NATURAL CONTROL OF KEY GRIP AND PRECISION GRIP MOVEMENTS FOR A MYOELECTRIC PROSTHESES

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ABSTRACT

Hand prosthesis function is augmented when the user can employ lateral grasp as well as traditional palmer grasp. Our goal in this investigation was to enable the below-elbow (BE) prostheses user to switch between and use these grasp modes in a natural and reliable manner. We recorded the EMG from residual muscles (*flexor dig; ext. dig; flex. pollicis longus; ext. pollicis longus*) involved in these grasp activities in an adult subject with below elbow (BE) amputation while she contracted her residual forearm muscles to mimic computer animations of different hand movements. To reduce crosstalk between the recordings from separate muscles, and to enhance the stability of the recording interface over the 30-day duration of the experimental sessions, we used chronically implanted percutaneous coiled wire electrodes implanted for 30 days (12 one-day sessions). Artificial Neural Network (ANN) pattern recognition techniques were used to extract voluntary command signals from the EMG signals. The mean absolute value (MAV) of the EMG signals was selected as a feature for training multilayer perceptrons. Initially, we trained ANNs having 5 hidden neurons using data from the 10th and 12th session individually (3 training sessions each). Three additional ANNs (sizes 4:7:4, 4:8:4, 4:9:4) were designed and trained (3 training sessions each) with combined data from experimental sessions 10 and 12. Subsequently, we separately tested the performance of these ANNs with data from the 9th, 10th and 12th experimental sessions. While the results showed that data from different experimental days were substantially consistent, more reliable recognition of the grasp mode from any arbitrary test sample (i.e. taken from test sessions 9,10 or 12), was achieved when we used an ANN that was trained with representative samples from more than a single experimental day (e.g. using 10th and 12th experimental days data for training). This produced mean rates of recognition (averaged over the results from the three ANN training sessions with network size 4:8:4) of 97.6% key grip closing, 83.3% key grip opening, 85.7% precision grip closing, 96.4% precision grip opening, for the combined evaluation data from all test sets.

We conclude that intuitive operator selection, between key grip and precision grip modalities, is feasible for cases of BE amputation using recorded myoelectric signals.

INTRODUCTION

Loss of an arm transforms former simple tasks into difficult and tiresome challenges. Current prosthetic arms include body-powered devices and myoelectrically controlled hands. Although body powered devices have an advantage in providing the user with rough sensorial feedback through a control cable attached to a harness the bulkiness of this harness presents a serious drawback to the user [1]. Moreover, this approach has serious limitations for control of a multiple-degree of freedom artificial arm. Myoelectric prostheses offer better promise to achieve multiple-axis control in spite of inherent drawbacks such us maintenance problems, high weight, difficulty in operating and learning myoelectric control, inadvertent operation, and unreliability [1]. Myoelectric control is performed by means of the electrical activity of contracting muscles and, therefore, can be highly intuitive. Myoelectric multiple-axis control is feasible because the limit to the number of prosthesis functions is the amount of different contraction patterns produced by the user. However, control of present multiple axis prostheses is usually not natural from a motor-control point of view. To obtain more reliable and distinct contraction patterns, prostheses users are frequently requested to produce patterns which do not correlate in a natural way with the movement replaced by the prosthesis [2,3]. As the number of prosthesis functions increases so does the amount of training required for its operation. Additionally, separability of EMG patterns (regardless of the type of feature space being used) tends to decrease, as more patterns are required. Consequently, unfamiliar patterns of contraction may not be able to replace the normal motor control strategies for manual dexterity. Previous work [4,5] suggested that phantom limb phenomena are evidence of complex motor control skills still present in amputees and might be useful for prosthesis control. However, the issue of whether intuitive and reliable motor patterns can be conditioned through training is still unsettled. The present work utilizes a novel training protocol based on biofeedback and visual tracking tasks in a below-elbow (BE) amputee. The goal of the training was to rehabilitate the subject's motor control skills to control finger opening and closing for two different grip modalities, key grip and precision grip. Due to the expected day-to-day variation in the evoked contraction patterns, we employed a pattern recognition system based on Artificial Neural Networks to discriminate the users intended grasp motion.

