Evaluation of Neural Network Parameters Towards Enhanced Recognition of Naturally Evoked EMG for Prosthetic Hand Grasp Control

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Abstract-*Myoelectric prosthesis function can be enhanced with different grasp modalities such as palmar and lateral grasp. In the present investigation we recorded percutaneously from four residual muscles (flexor dig; ext. dig; flex. pollicis longus; ext. pollicis longus) of a below elbow (BE) amputee female subject while she contracted her residual muscles according to several computer animations representing the different grasps. Artificial Neural Network (ANN) techniques were applied to discriminate between the 4 intended movements (closing and opening of palmar grasp, and closing and opening of lateral grasp). In the present paper we compared ANNs with different characteristics to determine which combination would enhance performance and reliability. We evaluated variations in two ANN parameters; transfer function and different normalization boundaries for the selected EMG feature. The selected EMG feature was the Mean Absolute Value calculated from the EMG of each residual muscle.*

We applied the Correct Classification Measure coefficient developed by Triolo et al. [7] to compare the results from the ANNs. The best results were obtained with the following characteristics: sigmoidal transfer function in the output neurons and normalization boundaries selected as the maximum and minimum achieved across different experimental days plus a security margin applied to the upper boundary.

Keywords: EMG, Neural Networks, Myoelectric prosthesis.

1. Introduction

Upper extremity prostheses include body powered devices and myoelectrically controlled powered hands. While body powered prehension devices are mechanically operated through the movement of the subject's shoulder, myoelectric powered hands utilize the electrical activity of voluntarily contracted muscles to determine the movement intended by the prosthesis user. Due to this, myoelectric control can be highly intuitive and the number of controlled functions is, in principle, only limited by the number of different contraction patterns that the user can produce reliably. Myoelectric control, however, becomes more and more difficult as more functions are incorporated into the prosthesis. Reliable control then requires cumbersome operation and time-consuming training [1]. In those cases, control strategies frequently involve the contraction of muscles groups not naturally linked to the intended motion. Efforts to obtain intuitive operation in multifunctional prosthesis include those of Hudgins *et al*. [2]. and Kelly *et al*. [3]. However, those studies evaluated intuitive control only for movements of the forearm and wrist. To our knowledge, no one has previously attempted to evaluate the feasibility of intuitive control of grasp functions. In light of the work of Ramachandran *et al*. [4]. and Lotze *et al.* [5] we believe that the repetition of movements combined with enhanced visual feedback from that movement would help to rehabilitate an amputee to perform the hand grasp. Finally we evaluated two of the settings of an ANN based pattern recognition system: two different transfer functions and normalization modalities. Our goal was to determine which setting combination would provide enhanced performance.

2. Methods

The subject was an adult female (age 33) who suffered a below-elbow amputation of her left arm (which was her non-dominant hand) 13 years prior to the time of the experiments. Additionally, the subject had never used a prosthesis and presented strong phantom limb sensation. Prior to the experimental sessions we evaluated the position and availability of the extrinsic residual muscles naturally linked to the investigated grasp modalities by applying Magnetic Resonance Imaging techniques. Subsequently, a pair of coiled wire 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. The electrodes remained chronically implanted during 12 recording sessions that spanned a period of 30 days. We used the data obtained during 3 of the last experimental sessions (9th, 10th, 12th sessions) for analysis since any benefits of training could be expected to be achieved nearer to the end of the protocol. During the 11th recording session, the subject reported that she could not move the fingers of her phantom hand as if they were "asleep". Since the subject relied strongly on her phantom limb perception to produce the contractions associated with the grasp movements, we decided to omit the data obtained during the 11th session from the analysis.

During the experiments a computer display executed repeated animations of each grasp modality (lateral grasp closing/opening, palmar grasp

closing/opening). The subject was requested to mimic the displayed movements by contracting her residual limb muscles. The exercises were performed in 4 sets of 25 repetitions of the same grip task before the task was shifted to the other grasp modality. In every case, the movements started with the virtual fingers extended (hand open position). A pause of 1s was included between each consecutive movement repetition. 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).

The 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 accompanied by a decrease 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 palmar grasp closing and opening the selected target muscles were *flexor digitorum* and *extensor digitorum*, respectively, while for lateral grasp closing and opening they were *extensor pollicis longus* and *flexor digitorum*. In this latter case the behavior of the muscles during the movements was counter intuitive. Lateral grasp closing was best correlated with the activity in the *extensor pollicis longus* while lateral grasp opening was best correlated with the activity in the *flexor digitorum*. Since the behavior of the subject was consistent during several experimental sessions, we assigned the controlling muscles in this way, despite the apparent paradox of using an extensor muscle to perform a grasp closing function.

