where ordered keystrokes involved 20 repeated strokes of each key, in the order j, k, l, and then *;*. Freely paced exercises allowed the subject to type at any comfortable pace under approximately three keystrokes per second. Exercises were guided by a computer program, written in MATLAB 7, which dictated the keystroke order, kept pace in paced exercises, and recorded the characters typed and corresponding time indices. Subjects were instructed to sit in a comfortable typing posture throughout each exercise.

A classification system was optimized empirically for each subject through the testing of different combinations of each system element: classifier, dimensionality reduction (DR) method and number of reduced dimensions, feature set, number of window divisions from which features were calculated (e.g., if two window divisions were used, then features were calculated for the first and second half of the window separately), window length, and window skew, i.e., the position of the classification window relative to the keystroke time [1]. Classification systems were optimized using the eight-electrode array. It should be noted that the movement detection method was off-line: the start of each typing movement was defined using the keystroke time index as recorded by the data collection software.

Several options for each of the six main system elements were used in the optimization process:

- Classifier: Linear discriminant analysis (LDA) classifier, multilayer perceptron (MLP), and statistical classifier (Stat.), which classified a feature set using the z-value of each feature relative to the training set distribution;
- DR method: No DR, principal components analysis DR to 48 dimensions (PCA-48), and PCA DR to 64 dimensions (PCA-64);
- Feature sets: Root-mean-square (RMS), Hudgin's time domain features (TD), variation on auto- and cross-correlation values (CV), spectral power magnitudes (SPMs), short-time Fourier transform (STFT), wavelet transform (WT), and higher order statistics (HOS);
- Window divisions: 1, 2, and 7;
- Window length: 160 ms, 224 ms, and 256 ms;
- Window skew: -105 ms, -125 ms, and -145 ms.

The optimization process and methods listed above are described in detail in the previous work [1].

Given the eight original electrode locations, 255 subsets of these data channels were possible; all subsets were tested as different electrode configurations. Classification systems were trained independently for each electrode configuration using the first trial data of the subject's four exercises. The classification accuracy for each system was then determined using the second trial data from the freely paced, non-ordered exercise, as it best reflects a realistic application scenario. To investigate the effect of electrode array size on classification accuracy, the best-performing electrode arrangement for each array size was first uniquely determined for each subject. The differences among the resulting classification accuracies were then tested for significance using a one-way repeated measures analysis of variance (ANOVA) and a comparison of means using Bonferroni correction.

III. Results

The optimal classification system previously determined for each subject is listed in Table I. These subject-specific systems were found to yield significantly higher classification accuracies than the single system that performed best, on average, over all subjects [1].

For each array size between one and seven electrodes, the optimal arrangement of electrodes was determined empirically for each subject. The number of subjects for which each electrode location was optimal is shown in Figure 2.

Classification accuracies were determined using the subject-specific optimal electrode arrangements for each array size; means and standard deviations across subjects are given in Table II and the effects of array size on classification accuracy are shown in Figure 3.

A one-way repeated measures ANOVA (α=0.05) showed significant difference in classification accuracy across array

TABLE I
OPTIMAL CLASSIFICATION SYSTEMS

Subject	Classifier	DR method (# of reduced dimensions)	Feature set	Window divisions	Window length (ms)	Window skew (ms)
1	LDA	none	CV	1	160	-125
2	LDA	PCA (48)	TD	2	160	-145
3	LDA	PCA (48)	TD	2	160	-105
4	LDA	none	CV	2	224	-125
5	LDA	none	RMS	7	224	-105
6	Stat.	none	TD	2	224	-145
7	LDA	PCA (48)	RMS	7	224	-105
8	LDA	none	TD	1	160	-125
9	LDA	PCA (64)	CV	2	256	-105
10	LDA	PCA (64)	TD	2	256	-125
11	LDA	PCA (64)	TD	2	160	-105
12	LDA	none	RMS	7	224	-145