EXPERIMENTAL PROTOCOL

The subject was an adult female (age 33) with BE left arm amputation (which was her non-dominant hand) with strong phantom limb sensation meaning that she could perceive the movement in her phantom hand and fingers when contracting her residual muscles. Eight of the subject's residual muscles were chronically implanted with bipolar pairs of percutaneous coiled wire electrodes for the duration of the 30-day study. Prior to the implantation protocol, the condition of the selected residual muscles was assessed by Magnetic Resonance Imaging techniques (MRI). Based on the MRI evaluation, localization strategies were developed to identify each of the target muscles. A pair of electrodes for bipolar recording was inserted with 2cm tip separation into each of the following muscles: (1) Flexor Digitorum, (2) Extensor Digitorum, (3) Flexor Pollicis Longus, (4) Extensor Pollicis Longus, (5) Pronator Teres, (6) Supinator (7) Flexor Carpi Radialis, and (8) Extensor Carpi Radialis, though only the first 4 muscles were studied with regard to the present investigation. Subsequently, the experimental protocol was conducted as 12 one-day sessions distributed over the 30-day period. We used data obtained during 3 of the last experimental sessions (9^{th}, 10^{th}, 12^{th} sessions) for analysis since any benefits of training could be expected to be achieved nearer to the end of the protocol. Results from session 11 were omitted because the subject reported during the recordings that on some occasions she could not move the fingers of her phantom hand as if they were "asleep". This phenomenon did not appear to be present during the other experimental sessions, however.

The subject was seated facing a PC visual display (Fig. 1), and she was requested to mimic with her phantom hand (as a kind of tracking task) animations of a hand performing key grip (closing-opening) and precision grip (closing-opening). She did this by contracting her residual limb muscles. The phantom hand movements were performed in 4 sets of 25 repetitions of the same grip task before the task was shifted to the other grasp type, In every case, the movements started with the fingers extended (hand open position). A pause of 1 s was included between each consecutive movement repetition. Additionally, the subject was permitted to rest between sets at her request. The multiple-channel EMG signals together with a reference signal with information about the phasing and progression of the animation were collected and stored digitally. The EMG signals were amplified between 1000 and 10000 and band-pass filtered (10Hz-1KHz) before being sampled (2KHz).

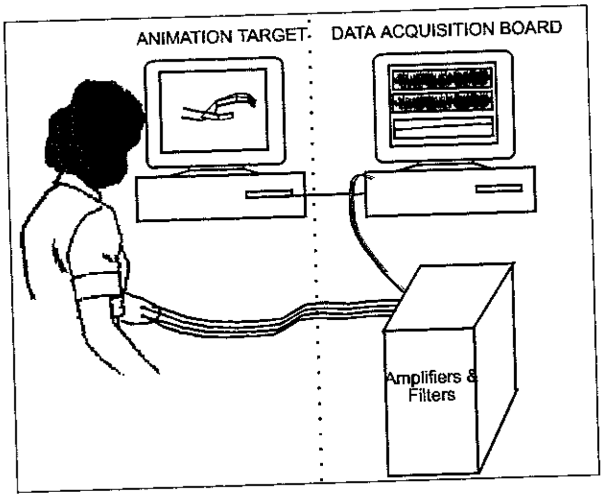

Fig. 1. Experimental setup

OFF LINE DATA ANALYSIS

EMG signals were further processed to remove DC offset and motion artifacts (Digital high pass, Butterworth order 4, 20Hz). An initial visual examination of the EMG signals revealed which muscles presented reciprocal activity for opposing motor tasks (i.e. an increase in the activity of one muscle while a decrease occurs in the other). The muscles that presented the best signal/noise ratios and the greatest change of the EMG activity in the opposing motor tasks were selected as targets for detection of movement onsets. For precision grip closing and opening the selected target muscles were Flexor digitorum and Extensor digitorum, respectively, while for key grip closing and opening they were Extensor pollicis longus and Flexor digitorum.

