Published in final edited form as:

J Neural Eng. 2015 December ; 12(6): 066030. doi:10.1088/1741-2560/12/6/066030.

Use of probabilistic weights to enhance linear regression myoelectric control

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Abstract

Objective—Clinically available prostheses for transradial amputees do not allow simultaneous myoelectric control of degrees of freedom (DOFs). Linear regression methods can provide simultaneous myoelectric control, but frequently also result in difficulty with isolating individual DOFs when desired. This study evaluated the potential of using probabilistic estimates of categories of gross prosthesis movement, which are commonly used in classification-based myoelectric control, to enhance linear regression myoelectric control.

Approach—Gaussian models were fit to EMG feature distributions for three movement classes at each DOF (no movement, or movement in either direction) and used to weight the output of linear regression models by the probability that the user intended the movement. Eight able-bodied and two transradial amputee subjects worked in a virtual Fitts' Law task to evaluate differences in controllability between linear regression and probability-weighted regression for an intramuscular EMG-based three-DOF wrist and hand system.

Main Results—Real-time and offline analyses in able-bodied subjects demonstrated that probability weighting improved performance during single-DOF tasks ($p < 0.05$) by preventing extraneous movement at additional DOFs. Similar results were seen in experiments with two transradial amputees. Though goodness-of-fit evaluations suggested that the EMG feature distributions showed some deviations from the Gaussian, equal-covariance assumptions used in this experiment, the assumptions were sufficiently met to provide improved performance compared to linear regression control.

Significance—Use of probability weights can improve the ability to isolate individual during linear regression myoelectric control, while maintaining the ability to simultaneously control multiple DOFs.

1. Introduction

Transradial amputation is the most common level of major upper extremity amputation (Dillingham et al., 2002). Myoelectric prostheses are powered devices that use electromyogram (EMG) signals from the residual limb to control prosthesis movement.

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These devices have the potential to provide intuitive restoration of limb function because muscles originally controlling the lost wrist and hand are used to control prosthesis movement. Myoelectric prostheses that are clinically available to transradial amputees, using either conventional amplitude-based methods (Williams, 2004) or statistical pattern classification methods (Kuiken et al., 2014), are currently limited to controlling only one degree of freedom (DOF) at a time. Simultaneous myoelectric control is unavailable for this patient population, and therefore prevents the movement of these devices from replicating the coordinated, multiarticular movements of intact limbs.

Several approaches for providing simultaneous myoelectric control have been described in scientific literature, and can be largely divided into two categories: regression-based and classification-based methods. Regression methods aim to provide a continuous mapping between EMG signals and intended prosthesis movement at each DOF. Most studies, including clinically available pattern recognition myoelectric control (Kuiken et al., 2014), have instead focused on developing intuitive user-specific decoders where systems learn the user's pattern of muscle activity for each movement. Others have successfully demonstrated that users can learn abstract mappings between EMG activity and prosthesis output (Radhakrishnan et al., 2008, Pistohl et al., 2013, Antuvan et al., 2014). Both linear (Hahne et al., 2014, Jiang et al., 2014b, Smith et al., 2015a) and nonlinear (Jiang et al., 2012, Hahne et al., 2014, Kamavuako et al., 2012, Ameri et al., 2014, Ngeo et al., 2014, Muceli and Farina, 2012) methods of mapping EMG activity to prosthesis movement have been evaluated, though a large emphasis of real-time evaluation has focused on linear methods and is commonly motivated by the motor control concept of muscle synergies (Jiang et al., 2009, d'Avela et al., 2006). EMG amplitude estimates (such as root-mean-square or mean absolute value (MAV)) are typically the primary signal feature used as inputs into these systems (Hahne et al., 2014, Jiang et al., 2014b, Smith et al., 2015a), as they positively correlate with contraction intensity (De Luca, 1997). This approach has successfully demonstrated simultaneous control of two wrist DOFs with and without a hand DOF (Jiang et al., 2014a, Smith et al., 2015a) during realtime tasks. However, regression methods have also demonstrated difficulty in isolating individual DOFs to perform single-DOF tasks with high path efficiency when desired (Smith et al., 2015a, Jiang et al., 2014a).

In contrast, classification-based approaches divide intended prosthesis movement into a finite set of "motion classes," which may involve activity in a single DOF, multiple simultaneous DOFs, or no DOFs (a rest state). Statistical pattern recognition methods have been used to predict the most probable intended class of movement, using a variety of different classification architectures (Ortiz-Catalan et al., 2013, Young et al., 2013, Young et al., 2014, Wurth and Hargrove, 2014, Young et al., 2012). These approaches have used different features of the EMG signal, including multiple time-domain (Ortiz-Catalan et al., 2013, Young et al., 2013, Young et al., 2014, Wurth and Hargrove, 2014, Young et al., 2012) and autoregressive features (Young et al., 2014, Wurth and Hargrove, 2014). This approach has been implemented to simultaneously and independently modulate control of two DOFs, but resulted in velocity mappings that did not seamlessly transition between single-DOF- and multi-DOF movements (Wurth and Hargrove, 2014). However, this approach has provided the ability to isolate single DOFs with path efficiencies similar to sequential control methods.

