Nonlinear Mappings between Discrete and Simultaneous Motions to Decrease Training Burden of Simultaneous Pattern Recognition Myoelectric Control

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***Abstract*—Real-time simultaneous pattern recognition (PR) control of multiple degrees of freedom (DOF) has been demonstrated using a set of parallel linear discriminant analysis (LDA) classifiers trained with both discrete (1-DOF) and simultaneous (2-DOF) motion data. However, this training method presents a clinical challenge, requiring large amounts of data necessary to re-train the system. This study presents a parallel classifier training method that aims to reduce the training burden. Artificial neural networks (ANNs) were used to determine a nonlinear mapping between surface EMG features of 2-DOF motions and their 1-DOF motion components. The mapping was then used to transform experimentally collected features of 1-DOF motions into simulated features of 2-DOF motions. A set of parallel LDA classifiers were trained using the novel training method and two previously reported training methods. The training methods evaluated were (1) using experimentally collected 1-DOF data and ANN-simulated 2-DOF data, (2) using only experimentally collected 1-DOF data and (3) using experimentally collected 1- and 2-DOF data. Using the novel training method resulted in significantly lower classification error overall (p<0.01) and in predicting 2-DOF motions (p<0.01) compared to training with experimental 1-DOF data only. These findings demonstrate that using a set of ANNs to predict 2-DOF data from 1-DOF data can improve system performance when only discrete training data are available, thus reducing the training burden of simultaneous PR control.**

I. Introduction

Myoelectric upper limb prostheses use electromyography (EMG) signals to control actuated joint movements. Advancements in prosthetic hardware have resulted in multifunctional motorized devices capable of performing complex movements involving multiple degrees of freedom (DOF) simultaneously[1], which are better suited to replicate the natural movements produced by intact limbs. However, these devices require appropriate control strategies that allow upper-limb amputees to use the advanced functions of these devices.

Pattern recognition (PR) using surface EMG has been shown to provide robust classification of single DOF motions[2]. This technique is advantageous because it allows patients to use physiologically appropriate contractions to control the prosthesis, and does not require the localization of discrete physiological muscle sites[3]. PR control also demonstrated improved performance in functional tasks compared to conventional control[4] and has been recently commercialized[5]. However, commercially available pattern recognition is limited to controlling one DOF at a time, requiring the user to operate the prosthesis in a sequential manner.

Methods to provide simultaneous control of prosthetic DOFs have been previously investigated using both surface EMG[6], [7] and intramuscular EMG[8]; more studies have focused on surface EMG because it is less invasive. Most work has focused on regression-based simultaneous control of multiple wrist DOFs[6], but pattern recognition methods have shown promise for simultaneous control of the wrist and hand[7]. A variety of different pattern recognition-based algorithms have been evaluated[9], [10]. The "parallel classifier" architecture (in which multiple classifiers are used in parallel to independently classify different DOFs simultaneously) has successfully demonstrated real-time simultaneous control with independent proportional control of each DOF[7].

Parallel classifiers have been trained using discrete motions only, and both discrete and simultaneous motions. Smith reported significantly lower classification error predicting simultaneous motions using a parallel classifier trained with 1- and 2-DOF motions compared to a parallel classifier trained with 1-DOF motions only (17% vs 76% error, respectively)[11]. Unfortunately, a system trained with 1- and 2-DOF motions presents a clinical challenge due to the large amount of training data (i.e., exemplars from every discrete and simultaneous motion class) that must be collected each time the system is to be re-trained. For a clinical prosthesis user, variable electrode position after donning the myoelectric socket and changes in skin impedance and limb volume due to environmental conditions[12] can lead to changes in signal properties, requiring re-calibration of the system. Therefore, in a clinically viable system, it is critical to minimize the time and amount of data necessary for re-training.

Despite the non-stationary properties of surface EMG signals, it is possible that a consistent relationship between the EMG features of 1-DOF motions and the features of their combined 2-DOF motions exists. Evidence for such relationship includes the successful control of 2-DOF wrist movements using regression systems trained with only 1-

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DOF data[6]. Successful characterization of these mappings may allow for the simulation of 2-DOF training data from user-provided 1-DOF data. A linear implementation of this idea, called Linear Enhanced Training, has recently been investigated in a preliminary study that evaluated simultaneous control of digits[13]. Here we extend the idea to work with parallel classifiers.

