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Reducing Classification Accuracy Degradation of Pattern Recognition Based Myoelectric Control caused by Electrode Shift using a High Density Electrode Array

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Abstract— **The robustness and usability of pattern recognition based myoelectric control systems degrade significantly if the sensors are displaced during usage. This effect inevitably occurs during donning, doffing or using an upper-limb prosthesis over a longer period of time. Electrode shift has been previously studied but remains an unsolved problem. In this study we investigate if increasing the number of electrode channels and recording locations can improve the degraded classification accuracy caused by electrode shift. In our experiment we use a 96 channel high density electrode array to distinguish 11 different hand and wrist movements. Our results show that for electrode shifts up to 1 cm an array of about 32 sensors in combination with state-of-the-art pattern recognition algorithms is sufficient to compensate the electrode displacement effect.**

I. Introduction

Modern myoelectric upper-limb prostheses are able to assist the amputee in performing activities of daily living and restore a great amount of independence and quality of life. Despite the constant improvement of upper-limb prostheses during the last decades, their restricted control and limited degrees of freedom (DOF) are repeatedly referred to as the main reasons for their low acceptance rate among amputees [1].

Powered upper-limb prostheses are typically controlled using multi-channel surface myoelectric signals (MES) recorded from residual muscles in the amputation stump and can be generally classified into two groups: conventional myoelectric control, and pattern recognition based myoelectric control schemes [2]. Current commercially available myoelectric transradial prostheses typically use a set of two bipolar electrodes to acquire MES from the upper and lower forearm muscles. Information extracted from the amplitude [3] or rate of change [4] of the recorded signals is used to proportionally control one degree of freedom. Additional prosthetic functions can be achieved by mode switching using co-contractions or hardware switches [5], which is often cited as counter-intuitive and cumbersome for the amputee.

Pattern recognition based control schemes are an active research area and can potentially enable the amputee to intuitively operate multiple DOFs [6]. They are based on the assumption that a set of features extracted from MES is repeatable for a specific movement and distinguishable from a set of features extracted during another movement. In today's literature the signal processing chain is often broken down to three components: the feature extraction, the dimensionality reduction and the pattern classification. During the first two steps attributes are extracted from MES and reduced by selecting features for more robust and accurate classification. In the last step pattern matching algorithms are applied to detect the category of the input data [7]. A variety of feature extraction methods and classification algorithms have been successfully used for upper-limb prosthesis control in laboratory settings [8]–[13].

One challenging factor in pattern recognition based control schemes is variation in electrode recording placement. Donning, doffing or using a myoelectric prosthesis over a longer period of time can cause the electrodes inside the shaft to change their recording locations which results in a degradation of classification accuracy. This effect has been previously studied but remains an unsolved problem. Hudgins et al. [2] acquired MES from two electrodes placed on the biceps and triceps to distinguish four contraction types. The small number of contractions could be relatively easily differentiated and electrode shifts up to 2 cm did not have a major effect on the classification accuracy in this study. Hargrove et al. [14] used a setup of five electrodes to classify 9 movements and found that shifts of 1 cm from a training position caused a reduction of classification accuracy by more than 30%. Hargrove et al. [15] showed that the displacement effect can be alleviated by performing a training in all expected displacement positions. This method is unsuitable for commonly available electrode setups used in prostheses since the system would have to be trained multiple times in all expected displacement locations. Young et al. [16], [17] used four bipolar EMG electrodes placed on the upper and lower forearm to classify 7 hand and wrist movements. Using input generated from different transverse and longitudinal combinations of the four electrodes, the classification error for a shift distance of 1 cm could be reduced to around 15%.