Visual examination of the data from sessions 9 and 10 revealed a substantial reduction of differences between contraction patterns for some grip trials. Consequently, some of the signals that showed deteriorated reciprocal behavior were not considered for further analysis. After we discarded these signals [6], 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

Visual examination of the trials revealed the occasional presence of brief bursts of EMG activity that did not correlate with the grasp movement. In those trials, however, the bursts were followed by segments of EMG activity that behaved monotonically in accordance with the grasp movement. Due to this behavior we set a condition for the existence of an onset event which was not only based on the spatial (amplitude) information of the EMG signal, but also on its temporal characteristics (density of spikes). A 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 onset detection algorithm applied a 200ms sliding window to the moving average signal. If the number of samples in this 200ms window exceeded the threshold for 175ms (not necessarily consecutively) then the first point of this 200ms window was labeled as the movement onset. Then, the algorithm 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 in order to compensate for the delay associated with using a thresholding method for onset detection. The value of 25ms was selected because we felt it was the largest value that would not risk contaminating the onset event with pre-onset activity. The data were stored for subsequent feature extraction.

To properly train and test an ANN the amount of samples has to be the same for each movement. We detected 8 onsets for palmar grasp closing in session 9; 44 onsets for palmar grasp opening in session 10; and 45 onsets for palmar grasp opening in session 12. Although the other movements yielded greater numbers of detected onsets, the amount of data available for training and evaluating an ANN had to be 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 Analysis

We employed the EMG amplitude mean absolute value (MAV) as input to an ANN based pattern recognition system. Our reasons for selecting this feature were several: First, several authors have commented on the importance of EMG amplitude to adequately represent the muscle activity, and because it has been extensively used in myoelectric control [2]. Secondly, MAV is a fast and straightforward feature to calculate and renders a scalar value. We performed the feature extraction individually for each experimental day, and calculated the MAV values for the multiple-channel EMG samples collected at each of the movement onsets. The resulting values were vectorial input samples with 4 dimensions (one MAV value per

each muscle channel). Input samples were normalized between [-1,1] in two different ways: (1) independently for each day, using as boundaries the global minimum and maximum MAV values extracted from the data we selected for the ANN analysis obtained during that day's session (Norm 1) and (2) using the global minimum and maximum values achieved from the data which we selected for the ANN analysis occurring during the three days. In this case, we considered an additional 75% of the maximum value in order to prevent overflow of the boundaries by a possibly larger MAV activity occurring in different days. For the selection we began accepting onsets for each of the movements and stopped this process when no further onset could be detected for one of the movements. Therefore, the number of onsets used for the ANN analysis was limited by the common minimum number of onsets for any of the movements. Subsequently these samples were randomly assigned to training and test sets (80% and 20%, respectively, of the total amount of samples).

Since one of our goals was to evaluate whether the ANNs were able to account for the day-to-day variability, we evaluated the behavior of the pattern recognition system under two different situations. First, we trained the ANN using individual data from the experimental sessions 10 and 12 and secondly, we pooled the training data from sessions 10 and 12 into a single training set. NeuroSolutions^{TM} 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, 4:9:4] for the ANNs trained with the combined 10th and 12th sessions' data. The ANN architecture was feedforward (complete connectivity between adjacent layers) with a hyperbolic tangential transfer function for the hidden layer and with (1) Softmax or (2) Sigmoid transfer functions for the output layer. Fahlman's quickpropagation algorithm [31,32] was used for gradient descent and batch learning was the selected training mode. For each of the combinations of transfer function and normalization type of the input samples, we trained three ANNs. The resulting ANNs were stored for subsequent evaluation of their performance. To stop the training of each ANN we supervised the *Average Cost* value and when this was between [0.0030 0.030] we stopped the training. In addition another requirement was imposed over the group of three ANNs featuring the same training set and combination of transfer function and normalization type of input samples: 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 (U test: $p>0.05$). This last condition together with the stopping criterion warranted that all three ANNs were exposed to the same amount of knowledge. The evaluation of each ANN was performed with each individual test set (i.e. test sets 9,10 and 12).

Methods to Evaluate ANN Results

We compared the output samples of the ANNs with the desired targets in order to determine whether an evaluation sample was correctly recognized. The desired outputs that identified each of the intended motions are described in Table 1.