Statistical pattern recognition approaches used for myoelectric control provide a discrete classification for intended prosthesis movement. However, the probabilities calculated to make the classification decisions could instead be used to continuously weight the outputs of a linear regression system, and provide an improved expected value prediction of intended prosthesis movement. Combining regression and probabilistic class predictions has been rarely evaluated in the simultaneous myoelectric control literature. Hahne et al. used a logistic regression to weight and sum the two linear regression models trained for each DOF (a linear regression model was trained for each direction of movement at a DOF) (Hahne et al., 2014). This approach did not include a “no motion” class at each DOF, which is typically used in pattern classification methods (Young et al., 2013). Training a no motion state has the potential to minimize extraneous movements, by weighting each regression model’s velocity output by the probability that the user intended movement at the DOF. Probabilistic weighting using a no motion state has been successfully used in other neural interface applications (Chen et al., 2014), but has not been evaluated as users work in a closed-loop interface with feedback and has not been fully evaluated for myoelectric control. Furthermore, though the pattern classification literature has described the benefit of using additional features besides EMG amplitude (Scheme and Englehart, 2014), no previous studies have evaluated a probability-weighted regression using additional features to calculate the probabilistic weights.

The objective of this study was to evaluate the real-time performance of a probability-weighted regression system, using statistical models at each DOF to predict the probability of movement in either direction or of no movement. We hypothesized that compared to linear regression myoelectric control, a probability-weighted regression would improve the ability to isolate individual DOFs when desired and lead to improved real-time controllability for tasks requiring use of only one DOF. The two control systems were evaluated in a sample of able-bodied subjects and in two subjects with transradial amputation to evaluate whether trends extended to the amputee user population. We evaluated these systems using intramuscular EMG as the signal source, because intramuscular signals recorded from chronic implantable devices (Weir et al., 2009) have recently shown promising ability to provide simultaneous control of three DOFs at the wrist and hand in amputee subjects with a physical prosthesis (Pasquina et al., 2015). Preliminary findings have also demonstrated improved offline prediction accuracies for both regression and classification-based simultaneous control methods compared to surface EMG (Smith and Hargrove, 2014, Smith and Hargrove, 2013).

2. Methods

Eight able-bodied subjects and two subjects with transradial amputation (Table 1) were recruited for this study, which was approved by the Northwestern University Institutional Review Board. The subjects used fine-wire EMG to control a cursor in a virtual task that enabled control of three DOFs: wrist supination/pronation, wrist flexion/extension, and hand open/close (Figure 1). All subjects were experienced with sequential myoelectric control but naïve to simultaneous control of three DOFs. All subjects also were provided two practice sessions using sequential pattern recognition myoelectric control (Kuiken et al., 2014) to learn the virtual task. Able-bodied subjects participated in a single experimental session.

Subjects provided a single set of training data, which was used to configure both a linear regression and a probability-weighted regression myoelectric control system. The two amputee subjects participated in two experimental sessions, where the two myoelectric control systems were evaluated on separate days with a new set of training data collected each day. This component of the experimental design was altered to account for the high risk for fatigue in the amputee population given forearm muscle atrophy.

2.1. EMG Acquisition and Processing

Fine wire EMG was recorded from the following six muscles in the forearm for the able-bodied subjects: *pronator (PT)*, *supinator (SUP)*, *flexor carpi radialis (FCR)*, *extensor carpi radialis longus (ECRL)*, *flexor digitorum profundus (FDP)*, and *extensor digitorum communis (EDC)*. For the two amputee subjects, the same muscles were used except *flexor digitorum superficialis (FDS)* was used instead of *profundus*. Hooked bipolar fine wire electrodes with 0.051 mm diameter and 5 mm bare-wire terminations were used (Motion Lab Systems, Inc.). For the able-bodied subjects, fine wires were inserted as recommended by Delagi et al. (Delagi et al., 1980) and by palpation. They were confirmed using test contractions and/or electrical stimulation. For the two amputee subjects, their forearm musculoskeletal anatomy was characterized by ultrasonography prior to insertions. Fine wires were inserted as recommended by Delagi, with modifications made as necessary given their altered forearm anatomy. Insertions were confirmed using test contractions. After the wires were inserted, able-bodied subjects were restrained in a custom brace to enforce isometric contractions. One of the two amputee subjects also requested that his forearm be restrained to decrease discomfort by minimizing forearm movement while the wires were in place.