It has not yet been thoroughly investigated if increasing the number of electrode channels and recording locations could improve the reduced classification accuracy caused by electrode shift. With advancements in microprocessor and signal processing technology, efficient classification of MES recorded from an array of many high density electrodes in an embedded system will be possible. In this study we

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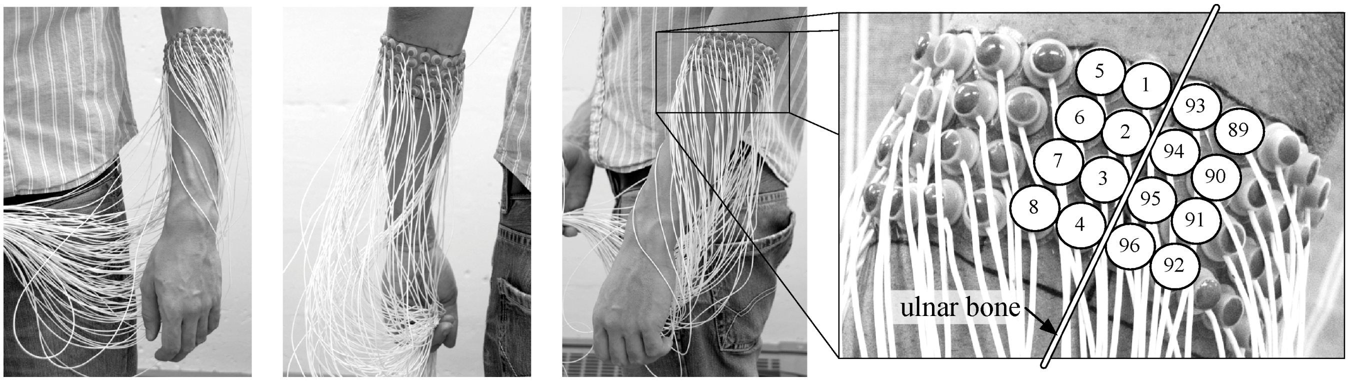

Fig. 1. Experimental setup. EMG channels are enumerated column-wise starting at the ulnar bone.

investigated the classification accuracy and the effect of electrode shift using a 96 channel high density electromyography (EMG) system to distinguish 11 different hand and wrist movements.
The paper is structured as follows. The setup of the EMG sensor system and the conducted experiment, as well as the signal processing and feature extraction are presented in Section 2. The experiments are evaluated in Section 3. Finally, Section 4 concludes the paper.

II. Experiment

A. Methods

To investigate the effect of electrode displacement in pattern recognition based myoelectric control, an experiment was conducted. EMG data corresponding to 11 hand and wrist motions were acquired from one healthy normally limbed 30 years old male subject.
The data were collected from an array of 96 electrodes consisting of 4 rows of 24 electrodes wrapped around the forearm. Each electrode had a diameter of 1 cm and the center to center distance between adjacent electrodes was about 1 cm. A reference electrode was placed on the neck. Fig.1 illustrates the experimental setup.
A TMS International REFA 128 [18] high density EMG system was used for data acquisition. It is capable of measuring up to 128 monopolar EMG channels with a sample frequency of 2048 Hz with a resolution of 22 bit. The data were saved to files and processed by a framework of MATLAB programs. The subject was prompted to perform 10 contractions according to Table I. Furthermore a no movement class was recorded. Each contraction was held for 5 seconds, followed by a 2 seconds rest period. During the experiment 11 different trials were recorded, each consisting of 12 repetitions of the same contraction. After each trial a one minute rest period was included to avoid muscle fatigue effects. From each contraction, 4 seconds of data from the steady state phase were extracted. In total 12 × 4 sec = 48 seconds of data were recorded for each movement class. The first 24 seconds were used for training the classifier, the remaining 24 seconds were used for classification.