In this study, we used artificial neural networks (ANNs) to learn a mapping between the EMG features of two 1-DOF movements and their resultant 2-DOF movement. The ANNs were used to produce simulated 2-DOF training data from experimentally collected 1-DOF training data, thereby reducing the training burden of simultaneous PR control after the ANNs were configured. The classification accuracy of this training method was compared to the accuracy of two previously described methods in the literature – training with both experimentally collected 1-DOF and 2-DOF training data, and training with only 1-DOF data. We hypothesized that using the ANNs would result in classification accuracies bounded by these two other training methods.

II. Methods

A. Experimental Protocol

Three able-bodied subjects (2 female, 1 male; ages 24-27) participated in this experiment after giving informed consent to a protocol approved by the Northwestern University Institutional Review Board. Surface EMG data were collected from subjects during five 60-minute experimental sessions over 5-10 days, which were then later used in an offline cross-validated analysis. Subjects wore a fabric cuff around their right proximal forearm, which was embedded with 6 bipolar pairs of 1.5 cm stainless steel electrode domes, arranged equidistantly around its circumference. Between sessions, electrode locations were marked on the skin of the subject, and care was taken to replicate the electrode placement between days. A reference electrode was placed on the olecranon. EMG signals were sampled at 1000 Hz and amplified using a custom-built Texas Instruments TI-ADS1299 analog front end system. Signals were filtered using a digital bandpass filter between 30-350 Hz and amplified to maximize the dynamic range.

During each session, subjects were prompted to perform 18 different motions using an image-guided screen training method[14]. Six of these motions involved only a single DOF and were forearm pronation (FP), forearm supination (FS), wrist flexion (WF), wrist extension (WE), hand open (HO), and hand close (HC). The remaining twelve motions were all 2-DOF combinations of these six motions. Subjects were instructed to perform each motion using a comfortable, constant force and to hold each contraction for 3 seconds. 16 repetitions of each 1-DOF and 2-DOF motion were collected in this manner.

B. Signal Processing

Data were segmented into 250 ms windows with an increment of 50 ms[15], resulting in 900 analysis windows per movement per session. For each of the 6 EMG channels, 4 time-domain features (Hudgins' set) and 6 autoregressive coefficients of a sixth order autoregressive model were extracted from each window to represent the signals[16].

C. Classifier Structure and Training Methods

The three training methods were evaluated using four different parallel classifiers: a 3-DOF parallel classifier predicted activity in all three DOFs (rotation, wrist, and hand) and three 2-DOF parallel classifiers predicted activity in each possible pairing of DOFs (rotation/wrist, rotation/hand, and wrist/hand). Each parallel classifier consisted of multiple LDA classifiers, such that one LDA was configured for each DOF and discriminated between the two opposing motion classes for the given DOF (e.g., wrist flexion, and wrist extension) and a no motion (NM) class[11]. The following three training methods were evaluated for all four classifier types using data from the fifth experimental session.

1) Training Method Exp1

This method used only 1-DOF training data provided experimentally by the subject during session 5. Each LDA classifier was trained using discrete motions belonging to that DOF. All discrete motions belonging to the other DOFs were included in the no motion class of that DOF's classifier[11].

2) Training Method Exp1+Exp2

This method used both 1- and 2-DOF training data provided experimentally by the subject during session 5. Each LDA classifier was trained using both discrete motions belonging to that DOF and all simultaneous motions involving that DOF. Discrete and simultaneous motions from the other DOFs were included in the no motion class of that DOF's classifier[11].

3) Training Method Exp1+ANN

This method used both 1-DOF training data provided experimentally during session 5, and simulated 2-DOF training data provided by multiple ANNs. An ANN was trained for each simultaneous motion (12 total) to learn the mapping between the simultaneous motion's EMG features and the features of its discrete motion components.

Each ANN had 120 input neurons (the concatenated feature vectors from the two component 1-DOF motions), a single hidden layer with 5 neurons, and 60 output neurons (features of the combined 2-DOF motion). The hidden and output layers used tan-sigmoid and linear transfer functions, respectively. To train these mappings, experimental 1-DOF and 2-DOF data from sessions 1-4 were used. The feature sets described in section II.B were down-sampled to include only non-overlapping windows; these data constituted the ANN training set.

Within each session, for the ANN corresponding to a given 2-DOF motion, 200 windows from the component 1-DOF motions were randomly sampled from the ANN training set without replacement and concatenated. The training label for each input vector was randomly sampled from the corresponding 2-DOF motion in the ANN training set. All sessions were then concatenated and used to train the ANN. Levenberg-Marquardt backpropagation was used.