EMG signals were collected using a Motion Lab MA330 system, where gains were applied to maximize the dynamic range and a band-pass filter between 10 Hz and 2000 Hz was applied. Signals were sampled at 5000 Hz using a 16-bit National Instruments acquisition system (NI USB-6218). Signals were digitally high-pass filtered at 20 Hz using a 3rd order Butterworth filter. Signals were partitioned into 250 ms windows with a frame increment of 50 ms (Smith et al., 2011) for feature extraction. Four time domain features (mean absolute value (MAV), waveform length, slope-sign changes, and zero crossings (Hudgins et al., 1993)) and sixth-order autoregressive model parameters (Huang et al., 2005) were calculated for each EMG channel. Linear regression myoelectric control exclusively used the vector of MAVs, $\mathbf{m}$, as input to predict intended prosthesis movement. Posterior-weighted regression used both $\mathbf{m}$ and a vector of all available features, ϕ , as inputs to the system.

Training Data Collection—Subjects provided a training data set in the beginning of each experimental session. For able-bodied subjects, this training data set was used to train both the linear regression and the probability-weighted regression systems. For the two amputee subjects, a new training data set was collected for each session. Subjects were provided a visual prompt (Figure 2) consisting of a moving cursor that guided them through ramped contractions using one, two, or three DOFs. Two 1-DOF prompts were presented for each movement, and 2- and 3-DOF prompts were presented multiple times to include all possible orders in which the component movements could be presented.

The height of the cursor represented different levels of contraction intensity, and mapped to different levels of intended prosthesis velocity. Subjects were instructed to provide comfortable level contractions when the cursor was at the middle level peak of 1-DOF prompts and the top of the ramps for the 2- and 3-DOF prompts (Figure 2). Subjects linearly increased their perceived contraction intensity with the linear ramps on the visual prompt. Feature vectors were extracted from the training signals, and the height of the visual prompts were used as the training labels for the linear regression models (Smith et al., 2015a). The height of the middle level peak of 1-DOF prompts and the top of the ramps for the 2- and 3-DOF prompts was mapped to 50% of maximum velocity. The height of the higher level peak was mapped to 75% of maximum velocity. To train the statistical models used to calculate the probabilistic weights, the data was also relabeled to reflect the gross class of movement at each DOF. For each DOF, the data was relabeled to be either movement in the positive direction, movement in the negative direction, or no movement. The entire training data set was used to train each regression model and each statistical model. Training data from prompts not corresponding to a regression model's motion type were labelled as 0% velocity (Smith et al., 2015a).

2.2. Myoelectric Control System

Both myoelectric control systems utilized six linear models to map the EMG channel MAVs to the velocity output of each of the six possible motion types (Hahne et al., 2014, Jiang et al., 2014a, Smith et al., 2015a):

$$v_i = \mathbf{a}_i^T \mathbf{m} + b_i \quad (1)$$

where i was one of six motion types (supination, pronation, wrist flexion, wrist extension, hand open, hand closed), v_i was the predicted velocity for the motion type as a percentage of maximum, $\mathbf{a}_i$ was the vector of multiplicative coefficients for each MAV, $\mathbf{m}$ was the vector of MAVs for each of the six muscles, and b_i was the constant offset. $\mathbf{M}$ was chosen as the input vector for linear regression control instead of ϕ to be consistent with previous work with linear regression control (Hahne et al., 2014, Smith et al., 2015a) and because use of ϕ as the input vector led to overfitting and poorer real-time performance during pilot experiments. The values of $\mathbf{a}_i$ and b_i were identified using least squares regression and the above described training data set. For each linear regression model, predictions below 10% velocity were forced to 0% to reduce small unwanted movements.

For linear regression myoelectric control, the output velocity of each DOF was given by the difference between the regression models trained for the two possible directions of movements at the DOF:

$$V_j = v_{j+} - v_{j-} \quad (2)$$

where V_j is the velocity output for the DOF of interest j , v_{j+} is the output of the regression model corresponding to movement in the positive direction (supination, wrist extension, or hand open), and v_{j-} is the output of the regression model corresponding to movement in the negative direction (pronation, wrist flexion, or hand close).

