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EMG Pattern Recognition Control of Multifunctional Prostheses by Transradial Amputees

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Abstract— **Electromyogram (EMG) pattern recognition approach has been investigated widely with able-bodied subjects for control of multifunctional prostheses and verified with high performance in identifying different movements. However, it remains unclear whether transradial amputees can achieve similar performance. In this study, we investigated the performance of EMG pattern recognition control of multifunctional transradial prostheses in five subjects with unilateral below-elbow amputation. Testing results on both residual and intact arms showed that the average classification error (21%) of amputated arms for ten motion classes (four wrist movements, six hand grasps) and a 'no movement' class over all five subjects was about 15% higher than that of intact arms. For six basic motion classes (wrist flexion/extension, wrist pronation/supination, and hand open/close), the average classification error over all five subjects was about 7% from residual arms, which was similar to the result from intact arms (6%). Only six optimal electrode channels might be needed to provide an excellent myoelectric control system for the six basic movements. These results suggest that the muscles in the residual forearm may produce sufficient myoelectric information to allow the six basic motion control, but insufficient information for more hand functions with fine finger movements.**

I. INTRODUCTION

TRANSRADIAL amputation is the most common type of upper limb amputations. For transradial amputees, either the remaining shoulder motion can be harnessed for body-power or myoelectric recordings from the residual muscles can be used to control one motion at a time in an externally powered artificial limb. Most commercially available myoelectric transradial prostheses use the amplitudes of surface electromyography (EMG) signals from the forearm flexors and extensors to control hand closing and opening. If wrist movements are desired, the patients must co-contract their forearm muscles to switch into a wrist movement mode [1, 2]. Switching between different modes is slow and cumbersome and is not intuitive to use the same muscle contractions to control two different functions.

A significant improvement over conventional myoeletric control strategy is implicit in pattern recognition based myoelectric prosthesis control, in which the users elicit the contraction corresponding to a movement that they want to control, and an EMG pattern recognition based classifier chooses the appropriate class of motion [3-15]. The classifier is trained by having the user perform repetitions of the movements. When the trained classifier predicts the intended movement, a corresponding motion command is sent to a prosthesis controller for implementation of the movement. As a result, this control scheme may allow users to more easily and intuitively control their prostheses with multiple degrees of freedom.

The feasibility and performance of pattern recognition algorithms with forearm muscles have been investigated in a number of studies with able-bodied subjects [3-12]. In each case, several bipolar electrodes (from 4-16) were placed on the circumference of the mid-portion of the intact forearm to mimic the case of transradial amputation for EMG recordings. Using different pattern recognition algorithms, such as linear discriminant analysis (LDA) [4,15], artificial neural networks [14], and fuzzy logic [9, 13], high classification accuracies (>93%) for six to ten wrist and hand movements were consistently achieved with able-bodied subjects. However, the studies on transradial amputees who are the users of transradial prostheses are rarely conducted. As a result, it is unknown whether similar classification performance can be achieved with transradial amputees with limited muscles of their residual forearms. A recent study included two transradial amputees (one with a trauma-induced unilateral transradial amputation and another with a congenital unilateral transradial limb-deficiency) and used three electrodes to collect surface EMG signals on the residual forearm [13], but only three wrist classes (wrist flexion/extension and either wrist pronation or supination) were included. In this study, we investigated the performance of pattern recognition algorithm for classification of different hand and wrist movements with five unilateral transradial amputees. We also conducted an analysis of the electrode configuration to investigate the feasibility of using a reduced number of electrodes without compromising classification accuracy. The results of this study could aid the future development of a multifunctional myoelectric prosthesis for transradial amputees.

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II. METHODS

A. Subject and Experiment

Five people with unilateral transradial (TR) amputations participated in the study. Their ages ranged from 28 (TR1) to 77 years (TR5) and their post-amputation times varied from 3 months to 21 years. Three subjects used a myoelectric prosthesis, one subject used a body-powered prosthesis and one subject (only 3 months post amputation) had not yet received any prosthesis when the study was conducted. This study was approved by the Northwestern University Institutional Review Board and the informed consent was obtained from all subjects.

Each subject attended three consecutive experiments. The first experiment was conducted on the amputated side (*Trial 1*), the second on the intact side as a control (*Trial 2*), and the third on the amputated side again for possible performance improvement (*Trial 3*). The time between two consecutive experiments ranged from a few days to approximately three months, depending on subject availability.

B. EMG Data Acquisition

Twelve self-adhesive bipolar electrodes with a circular contact surface diameter of 1.25 cm and a center-to-center distance of 2 cm were used for EMG recordings. For amputated arms, 8 of the 12 electrodes were uniformly placed around the proximal portion of the forearm and other 4 electrodes were positioned on the distal end (Fig. 1(a)). For intact arms, the 12 electrodes were placed on the proximal forearm (6 around), the wrist (3 around), and the hand (Fig. 1(b)). A large circular electrode was placed on the elbow of the tested arm as a ground. The EMG signals were amplified and band-pass filtered (5-400 Hz), and then sampled at a frequency of 1 kHz and acquired with a custom data acquisition and processing system [15].