TABLE II
MEAN AND STANDARD DEVIATION (SD) OF CLASSIFICATION ACCURACIES (CA) ACROSS SUBJECTS FOR EACH ARRAY SIZE

# of electrodes	Mean CA (%)	SD CA
1	54.3	12.0
2	64.0	18.5
3	70.0	22.8
4	73.0	24.1
5	83.9	20.0
6	83.4	22.0
7	92.7	3.9
8	91.4	5.7

sizes. A comparison of means using Bonferroni correction showed significant differences ($p<0.05$) in classification accuracy for the following pairs of array sizes: 1&5 ($p=0.005$), 1&6 ($p=0.012$), 1&7 ($p<0.001$), 1&8 ($p<0.001$), 2&7 ($p=0.011$), and 2&8 ($p=0.024$). Consequently, the smallest array size that yielded classification accuracy values not significantly different from the best case (seven electrodes) was three; however, the three-electrode array yielded performance much lower than the seven-electrode array for four of the twelve subjects—by between 47.5 and 61.3 percentage points. The seven-electrode array yielded classification accuracy values above 85% for all subjects, while values below 50% were obtained for four subjects using array sizes of three or four, and for two subjects using array sizes of five or six.

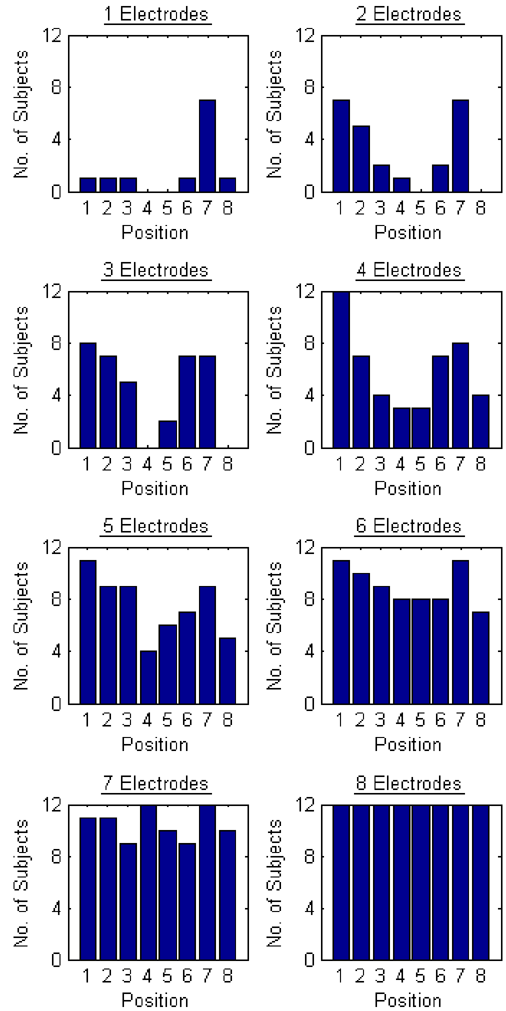

Fig. 2. The number of subjects for which each electrode location was optimal, for array sizes of one to eight electrodes.

IV. DISCUSSION

The effect of the number and location of electrodes on finger movement classification during a typing task was investigated. Eight electrodes were positioned around the forearm to detect muscle activity associated with the finger movements. The classification accuracy for each of the 255 possible electrode configurations was then determined using classification systems previously optimized for each subject [1].