For probability-weighted regression, intended activity at each DOF j was considered to be one of three mutually exclusive states: (1) movement in the positive direction (S_{j+}), (2) movement in the negative direction (S_{j-}), and (3) no movement (S_{j0}). The probability that the user intended each of the possible states, given the feature vector ϕ , was used to weight the linear regression outputs to provide an expected value estimate of intended prosthesis velocity at each DOF:

$$V_j = [v_{j+} \times P(S_{j+} | \phi)] - [v_{j-} \times P(S_{j-} | \phi)] + [0 \times P(S_{j0} | \phi)] \quad (3)$$

$$= [v_{j+} \times P(S_{j+} | \phi)] - [v_{j-} \times P(S_{j-} | \phi)] \quad (4)$$

The probabilities $P(S_{j+} | \phi)$, $P(S_{j-} | \phi)$, and $P(S_{j0} | \phi)$ for each DOF j were calculated as the posterior probabilities using Bayes' Law:

$$P(S_{j+} | \phi) = P(\phi | S_{j+}) \times P(S_{j+}) / P(\phi) \quad (5)$$

$$P(S_{j-} | \phi) = P(\phi | S_{j-}) \times P(S_{j-}) / P(\phi) \quad (6)$$

$$P(S_{j0} | \phi) = P(\phi | S_{j0}) \times P(S_{j0}) / P(\phi) \quad (7)$$

where the likelihood functions $P(\phi | S_{j+})$, $P(\phi | S_{j-})$, and $P(\phi | S_{j0})$ were Gaussian distributions fit to the training data set, the prior distributions were uniform:

$$P(S_{j+}) = P(S_{j-}) \times P(S_{j0}) = 1/3 \quad (8)$$

, and $P(\phi)$ was a normalizing constant to enforce that

$$P(\phi | S_{j+}) + P(\phi | S_{j-}) + P(\phi | S_{j0}) = 1. \quad (9)$$

The likelihood functions for each DOF j were fit by distributing the training data set into the three possible states — S_{j+} , S_{j-} , or S_{j0} — and fitting Gaussian distributions to each subset using a pooled covariance matrix. These assumptions are similar to a parallel configuration of linear discriminant analysis classifiers previously investigated for pattern recognition-based simultaneous myoelectric control (Young et al., 2013).

During real-time control, both control systems implemented a post-processing velocity ramp, originally developed for use with sequential pattern recognition control (Simon et al., 2011), to minimize abrupt changes in DOF activity. The ramp caused the output velocity to linearly increase to 100% of the intended velocity, calculated by Eq. 2 or Eq. 4, over 500 ms of continuous activity.

2.3. Offline and Real-Time Performance Evaluation

Offline prediction accuracy of each myoelectric control method was evaluated using random sub-sampling validation with the training data set. Accuracy was averaged over 100 repetitions, where for each repetition, 90% of the data was randomly sampled for training, and the remaining 10% of the data was used for testing. Prediction accuracy for each repetition was quantified by the coefficient of determination (R_i^2) for each DOF, i , was calculated by:

$$R_i^2 = 1 - \frac{\sum (V_i(t) - \hat{V}_i(t))^2}{\sum (V_i(t) - \bar{V}_i)^2} \quad (10)$$

where $V_i(t)$ was the prompted velocity for DOF i at time t , $\hat{V}_i(t)$ was the velocity predicted by the myoelectric control system for DOF i at time t , and $\bar{V}_i$ was the average value of the prompt. The overall R^2 was calculated for each of the three DOFs and averaged. Accuracy was also quantified by how frequently the control system accurately predicted activity in the intended DOFs, or whether the system predicted additional unintended movement, unintended no-movement, or incorrect movement of a DOF.

Real-time performance was evaluated using a pseudo three-dimensional Fitts' Law test in a virtual environment (Figure 1) (Scheme and Englehart, 2012, Smith et al., 2014). The output of the myoelectric control systems controlled the velocity of a ring-shaped cursor. Wrist flexion/extension controlled the speed of horizontal displacement, wrist rotation controlled the speed of vertical displacement, and hand open/close controlled the speed of change in cursor radius. Subjects were prompted to move the ring cursor into a variety of annulus-shaped targets as quickly as possible, and were neither encouraged nor discouraged from using simultaneous control. Successful trials required target acquisition within 30 s, with less than five overshoots (i.e., moving into and then out of the target). Targets were acquired by a 2 s dwell period. Three levels of target complexity were presented with equal frequency: "1-DOF targets" required use of only one DOF, "2-DOF targets" required use of two DOFs, and "3-DOF targets" required use of three DOFs to successfully complete the trial. Fitts' Law trials were presented to subjects in experimental blocks, during which three targets were presented for each combination of target complexity and index of difficulty (Table 2), resulting in 54 trials per block.