Ten wrist and hand motion classes plus a "no movement" class were included in the study (Fig. 2). In each experiment,

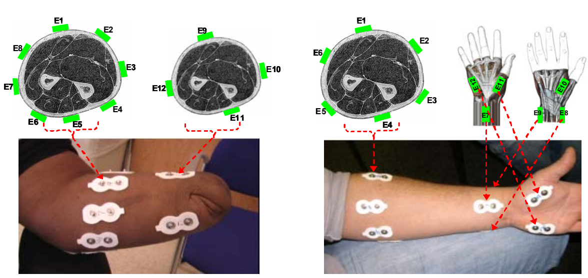


Fig. 1. Placement of 12 bipolar electrodes for EMG recordings on an (a) amputated arm and (b) intact arm.

EMG data were acquired in eight consecutive trials. In each trial, all the 11 classes were repeated twice and held for 4 s, producing 8 s of EMG recordings per class. There was a 3 s interval between consecutive movements in the four even-numbered trials, and a variable time interval (3 s, 2 s, 0 s, and 1 s, in turn) in the four odd-numbered trials in an attempt to enhance the classifier's robustness.

C. EMG Pattern Classification

Fig. 2. Ten classes of wrist functions and hand grasps and a 'no movement' class included in the study.

EMG pattern classification was performed on analysis windows. EMG recordings were segmented into a series of analysis windows with a time length of 150 ms and a time increment of 100 ms. Commonly used four time-domain features (mean absolute value, number of zero crossings, waveform length and number of slope sign changes) [3] were extracted from each analysis window. EMG features from the four odd-numbered trials were used as the training data set to train a linear discriminant analysis (LDA) [15] classifier for the 11 motion classes, and EMG features from the four even-numbered trials were used as the testing data set to evaluate the performance of EMG pattern recognition algorithm for the classification of the 11 motion classes.

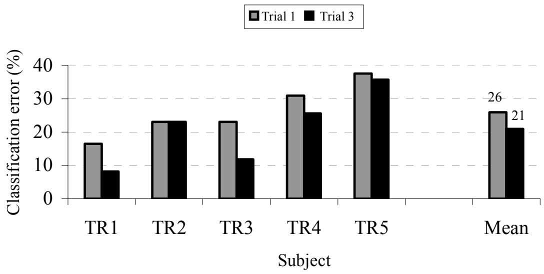
D. EMG Channel Selection

Using a larger number of electrodes can capture more myoelectric signals, but it simultaneously adds more complexity, weight, and cost to a prosthesis. In order to evaluate the feasibility and performance of using a reduced number of electrodes for control of multifunctional transradial prostheses, an exhaustive search algorithm was used to determine the "optimal" number and location of EMG electrodes based on the 12-channel EMG recordings. All possible electrode combinations for a reduced number of channels (1~11) were analyzed with classification error for different wrist and hand movements. The EMG recordings from the channels in each combination were selected from the 12-channel training data set and used to train individual LDA classifiers. The EMG recordings from the same channels were selected from the 12-channel testing data set and used to evaluate each classifier's performance in identifying different motion classes. For each number of channels, the channel combination that produced the lowest classification error was considered the 'optimal' channel configurations.

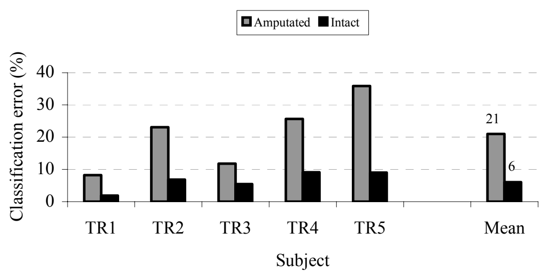
III. RESULTS

A. Classification Performance for 11 Classes

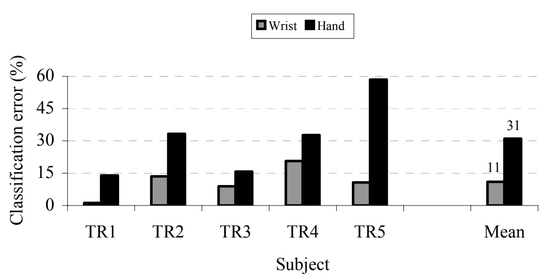
For the classification of all 11 classes, EMG pattern recognition testing on amputated arms produced lower or equal classification errors in the second residual arm experiment (*Trial 3*) for all five subjects than in the first (*Trial 1*) (Fig. 3(a)). The average classification error over the five subjects was about 5% lower in the second residual arm experiment than in the first, but this difference was not significant (p<0.4, t-test). Amputated arms over all five subjects produced significantly higher classification errors (*Trial 3*) than their intact arms (p<0.02) (Fig. 3(b)). The average classification error over all five subjects was



(a)