Examination of the data from sessions 9 and 10 revealed a substantial reduction of differences between contraction patterns for some grip trials. Consequently, we applied a set of simple criteria to exclude some of those trials: (1) a highly deteriorated reciprocal activity during opposing motor tasks; (2) an insufficient level of contraction (peak value) of the agonistic muscle (less than 2 times the amplitude of the background activity). Additionally, in those cases where reciprocal activity could still be observed but was significantly reduced, the trials were excluded if they did not fulfill at least one of the following conditions: (a) existence of a clear delay from the first EMG spike of the agonistic muscle to the first EMG spike of the co-activating muscle, (b) a greater than 50% change in the peak to peak value of one of the muscles during the reciprocal movement.

After applying these criteria, 42 and 33 trials were excluded from session 9 and session 10, respectively. Furthermore, the last 25 trials of the precision grip movement in session 9 were also excluded because the subject complained of a sensation of "tiredness" in her phantom fingers during the execution of the precision grip motor tasks. Therefore, the number of precision grip trials passed onto the next stage of processing for onset detection were 33 for session 9 and 65 for session 10.

Onset detection

An arbitrary threshold was determined for each target muscle to be used in the detection of the movement onset. The mean value plus 2 times the standard deviation of the rectified background activity was used to specify the threshold value. To determine the existence of an onset event, the mean value of the rectified EMG signal from the target muscle was computed (over a 25ms sliding window) and compared to the appropriate threshold. The condition for the existence of an onset event was based on the spatial (amplitude) and temporal (density of spikes) characteristics of the moving average signal. The algorithm applied a 200ms sliding window to the moving average signal. If the number of samples in this 200ms window exceeded the threshold for at least 175ms (not necessarily consecutively) then the first point of this 200ms window was labeled as the onset. The algorithm then began a search for an offset event, again using a sliding window of 200ms. An offset event was detected when the number of samples below the threshold exceeded 150ms. Following each onset detection, we extracted 200ms of raw EMG data from each of the muscles. These 200ms of data included an epoch of 25ms that preceded the onset event. These data were stored for subsequent feature extraction.

To train and test an ANN the amount of samples has to be the same for each movement. We detected 8 onsets for precision grip closing in session 9; 44 onsets for precision grip opening in session 10; and 45 onsets for precision grip opening in session 12. Although the other movements yielded a greater number of detected onsets, the amount of data available for training and evaluating an ANN was then limited to 8 samples per movement in the case of session 9; 44 per movement in session 10; and 45 per movement in session 12. Because there were so few input samples from session 9, we decided to use this set only for evaluation of the ANNs.

ANN studies protocol

The mean absolute value (MAV) was selected as the primary EMG feature for this study because of its computational simplicity and its extensive use in myoelectric prosthesis [3,6]. For every set of data collected at each detected movement onset, MAV was calculated for each of the 4 muscles. These values produced sample MAV vectors (input data samples) of four components. Input samples were normalized between [-1,1] independently for each day, using as boundaries the maximum and minimum values extracted from that day's session. Subsequently these samples were randomly assigned to training and test sets (80% and 20%, respectively, of the total amount of samples).