TABLE I
HAND AND WRIST CONTRACTIONS PERFORMED DURING THE EXPERIMENT

no.	contraction	no.	contraction
1	extension	7	key grip
2	flexion	8	pincer grip
3	supination	9	lateral grip
4	pronation	10	hand open
5	ulnar deviation	11	no movement
6	radial deviation		

B. Signal Processing

All EMG channels were low pass filtered at 500 Hz using a 5th order Butterworth filter. The data were segmented using a 100 ms sliding window with 50 ms increment for feature extraction.
Four time domain (TD) features were extracted, consisting of mean average value features (MAV, 1), wave length features (WL, 2), zero crossing features (ZC, 3) and slope sign change features (SSC, 4) that can be expressed as follows:

$$MAV = \frac{1}{N}\sum_{n=0}^{N} x_n \tag{1}$$

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \tag{2}$$

$$\begin{gathered} ZC = \sum_{n=1}^{N-1} \left(sgn\left(x_n \times x_{n+1}\right) \cap |x_n - x_{n+1}| \geq th\right); \\ sgn(x) = \left\{ \begin{array}{ll} 1, & \text{if } x \geq threshold \\ 0, & \text{otherwise} \end{array} \right\} \end{gathered} \tag{3}$$

$$\begin{gathered} SSC = \sum_{n=2}^{N-1} \left(f\left((x_n - x_{n-1}) \times (x_n - x_{n-1})\right)\right); \\ f(x) = \left\{ \begin{array}{ll} 1, & \text{if } x \geq threshold \\ 0, & \text{otherwise} \end{array} \right\} \end{gathered} \tag{4}$$

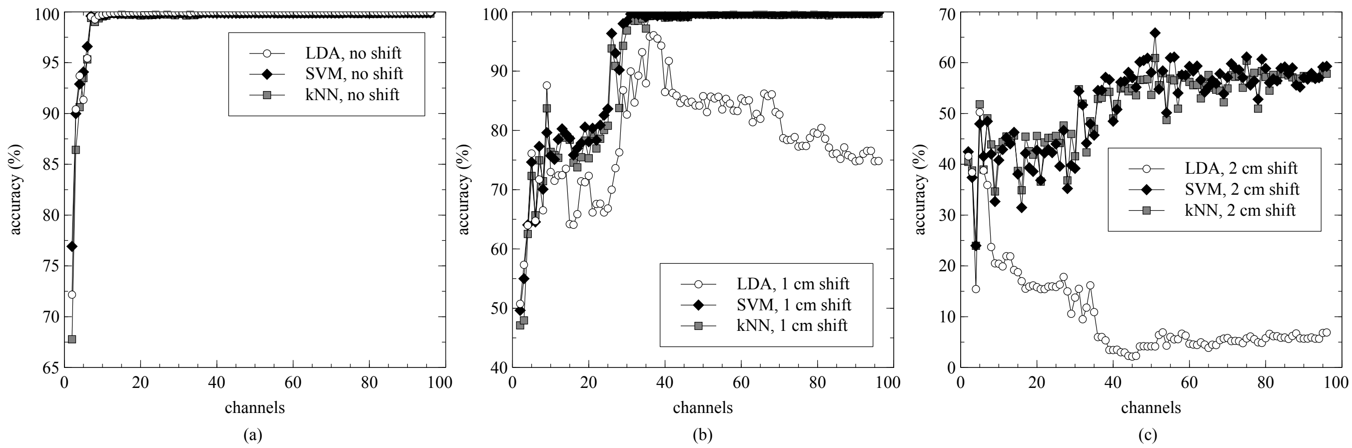

Fig. 3. Classification accuracies of the LDA, SVM and kNN classifier. The number of channels is shown on the X-axis, the accuracy on the Y-axis. The system was trained using the first 24 seconds of the recorded contractions as training data, while the remaining 24 seconds were used for classification. First, the unmodified testing data were used in (a). For (b) and (c) the testing data were shifted by 1 cm and 2 cm.

In equations (1) - (4), x_n represents the EMG signal in a segment and N denotes the length of the signal [19].
As previously indicated, the first 24 seconds of each contraction class were used to train the pattern recognition system while the remaining 24 seconds were used for classification. As classifiers we used linear discriminant analysis (LDA), support vector machines (SVM) and k-nearest neighbor (kNN). All three classifiers have shown good accuracies in classifying upper-limb EMG signals [2], [20]. To simulate the electrode shift effect, the representation of the electrode array was horizontally shifted by 1 cm and 2 cm in software. This is illustrated in Fig. 2.