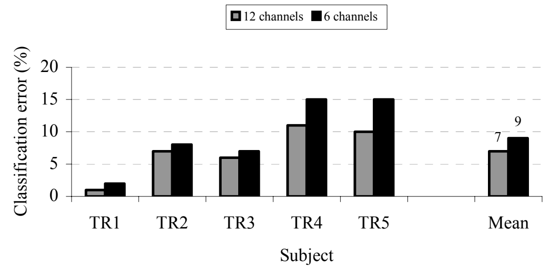
(b)



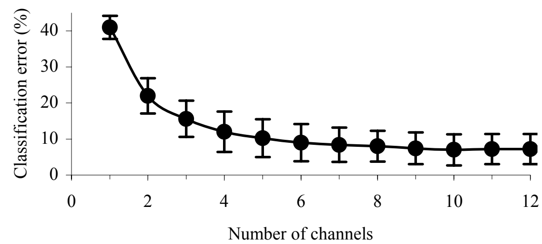
(c)

Fig. 3. Classification errors for 11 classes of movements. The mean of classification errors over the five subjects is shown on the right side. (a) The classification errors in the five subjects from two amputated arm tests (*Trial 1 & Trial 3*). (b) The classification errors in the five subjects from the second residual arm test (*Trial 3*) and the intact arm test (*Trial 2*). (c) The wrist and hand classification errors from the second residual arm test (*Trial 3*).

approximately 21% for the residual arms, which was about 15% higher than that for the intact arm. All five subjects achieved significantly lower classification errors in performing wrist functions with their residual arms than in doing hand grasps (p<0.05) (Fig. 3(c)). The average hand-function classification error (31%) over five subjects was 20% high in comparison with the wrist-movement classification error (11%).



(a)



(b)

Fig. 4. (a) Classification errors for six classes of movements from the second amputated arm test (*Trial 3*) when using all 12 channels and the 6 optimally selected channels, respectively. The mean of classification errors over the five subjects is shown on the right side. (b) Average classification errors over all five subjects versus number of surface electrodes for the classification of the six basic movement classes.

B. Classification Performance for Six Motion Classes

When the motion classes were reduced from ten classes of wrist and hand movements to six basic motion classes (wrist flexion/extension, wrist pronation/supination, and hand open/close (power grip)), the classification performance achieved with residual arms was significantly improved in five subjects (p<0.03) (Fig. 4(a)). The average classification error over all five subjects decreased from 21% for the 11 motion classes to about 7% for the 6 motion classes, which is similar to the result from the intact arm test (6%).

C. Channel Reduction

As shown in Fig. 4(b), use of four to six optimally placed electrodes produced comparable performance to the use of all 12 electrodes for classification of the six basic motion classes. Reducing EMG channels from 12 to 6 only increased classification errors by 1-5% in the five subjects (Fig. 4(a)). Using six optimally selected electrodes produced an average error of 7% over the subjects for the six motion classes; this was only 2% larger than the average classification error when using all 12 electrodes.

IV. DISCUSSION

Use of able-bodied subjects may be inappropriate for assessment of the performance of EMG pattern recognition based transradial prosthesis control. In this study, we evaluated the performance of EMG pattern recognition in control of a transradial prosthesis with five people with transradial amputations. Our results showed that average classification error for 11 classes of wrist and hand functions was approximately 15% higher when subjects used their amputated arms, as opposed to using their intact arms. Getting familiar with the myoelectric control system can improve the prosthesis control performance, but could not entirely compensate for the effect of the loss of the myoelectric control information. The high classification errors for ten classes of wrist and hand functions with the amputated arms indicated that remaining muscles on residual forearm might not provide enough myoelectric information for control of a multifunctional transradial prosthesis with all ten classes of wrist and hand movements. The classification errors with amputated arms had an increasing trend from subject TR1 (28 yrs) to TR5 (77 yrs), which suggested that muscular atrophy in ageing would weaken myoelectric information.

Separate examination of wrist and hand movements demonstrated that the high classification errors for amputated arms were mainly due to decreased classification accuracies in recognizing hand grasps. This finding is not surprising, as the majority of muscles responsible for wrist movements remains following transradial amputation, while intrinsic hand muscles which share control of hand grasps are lost entirely. The exclusion of four fine figure movements (chuck grip, key grip, fine pinch grip and tool grip) could significantly decrease the classification errors for amputated arms. For the six basic motion classes (wrist flexion/extension, wrist pronation/supination, and hand open/close (power grip)), the average classification error over all five subjects was about 7% from their amputated arms, only 1% higher than the result from their intact arms. And only six optimal electrode channels might be needed to provide an excellent myoelectric control system (about 9% classification error on average) for the six basic movements. This suggested that the remaining muscles in the residual forearm may produce sufficient myoelectric information to allow the six basic motion control in a transradial prosthesis.

It should be noted that only offline pattern recognition classification performance was considered in this study. Future investigations needs to be conducted in real-time transradial prosthesis control to validate the performance of EMG pattern recognition based control.

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