Able bodied subjects evaluated both linear regression control and parallel-weighted regression in a single experimental session. The two amputee subjects participated in two experimental sessions, where the two myoelectric control systems were evaluated on separate days with a new set of training data collected each day. In both cases, the order in which the subjects used the two control systems was randomized. For the amputee subjects, subject TR1 used linear regression control during the first session and probability-weighted regression control during the second session. For TR2, this order was opposite. After configuring each system, subjects were allowed two abbreviated Fitts' Law sessions to learn the control system, as well as three repetitions of a modified Motion Test, as described in (Smith et al., 2014), to practice isolating individual DOFs. Able bodied subjects then evaluated each of the two myoelectric control systems using two full experimental blocks,

each containing 54 targets, as described above. For each of the amputee subjects' experimental sessions, the subjects completed as many experimental blocks as they could prior to fatiguing on the first session, which matched on the second session. Fatigue was qualitatively identified by the subjects.

Real-time performance metrics included throughput and path efficiency. Throughput was calculated by the mean of means method described by ISO 9241-9 (Soukoreff and MacKenzie, 2004), and path efficiency was calculated as the ratio of the shortest possible path length to the path length taken (Williams and Kirsch, 2008). Data for each control system was averaged across the experimental blocks. Subjects' use of simultaneous control was also quantified over total and normalized fractions of trial duration. A DOF was considered to be active if the velocity output was greater than 5% of maximum output.

2.4. Statistical Analysis

Paired t-tests were used to evaluate differences between R^2 and DOF accuracies between the control systems for 1-, 2-, and 3-DOF target complexities. Paired t-tests were also used to evaluate the effect of the control system and target complexity on throughput, path efficiency, and use of simultaneous control for 1-, 2-, and 3-DOF target complexities. The goodness-of-fit of the Gaussian distributions used for probability-weighted regression were evaluated using Q-Q plots (Kratz and Resnick, 1996). The Mahalanobis squared distance between the training data and the multivariate Gaussian fit to them was plotted against the quantiles of a χ^2 distribution with 60 degrees of freedom (the number of total features), as Mahalanobis squared distance has an approximate chi-squared distribution when data are multivariate-normal (Evans et al., 1993). Means are reported as $\pm$ standard error. Error bars in figures represent standard error. Significance was evaluated at $\alpha = 0.05$.

3. Results

3.1. Able-Bodied Subjects: Offline Analysis

For 1- and 2-DOF prompts, probability-weighted regression resulted in statistically significant higher R^2 values compared to linear regression methods (Figure 3, $p < 0.001$ and $p = 0.024$, respectively) in able-bodied subjects. No significant difference was observed between probability-weighted regression and linear regression for 3-DOF prompts ($p = 0.773$).

For 1- and 2-DOF target complexities, probability-weighted regression resulted in statistically significant increases in the frequency of correctly predicting DOF activity, significant increases in the frequency of incorrectly predicting no-motion at a DOF compared to linear regression control, and significant decreases in the frequency of predicting additional unintended DOF activity compared to linear regression control in able-bodied subjects (Figure 4, $p < 0.001$ for each). For 3-DOF target complexities, probability-weighted regression resulted in statistically significant increases in the frequency of correctly predicting DOF activity, and significant increases in the frequency of incorrectly predicting no-motion at a DOF compared to linear regression control compared to linear regression control ($p = 0.037$ and $p = 0.030$, respectively). There was no statistical

difference in the frequency of predicting the wrong direction of movement at the DOFs ($p = 0.123$, $p = 0.138$, and $p = 0.118$ for 1-, 2-, and 3-DOF targets, respectively).

3.2. Able-Bodied Subjects: Real-Time Analysis

During real-time evaluations, able-bodied subjects successfully completed $97.7\% \pm 1.8\%$ of targets using linear regression control, and $98.9\% \pm 0.5\%$ of targets using probability-weighted regression. Mean completion time for each control scheme varied linearly with index of difficulty and target complexity (Figure 5A–B). The R^2 values for these empirical Fitts' Law regression models ranged between 0.883 and 0.981, indicating that a Fitts' Law analysis was appropriate.

For 1-DOF targets, subjects experienced improved throughput and path efficiency when using probability-weighted regression compared to linear regression (Figure 5C–D, $p = 0.006$ and $p = 0.017$, respectively). For 2- and 3-DOF targets, there was no statistically significant difference between the two control systems in either throughput ($p = 0.213$ and $p = 0.348$, respectively) or path efficiency ($p = 0.858$ and $p = 0.550$, respectively).