ANN training was performed under two paradigms: with individual data from each of the sessions 10 and 12, and also with combined data from sessions 10 and 12. NeuroSolutions™ software was utilized exclusively for these studies. ANN sizes were [4:5:4] for the ANNs trained with only one session's data and the sizes were [4:7:4, 4:8:4 and 4:9:4] for the ANNs trained with the combined 10th and 12th sessions' data. ANN architecture was feedforward (complete connectivity between adjacent layers) with hyperbolic tangential and softmax transfer functions for the hidden and output layers, respectively. The latter function permits interpretation of the results as probabilities. Fahlman's quickpropagation algorithm [7] was used for gradient descent. Three ANNs were trained (batch learning) with each training set and stored for posterior evaluation. The stopping criterion was that of the *Average Cost* between [0.003 0.006]. As an additional requirement, the errors (i.e. the Euclidean distances between the output and the target values) in the training set had to be from the same statistical population for each of the three ANNs trained with the same data. This last condition together with the stopping criterion warranted that all three ANNs were exposed to the same amount of knowledge. The rates of recognition in the training sets for all the ANNs were above 94% per movement, which is sufficient to assure local generalization. The evaluation of each ANN was performed with each individual test set (i.e. test sets 9,10 and 12).

RESULTS AND DISCUSSION

Results of the evaluation for the three ANNs trained from session 10 presented the recognition results (mean recognition rates $\pm$ the standard deviation) shown in Table I. The results of the three ANNs from session 12 are presented in Table II.

Session	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
9	**100** ± 0	**66.6** ± 7.2	**95.8** ± 7.2	**100** ± 0
10	96.6 ± 5.7	**80** ± 10	**100** ± 0	**100** ± 0
12	100 ± 0	23.3 ± 5.7	86.6 ± 5.7	90 ± 0

Table I. ANN trained with set 10 and evaluated with test sets 9,10, and 12

Session	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
9	91.6 ± 7.2	62.5 ± 0	37.5 ± 0	0 ± 0
10	**96.6** ± 5.7	**70** ± 0	**90** ± 0	**80** ± 17.3
12	**80** ± 0	**96.6** ± 5.7	**90** ± 0	**90** ± 0

Table II ANN trained with set 12 and evaluated with test sets 9,10, and 12

The best performance was obtained with the ANNs trained using the set from session 10 and evaluated with the test set from session 10. Additionally, those ANNs showed excellent recognition rates for 3 out of 4 movements when evaluated with the test set from session 9. However, the recognition rates when the session 12 data were used as the test set were unexpectedly low for the case of Key grip opening. In marked contrast, the ANNs trained with the session 12 data presented the opposite results: Rates of recognition were acceptable for the test set from session 10, but the results were unacceptably low with the test set from session 9, for both precision grip opening (0%) and closing (37.5%).

The limited success described above for the ANNs to perform consistently when presented with test data other than those they were specifically trained with, led us to expand the training set to include representative data from two different sessions, specifically 10 and 12.

The results of the evaluation for the ANNs trained using the combined data are presented in Tables III, IV, and V for network sizes 4:7:4, 4:8:4 and 4:9:4, respectively. ANNs trained using combined data with a hidden layer size greater than eight, showed acceptable performance (i.e. rate of recognition above 80%) for all movements over the three sessions with the exception of Key Grip Opening. In this latter case the session 9 data yielded a mean recognition rate of 66.6% for the ANNs with size 4:8:4. However, the general performance (i.e. the rate of recognition for the combined evaluation data from all of the test sets) yielded recognition rates above 80% for each movement (table VI).

Session	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
9	87.5 ± 0	62.5 ± 0	66.6 ± 14.4	100 ± 0
10	**93.3** ± 5.7	**80** ± 10	**93.3** ± 5.7	**100** ± 0
12	83.3 ± 5.7	80 ± 0	86.6 ± 5.7	90 ± 0

Table III ANN (4:7:4) trained with combined data and evaluated with test sets 9,10 and 12

Session	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
9	100 ± 0	66.6 ± 7.2	87.5 ± 12.5	100 ± 0
10	**96.6** ± 5.7	**90** ± 10	**90** ± 0	**100** ± 0
12	96.6 ± 5.7	90 ± 10	80 ± 0	90 ± 0

Table IV ANN (4:8:4) trained with combined data and evaluated with test sets 9,10 and 12