After the ANNs were trained, they were used to transform experimentally collected 1-DOF data from session 5 into simulated 2-DOF data. For each ANN, 900 overlapping windows of EMG features for each component 1-DOF motion were randomly sampled, concatenated, and used as input data for the feedforward network. The output vectors of each ANN served as simulated 2-DOF EMG features. The experimentally collected 1-DOF data and ANN simulated 2-DOF data were then used as training data for each classifier type, as described above.

D. Classifier Evaluation

All combinations of training methods and classifier types were evaluated using data collected during the fifth experimental session (though Method Exp1+ANN also used data from sessions 1-4 to train the ANNs). Average classification error rates were determined using leave-one-out cross validation. For 3-DOF parallel classifiers, classification error was grouped and averaged for 1-DOF intended motions, 2-DOF intended motions, and no motion. For 2-DOF parallel classifiers, overall classification error of simultaneous movements (e.g., WF+HO) was subdivided into four categories based on error type, and included: 1 correct motion decision + 1 no motion decision (e.g., WF), 1 correct motion decision + 1 incorrect motion decision (e.g., WF+HC), 2 no motion decisions (i.e., NM), and 2 incorrect motion decisions (e.g., WE+HC). This analysis did not generalize to a 3-DOF system in a straightforward manner, so 2-DOF systems were used to investigate the type of errors produced.

E. Statistical Analysis

Repeated measures analysis of variance (ANOVA) and post-hoc comparisons with a Bonferroni correction factor were conducted to compare overall, 1-DOF, 2-DOF, and no motion classification error between classifier training methods. Significance was calculated using $\alpha = 0.05$.

III. RESULTS

For 3-DOF systems, classifier training method had a significant effect on classification error overall ($p<0.001$), and for 1-DOF ($p<0.05$), and 2-DOF ($p<0.001$) motions. Post-hoc comparisons showed that Exp1+ANN training provided significantly decreased classification error compared to Exp1 training in both overall error (32.8% versus 50.9%, respectively, p=0.001) and in predicting simultaneous movements (44.5% versus 78.8%, respectively, p=0.002) (Figure 1). Exp1+ANN training provided significantly increased classification error compared to Exp1 training for discrete movements (14.2% versus 3.1%, respectively, p=0.036).

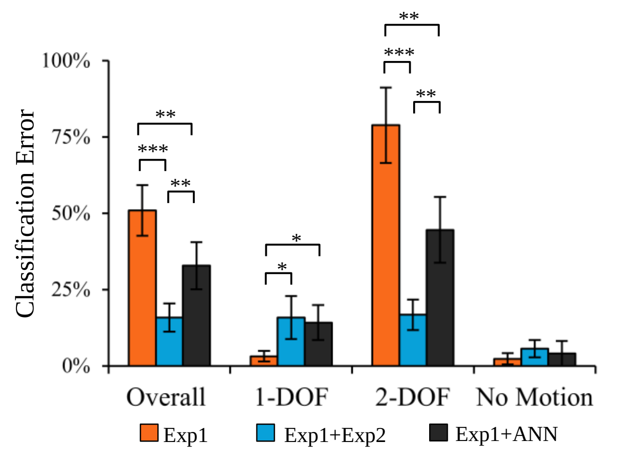

Figure 1. Group average (n=3) offline classification error for 3-DOF parallel classifiers trained with 1-DOF motions only (Exp1), 1- and 2-DOF motions (Exp1+Exp2), and 1-DOF and simulated 2-DOF motions (Exp1+ANN). Overall classification error is presented, as well as error broken down into 1-DOF, 2-DOF, and no motion intended activities. Error bars show +/- 1 SD. * p<0.05, ** p<0.01, *** p<0.001.

Post-hoc comparisons also showed that Exp1+ANN training resulted in significant increases in classification error compared to Exp1+Exp2 training in both overall error (32.8% vs. 15.9%, respectively, p=0.001) and in predicting simultaneous movements (44.5% versus 16.7%, respectively, p=0.004). No significant difference in classification error was found between Exp1+ANN training and Exp1+Exp2 training when predicting discrete movements (p = 1.0).

For all 2-DOF systems, the most common type of error made when predicting 2-DOF motions was misclassifying to one of the simultaneous motion's discrete motion class components (i.e., 1 correct motion decision + 1 no motion decision) (Figure 2).

IV. DISCUSSION AND CONCLUSION

In this study, we evaluated a novel method for training a simultaneous pattern recognition system, which used a set of ANNs to predict EMG features of 2-DOF motions from the features of 1-DOF motions (Exp1+ANN training). These ANNs were then used to produce simulated 2-DOF motion training data, to decrease the training burden on the user.