Table 3 lists the average percentage of trial duration that subjects used two or three DOFs simultaneously. Subjects used two DOFs simultaneously more often when using linear regression control for 1-, 2-, and 3-DOF targets than when using probability-weighted regression ($p = 0.02$, $p = 0.001$, and $p = 0.02$, respectively). Subjects used three DOFs simultaneously more often when using linear regression control for 2-, and 3-DOF targets than when using probability-weighted regression ($p = 0.035$ and $p = 0.034$, respectively). Subjects demonstrated an insignificant difference in use of three DOFs simultaneously for 1-DOF targets for the two control systems ($p = 0.052$).

3.3. Able-Bodied Subjects: Statistical Model Goodness-of-Fit

The training data, partitioned into the three states for each DOF, are depicted in Figure 7 as projections onto the first two linear discriminant axes. The different shapes of the distributions and the nonlinear nature of the QQ plots demonstrate deviation from normality and equal covariance assumptions.

3.3. Amputee Subject Results

The offline and real-time results for both of the subjects with transradial amputation were similar to the able-bodied results (Figure 8). Use of probability-weighted regression provided more correct offline predictions of intended DOF activity for 1-DOF targets. This occurred with a concurrent decrease in the frequency in which additional unintended movement was predicted (Figure 8a–b). Similar improvements were also seen for 2-DOF targets in each subject. For 3-DOF targets, TR1 demonstrated equivalent prediction of correct DOF activity between the two control systems. TR2 demonstrated a decrease in the frequency in predicting correct DOF activity when using probability-weights, with a concurrent increase in the frequency of unintentionally dropping an intended DOF. The real-time performance in the Fitts' law task mirrored the offline accuracy in predicting intended DOF activity. Both subjects demonstrated an increase in throughput and path efficiency for 1- and 2-DOF targets when using probability-weighted regression. For 3-DOF targets, real-

time performance showed no trend between the two amputee subjects – subject TR1 demonstrated better performance using probability-weighted regression and TR2 demonstrated equally better performance using linear regression.

4. Discussion

The results of this study demonstrate that linear regression-based methods of simultaneous myoelectric control may benefit from incorporating probabilistic measures of the intended DOF state (i.e. the probability that the user intends no-motion, motion in the positive direction, or motion in the negative direction). These results were demonstrated in multiple able-bodied subjects and confirmed in a preliminary cohort of two transradial amputee subjects. Probability-weighted regression improved subjects' ability to perform single DOF tasks (1-DOF targets) without significantly hindering their realtime performance during 2- and 3-DOF targets in the Fitts' Law task (Figures 5 and 8). For the two able-bodied subjects, use of probability-weighted regression also improved the real-time performance during 2-DOF tasks. The two myoelectric control systems were presented to the amputee subjects in opposite orders, suggesting that learning across sessions did not contribute to the observed differences between the control systems. Previous reports have demonstrated that linear regression control without probabilistic weights provided improved simultaneous control compared to conventional dual-site methods using intramuscular EMG, but at the expense of allowing unintended movements when trying to isolate the DOFs (Smith et al., 2015a). Probabilistic weights may therefore address limitations of linear regression control during tasks where users wish to use only one DOF at a time without degrading performance in more complex tasks.

Offline analysis demonstrated that probability-weighted regression resulted in significantly improved accuracies in predicting movement at a single DOF and at two DOFs simultaneously (Figure 3). The improved accuracy in predicting intended prosthesis movement may in part be attributed to the inclusion of EMG features in the statistical models that predict intended movement but do not necessarily correlate linearly with intended velocity output (and are therefore not suitable for inputs to the linear regression models). A majority of this improvement resulted from a significant reduction in the frequency of extraneous unintended DOF movements inappropriately output by the myoelectric control system (Figures 4 and 8), and can be attributed to the presence of a no-motion state in the statistical model. The probabilistic weights suppressed the regression model outputs when it was highly unlikely that the user desired movement at the DOF. Such results were similarly reflected during real-time acquisition of 1-DOF targets in the Fitts Law task, where users were able to better isolate single DOFs (Figure 6, Table 3), leading to improved throughput and path efficiency for these targets (Figure 5). The ability to isolate single DOFs when desired is an important component of functional simultaneous myoelectric control systems, as previous studies have demonstrated that users implement a combination of both simultaneous-and sequential-DOF control while accomplishing tasks. Users frequently use simultaneous control for ballistic movements during gross positioning, and then sequential control during fine corrections at the end of tasks (Smith et al., 2015b, Amsuss et al., 2014).

Implementing probability-weighted regression also resulted in small, statistically significant decreases in the amount of simultaneous control used (Figure 6, Table 3). Offline analyses suggest that probability-weighted regression made it more challenging to activate multiple DOFs simultaneously when desired, as the offline predictions more frequently resulted in silenced movement at a DOF that users intended to actuate (Figure 4, Figure 8). This increased challenge in implementing simultaneous control may explain why able-bodied subjects did not exhibit improved real-time performance metrics for 2-DOF targets when using probability-weighted regression, even though this control system was significantly less likely to produce unintended movements. These results also replicated similar findings with simultaneous pattern recognition approaches, which used a similar statistical model (Gaussian distributions, equal covariances across all classes), and found that a majority of classification error when predicting simultaneous-DOF-activity resulted from incorrectly predicting that only one of the DOFs was active (Young et al., 2013).