Movement	Sigmoid transfer function (2 outputs)	Softmax transfer function (4 outputs)
Key grip closing	11	1000
Key grip opening	10	0100
Prec. grip closing	01	0010
Prec. grip opening	00	0001

Table 1 - Network outputs representative of each movement class.

We evaluated the performance of the ANN using two different conditions for correct classification: one more restrictive than the other. In this way we evaluated the data using two different scales, providing us with information about the distribution of the samples in the output space, and their distance to the decision boundary. Therefore, to decide whether a sample was correctly identified we applied the following rule: if the absolute value of the difference between each individual neuron output and its desired target (1 or 0 depending on the movement) was less than 0.5 we considered that the ANN correctly identified the sample. For example, for the case of a sigmoid transfer function of 2 outputs, an output vector of [0.6 0.4] would be identified as a "key grip opening" movement. In addition, we performed a second evaluation, but this time with a more restricted condition: if the absolute value of the difference between each individual output and the corresponding target was less than or equal to 0.3, then we considered that the ANN correctly identified the sample. We called this last situation, the tolerance condition. Subsequently, we applied the Correct Classification Measure (CCM) coefficient developed by Triolo *et al.* [7] to pool the correct classification percentages of all 4 movements and all 3 evaluation sets into a single measure. This coefficient performs a squared correction to the deviation from the perfect classification (100 percent). This correction yields a more adequate estimate of the performance of the pattern recognition system, since poor performance in one class would not be concealed by good performance in the others.

3. Results and Discussion

Normalization Results

For each training set (session 10, 12, and combined set) we compared the CCM values resulting from every combination of transfer function and normalization type (Tables 2 and 3). We observed that when the individual training sets were utilized, the ANNs yielded higher CCM values when the second normalization type was applied. A two sided sign test showed that our conclusion had statistical significance (P= 0.0078: n=8, p=0.5, r=0). When the combined training set was utilized, we observed the opposite tendency. In 3 out of 4 comparisons the ANN utilizing Norm1 gave higher CCM values than the ANN utilizing Norm2. However, due the limitation of available data was not possible to evaluate the statistical significance of this result.

Session	Softmax Norm1	Softmax Norm2	Sigmoid Norm1	Sigmoid Norm2
10th day	74.34	**80.13**	51.74	69.14
12th day	61.61	73.24	65.78	**74.99**
Combined set	**85.83**	80.26	83.17	83.68

Table 2 - Values of the CCM coefficients (%) (standard condition) obtained with ANNs trained using different combinations of transfer function in the output layer and type of normalization for the input samples.

Session	Softmax Norm1	Softmax Norm2	Sigmoid Norm1	Sigmoid Norm2
10th day	72.15	**75.20**	49.57	61.10
12th day	61.25	**71.03**	62.24	69.62
Combined set	81.39	72.68	**81.87**	75.82

Table 3 - Values of the CCM coefficients (%) (tolerance condition).

Transfer Function Results

For each training set (session 10, 12, and combined set) we compared the CCM values for both transfer functions with each normalization type (Norm1 and Norm2). Again, we took into account the number of times that the ANN featuring Sigmoid function has higher CCM values than one presenting a Softmax function. Initially we evaluated the ANNs trained with data from only one experimental session. We performed a two-sided sign test and concluded that there was no statistical difference in the performance of one group of ANNs over the other (P= 0.7266: n=8,p=0.5, r=3).

We then repeated the same analysis, this time considering the combined data sets. In this case, in 3 out of 4 comparisons the ANNs presenting Sigmoid function gave larger CCM values. However, again, the lack of analysis data has not permitted us to test for the statistical significance of the result.

Overall, a close look at the results revealed that for the standard condition, Softmax function and Normalization 1 and Sigmoid function and Normalization 2 were the most successful combinations of settings. When more training data were utilized (and the tolerance condition was evaluated) the ANNs that utilized the sigmoid function obtained the highest CCM values.

4. Conclusions

We showed the influence that normalization and type of transfer function have over the performance of an EMG pattern recognition system based on ANNs. The settings that were more suitable were determined based on good generalization behavior. Better generalization was obtained with an ANN that featured Normalization type 2 in the input data and Sigmoid function in the output layer. This type of setting also yielded a CCM value of 83.68% with the standard condition. This result is very encouraging in our search for a multifunctional myoelectric control.

The authors would like to acknowledge the support of the Danish National Research Foundation.

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