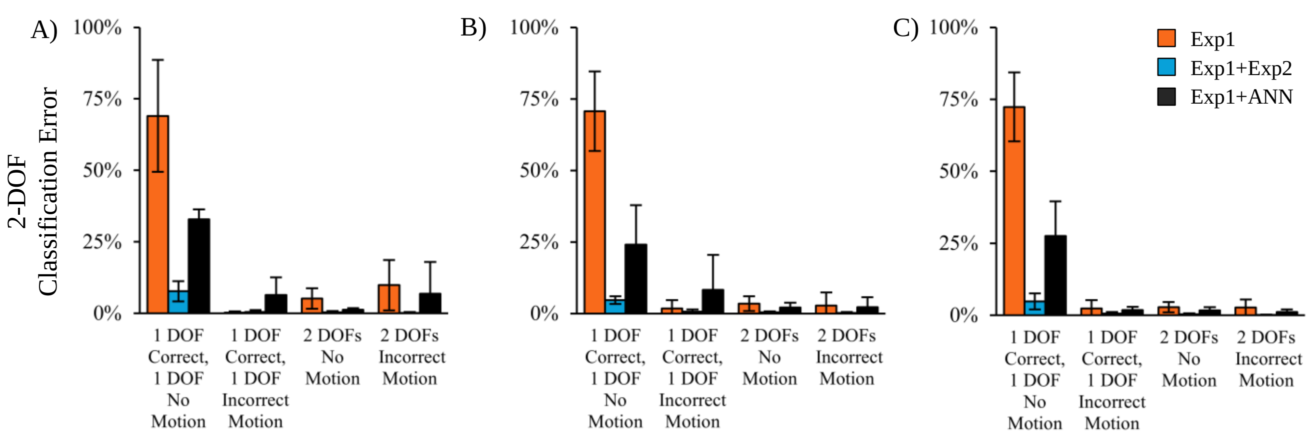

Figure 2. Group average (n=3) offline classification error of 2-DOF intended motions for each classifier training method for A) Rotation/Wrist, B) Rotation/Hand, and C) Wrist/Hand 2-DOF systems. Error is presented by number and type of incorrect LDA classifier decisions.

After the ANNs were trained, Exp1+ANN training required the same amount of training data as Exp1 training (i.e., exemplars of discrete motions only). However, Exp1+ANN training resulted in significantly decreased error rates for 2-DOF motions. This comparison demonstrates the benefit of using a set of ANNs to assist in training a set of parallel classifiers if only discrete training data are available. It also generally agrees with the findings previously reported by Castellini et al., who used Linearly Enhanced Training[13].

Although Exp1+ANN training only required discrete motion data to be re-trained on a daily basis, it also relied on the ANN nonlinear mapping between two 1-DOF motions and their resultant 2-DOF motion. To train the ANNs, it was necessary to collect several days of discrete and simultaneous data. Although the exact amount of data required to adequately define the mapping is currently unknown, it is feasible that PR myoelectric prosthesis users could initially visit the clinic to collect a robust data set to train the neural network. Subsequently, only discrete motion data would be necessary to train the system on a daily basis. This discrete motion data can quickly and efficiently be provided to the system using prosthesis-guided training methods[14].

There was also relative performance detriment when using simulated simultaneous motion data (Exp1+ANN training) compared to using simultaneous motion data collected from the user (Exp1+Exp2 training). These results demonstrate that the ANNs, as trained in this experiment, are not able to exactly predict the user's simultaneous motion data from discrete motion data. However, though some studies investigating the relationship between offline classification accuracy and real-time performance have showed a relationship[15], others have demonstrated that users are able to adapt and perform well with low classification accuracy metrics[6]. Future work should focus on evaluating the real-time controllability of a system trained with 1-DOF and simulated 2-DOF data.

In the 2-DOF systems, the classifier training method did not affect the types of error observed. Similar to previous work[10], most errors made when predicting simultaneous movements were misclassifications to one of the component discrete motions. Further work should investigate the impact that other types of error have on real-time performance and usability.

Limitations of this study include the small subject pool, all of whom were able-bodied subjects with extensive experience using pattern recognition. Future work should include evaluation of individuals with amputations; the stability of the nonlinear mapping as the individual learns myoelectric control should be investigated. Further testing is also necessary to determine how parameters of the ANN (e.g., the number of training examples, training algorithm, network architecture) affect parallel LDA classification accuracies and real-time performance metrics. This analysis should also quantify performance benefits, if any, resulting from using a nonlinear (compared to linear) mapping.

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