Successfully implementing probabilistic weights depends on the accuracy of the statistical model used. In this experiment, we used EMG features and statistical models that have been successfully used in linear-discriminant analysis-based pattern recognition myoelectric control (Kuiken et al., 2014, Englehart and Hudgins, 2003); these models assume that the likelihood functions for each state at a DOF follow a Gaussian distribution with equal covariances. These assumptions allow for a quickly trained system with less risk of overfitting small data sets, and have been previously demonstrated to provide equivalent performance to more complex statistical models for sequential pattern recognition control (Hargrove et al., 2007). Though the distributions of EMG features in this experiment showed some deviations from these statistical model assumptions (Figure 7), the assumptions were sufficiently met in this experiment to provide improved performance compared to linear regression control. Future work should investigate the potential for improving prediction accuracy and real-time control by relaxing these assumptions—for example, allowing different covariances for the likelihood (quadratic discriminant analysis assumption), or assuming no underlying likelihood distribution structure (multinomial regression). Such approaches are more burdensome to train, requiring larger training data sets and use of time consuming optimization algorithms. However, use of intramuscular EMG with a chronic implanted system would likely require less frequent retraining than surface EMG-based systems, such that more complex training regimens could be clinically acceptable.

This study is one of the first real-time demonstrations in amputee subjects of simultaneous control of three DOFs at the wrist and hand using regression methods. Previous demonstrations have been primarily limited to two DOFs at the wrist and used surface EMG as the signal source. It is also one of the first experiments to demonstrate real-time control in amputees using a closed-loop system with fine-wire EMG. However, the number of amputee subjects in this study was small, and future work should repeat this experiment with a greater number of subjects.

This study was designed to evaluate the difference between linear regression and probability-weighted regression given the constraints of using fine-wire EMG recordings. Each experimental session lasted approximately 4 hours, and time constraints prevented the

multiple repetitions and learning analysis that have been previously implemented in intramuscular EMG-based evaluations of simultaneous myoelectric control (Smith et al., 2014). Future work should therefore follow the learning of subjects over multiple sessions, and should track not only changes in real-time performance, but also changes in contraction patterns provided in the training data set. This study is also limited by the use of a virtual environment. Evaluation of these myoelectric control systems as amputees use physical prostheses during functional tasks should also be performed as implantable myoelectric sensors become available.

5. Conclusion

Our study demonstrates in both able-bodied and amputee subjects that use of probability weights can improve the ability to isolate individual DOFs when using linear regression myoelectric control, while maintaining the ability to simultaneously control multiple DOFs.

Acknowledgments

The authors would like to thank Ann Barlow, PhD and Sheila Burt for assistance in editing the manuscript. This work was supported by the National Institute of Neurological Disorders and Stroke (NINDS) award 1F31NS083166, the DARPA RE-NET Program administered through the Space and Naval Warfare Systems Center contract number N66001-12-1-4029, and the Chicago Biomedical Consortium with support from the Searle Funds at The Chicago Community Trust.

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Figure 1. Experimental setup

(a) Subjects used the myoelectric control system to work in a virtual Fitts' Law test. The able-bodied subject shown here was restrained in a custom brace to ensure isometric contractions. (b) The Fitts' Law test required users to move a ring-shaped cursor into annulus-shaped targets and dwell for 2 s. (c) Subjects controlled the ring-shaped cursor using an easy-to learn mapping.

Figure 2. Training interface used

Subjects provided EMG signals in response to a visual cursor for (a) 1-DOF prompts, (b) 2-DOF prompts, and (c) 3-DOF prompts. Subjects were instructed to increase the intensity of their contraction in response to the height of the moving cursor. The position of the cursor was used to label the training data for the linear regression models as a percentage of maximum velocity. Training prompts were also classified as one of three states for each DOF to group training data for fitting probabilistic models used to calculate the regression weights – no motion (0), movement in the positive direction (+), or movement in the negative direction (-). Tables in the figure represent labels used for the cursor position in each of the diagrams. Sample EMG signals are representative signals from one of the able-bodied subjects.

Figure 3. Cross-validated offline prediction accuracies for both myoelectric control systems in able-bodied subjects

Accuracy of predictions are divided into prediction of prompts requiring use of only one DOF, use of two simultaneous DOFs, or use of all three DOFs. Use of probability-weighted regression (PWR) resulted in significantly higher R² values for 1- and 2-DOF prompts compared to linear regression control (LR). * $p < 0.05$.