Session	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
9	95.8 ± 7.2	62.5 ± 0	91.6 ± 14.4	100 ± 0
10	**93.3** ± 5.7	**90** ± 0	**90** ± 0	**100** ± 0
12	96.6 ± 5.7	83.3 ± 5.7	86.6 ± 11.5	90 ± 0

Table V ANN (4:9:4) trained with combined data and evaluated with test sets 9,10 and 12

Size	Key grip closing	Key grip opening	Prec. grip closing	Prec. grip opening
4:7:4	88.0 ± 4.1	75 ± 3.5	83.3 ± 2.0	96.4 ± 0
4:8:4	**97.6** ± 4.1	**83.3** ± 2.0	**85.7** ± 3.5	**96.4** ± 0
4:9:4	95.2 ± 5.4	79.7 ± 2.0	89.2 ± 7.1	96.4 ± 0

Table VI Performance for (4:7:4), (4:8:4) and (4:9:4) ANNs evaluated with the combined data from all of the test sets

The improvement in the recognition rates obtained by training the networks with combined data can be better observed in figure 2

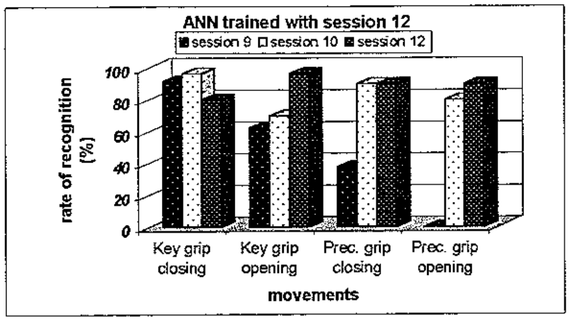

Fig 2.a Mean recognition rates for ANNs trained with 12 session's data

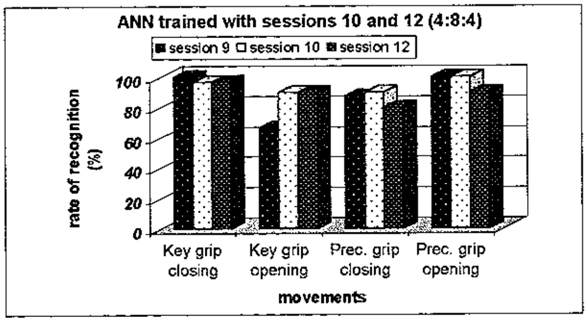

Fig2.b Mean recognition rates for ANNs trained with data combined from sessions 10 and 12.

CONCLUSIONS

The ability of a person with BE elbow amputation to produce intuitive EMG patterns to control the initiation of two different grip modalities has been demonstrated. Conversations with the subject revealed that she relied heavily on feedback from her phantom sensation throughout the training sessions. It is unknown to what extent the presence of phantom limb sensation is necessary for the success of the EMG command production. However, since the presence of non-painful phantom limb sensation in amputees has been reported to be between 80% and 100% [8], the training protocol might be workable for the majority of the amputee population. Moreover, an enhancement of phantom limb sensation might be achievable using a virtual reality training platform [9] to expedite the learning process. On the other hand, the amount of training required to achieve acceptable reliability of the EMG prosthesis control must still be determined. In the present studies, we have observed a certain degree of inconsistency in the generation of EMG activity. At least 3 different causes may contribute to this situation: (1) insufficient conditioning of the residual muscles, (2) insufficient training of the grip motor tasks and (3) disturbances in the user's phantom limb perception that may interfere in the generation of the motor commands. Nevertheless, for those signals that were processed, the ANN pattern recognition studies revealed a high level of consistency (MAV feature space) across different days. However, it was beneficial to combine data from two different sessions in order to achieve more uniform rates of recognition across all of the 4 hand functions studied. Future efforts include the extension of the combined EMG and ANN approaches to additional hand functions, such as voluntary wrist movements.

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