In array sizes of six or fewer electrodes, positions 4, 5, and 8 were least commonly selected and positions 1 and 7 were most commonly selected. Positions 7 and 8 were located approximately over the *flexor digitorum profundus*, a muscle responsible for finger movement, and so both electrodes likely received similar signals. The difference in their performance may be due to the proximity of position 8 to the *ulna*, so that position 7 yielded a stronger signal and was therefore often favoured over position 8. Positions 4 and 5 were located close to the *radius*, and farther from the finger movement muscles than many of the other electrode positions. The reason

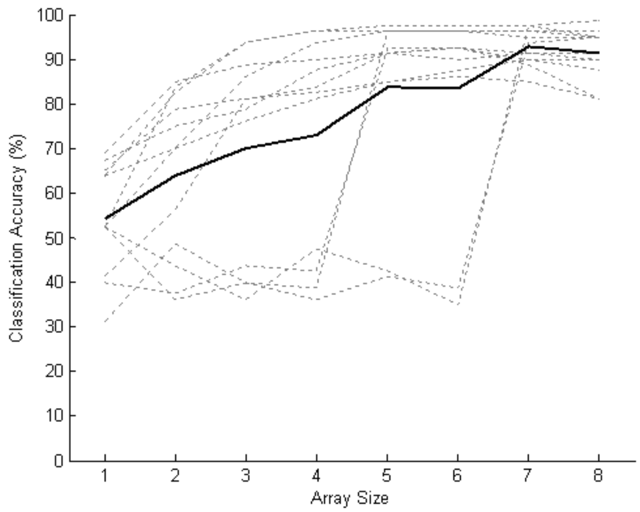

Fig. 3. The effect of array size on classification accuracy: individual subjects (dashed lines), average over all subjects (solid line).

for the good performance of position 1 is less clear, but may have been due to its proximity to the *extensor digitorum communis* muscle (responsible for finger movement and common to positions 1–3) and its proximity to fewer muscles than positions 2 and 3 that are unrelated to finger movement, such as the *supinator* and *extensor carpi radialis longus*, which would have affected signal-to-noise ratio. Despite the trends associated with the aforementioned electrode positions, there were still many different optimal electrode arrangements across the subjects for each array size, as shown in Figure 2. A preceding work [1] showed that optimal classification systems are subject-dependent, and therefore that it benefits classification accuracy to tailor classification systems to each subject. The results found in this study suggest that the best-performing electrode arrangement for each array size may also be subject-dependent.

For each array size, the best performing electrode locations were determined for each subject, with the resulting classification accuracies presented in Table II; however, it may be the case that other optimal arrangements exist: those that yield accuracy values not significantly different from those with the highest mean. Determining these other arrangements would provide more data on the effect of electrode configuration on classification accuracy.

The results in Figure 3 show a steady increase in classification accuracy for eight subjects from array sizes of one to three, followed by relatively constant accuracy for array sizes from three to eight. However, for four subjects the general trend was markedly different—classification accuracies remained very low for smaller array sizes and then rose sharply (by about 50 percentage points) once array sizes increased to five or seven electrodes. These results indicate that for many subjects an array size of three electrodes can provide comparable classification performance to array sizes of up to eight electrodes.

The optimal classification systems used in this study were determined for each subject using an array size of eight electrodes; the systems were not re-optimized for each of the other 254 electrode configurations due to the computational time required. Consequently, the accuracy values obtained using fewer than eight electrodes may be improved with the use of classification systems that have been optimized for electrode configuration. In practice, optimization of classification systems for electrode configuration could be integrated into the optimization scheme discussed in the previous work [1] when customizing a prosthesis control system to its user.

V. Conclusion

The performance of a myoelectric signal classification system depends on many factors, one of which is the configuration of the electrode array. Two specific improvements are possible through the optimization of the electrode array: first, an increase in classification accuracy, and second, a reduction in production cost and computational time, if comparable performance can be attained using fewer electrodes. A classification accuracy of $92.7 \pm 3.9\%$ was attained using seven electrodes; this was not significantly different from performance achieved with an array size of three electrodes, although performance for the smaller array size was poor ($<50\%$) for four of the twelve subjects. Optimization of the classification system for a smaller electrode array size—that is, choosing the best performing classifier, feature set, dimensionality reduction method, and window characteristics—may improve performance, yielding a classification system that can achieve consistently high accuracy with a small number of electrodes.

Acknowledgment

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