Figure 4. DOF prediction accuracies for both myoelectric control systems in able-bodied subjects
 Accuracy of predictions are divided into prediction of prompts requiring (a) use of only one DOF, (b) use of two simultaneous DOFs, or (c) use of all three DOFs. Use of probability-weighted regression (PWR) provided more correct predictions of intended DOF activity for each DOF ($p < 0.05$), fewer predictions resulting in unintended additional movement during 1- and 2-DOF targets ($p < 0.001$), and more frequent predictions where the control system predicted activity in fewer DOFs than intended ($p < 0.05$) than linear regression control (LR).

Figure 5. Fitts' Law performance

(A–B) Empirical Fitts' Law regression models, relationship between completion time and index of difficulty for the two control systems. (a) For linear regression control (LR), R^2 was 0.96, 0.91, and 0.96 for 1-, 2-, and 3-DOF targets, respectively. (b) For probability-weighted regression (PWR), R^2 was 0.91, 0.98, and 0.88 for 1-, 2-, and 3-DOF targets, respectively. (c–d): Fitts' Law performance metrics for the two control systems. Subjects exhibited higher values of throughput (c) and path efficiency (d) with probability-weighted regression for 1-DOF targets. There was no statistical difference between the two control systems for 2- or 3-DOF targets. * $p < 0.05$

Figure 6. Distribution of how frequently subjects used one DOF at a time, two DOFs simultaneously, or three DOFs simultaneously as a function of normalized trial duration (a) Linear regression control. (b) Probability-weighted regression. Both control systems demonstrated highest use of simultaneous control in the first half of the trial, and ended the trial with greater use of 1-DOF movements. For each target complexity, subjects experienced greater levels of simultaneous DOF activation when using linear regression control.

Figure 7. Distributions training data for each possible state for (a–b) the rotation DOF, (c–d) the wrist flexion/extension DOF, and (e–f) the hand DOF for a representative subject

(a, c, e) Data for each of the three states is projected onto the first two linear discriminant axes configured to distinguish between the three states. The different shapes of the spreads for each class suggest that the equal covariance assumption is not met. (b, d, f). QQ plots of the Mahalanobis squared distance of the data for each state to the distribution fit to it. Departure from linearity demonstrates non-normality of the data.

Figure 8. Offline and real-time performance of two subjects with transradial amputation (a–b) Offline analysis. Use of probability-weighted regression (PWR) provided more correct predictions of intended DOF activity for 1- and 2-DOF targets with a concurrent decrease in the frequency in which additional unintended movement was predicted, compared to linear regression control (LR). For 3-DOF targets, TR1 demonstrated equivalent prediction of correct DOF activity and TR2 demonstrated a decrease in the frequency in predicting correct DOF activity when using probability-weights. (c–f) Online analysis. Both subjects demonstrated an increase in throughput and path efficiency for 1- and 2-DOF targets when using probability-weighted regression.

Table 1

Amputee subject demographics

Subject ID	Age	Side of Amputation	Time Since Amputation
TR1	67 years	Right	30 years
TR2	27 years	Left	1 year

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Table 2

Target Conditions for the Fitts' Law Task

Distance, D (normalized distance unit)	Thickness, W (normalized distance unit)	Index of Difficulty, ID (bits)
40	10	2.32
40	20	1.59
40	30	1.22
80	10	3.17
80	20	2.32
80	30	1.87

Table 3

Percentage of Trial Duration with at Least Two DOFs Simultaneously Active

	1-DOF Targets		2-DOF Targets		3-DOF Targets	
	<i>Linear Regression</i>	<i>Probability Weighted Regression</i>	<i>Linear Regression</i>	<i>Probability Weighted Regression</i>	<i>Linear Regression</i>	<i>Probability Weighted Regression</i>
2 DOFs simultaneously active	20.6% (± 4.3%)	9.1% (± 1.6%)	44.6% (± 2.0%)	36.6% (± 1.7%)	38.9% (± 2.3%)	32.6% (± 2.0%)
3 DOFs simultaneously active	2.5% (± 0.9%)	0.7% (± 0.3%)	8.2% (± 1.9%)	4.2% (± 1.0%)	15.1% (± 3.2%)	9.6% (± 2.2%)

Subjects used a similar strategy of implementing simultaneous control between the two control methods. Use of simultaneous control peaked near the middle of the trial. Subjects used more 1-DOF movements at the end of the trial, typically for fine corrections. For all target complexities, linear regression control exhibited increased simultaneous activation of two or more DOFs.