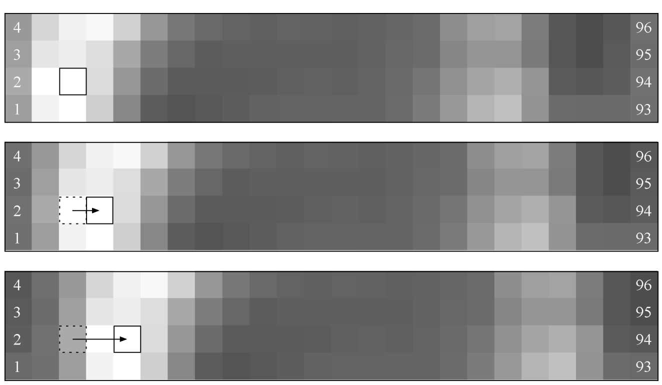

Fig. 2. Illustration of electrode shift simulation. The original electrode array during the steady state phase of an extension contraction is shown on top. The grayscale coloring represents the RMS activity of the EMG channels. The array is horizontally shifted by 1 cm (middle) and 2 cm (bottom) in software to simulate electrode displacement.

III. Results

We have performed the experiment to answer two specific questions. First, does adding EMG sensors improve the system's classification accuracy when the electrodes are shifted? Second, how do different classifiers perform compared with each other? In order to answer these questions, the system was initialized with 1 EMG sensor. Then three classifiers (LDA, SVM, kNN) were trained in the original sensor location. In the test phase, the system had to classify the testing data in three cases:

1) the testing data were not shifted
2) the testing data were shifted by 1 cm
3) the testing data were shifted by 2 cm

TABLE II
Rule for adding EMG sensors to the system

# sensors	adding rule
$n \leq 24$	n symmetrical equally spaced electrodes from the first row
$25 \leq n \leq 48$	complete first row and (n-24) equally spaced electrodes from the fourth row
$49 \leq n \leq 72$	complete first and fourth row and (n-48) equally spaced electrodes from the second row
$73 \leq n \leq 96$	complete first, second and fourth row and (n-72) equally spaced electrodes from the third row

This step was repeated 95 times, each time adding one more EMG sensor. The rule for adding a new sensor is described in Table II. The results are illustrated in Fig. 3. The accuracy was calculated using cross-validation. Fig. 3 (a) shows that using 7 sensors is sufficient for all three classifiers to distinguish between the 11 contractions with an accuracy of about 99% when the testing data were not shifted.
When the testing data are shifted by 1 cm (Fig. 3(b)), both the SVM and the kNN classifier need about 32 EMG sensors to achieve an accuracy of 99%. The accuracy of the LDA decreases after adding more than 32 channels.
Shifting the testing data by 2 cm (Fig. 3(c)) causes the SVM's and the kNN's accuracy to drop significantly. Using more than 40 sensors results in an average accuracy between 50 and 60%. The LDA's accuracy constantly decreases below 20% with additional sensors.

IV. DISCUSSION

Our results indicate that a higher robustness to electrode displacement in upper-limb prostheses may be gained by adding more EMG sensors to the system. Using SVM or kNN classifiers, about 32 sensors are needed to compensate the electrode displacement effect if the electrodes are shifted by 1 cm. Shifting the electrodes by 2 cm caused the SVM's and kNN's accuracy to drop below 60%. Here, further optimizations are necessary to enable reliable prosthesis control. Investigations must also be carried out aiming at identifying realistic amount of electrode shift during upper-limb prosthesis usage.

Our future study will consider reducing the amount of sensors and repeating the experiment with upper-limb amputees to gain a better understanding of the correlation between classification accuracy and actual prosthesis usability and robustness.

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