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Multi-position Training Improves Robustness of Pattern Recognition and Reduces Limb-Position Effect in Prosthetic Control

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Introduction

Electromyogram (EMG)-based control strategies represent the current state-of-the-art for control of complex upper-limb prostheses. High levels of classification accuracy can be obtained through the use of pattern recognition-based control algorithms using time domain features extracted from surface EMG.^{1,2} Advanced prosthetic users have appreciated a more intuitive control scheme for multiple degrees of freedom (multi-DoF) compared with traditional two-site control methods.³ Despite the significant benefits of pattern-recognition systems, these systems lack reliable implementation many in real-world applications.²

One of the most significant limitations arises when a user attempts to use the limb in a different position from which it was trained, resulting in a significant decrease in classification accuracy.^{1,4–7} This phenomenon has been referred to as the “limb-position effect” and can drastically negatively impact the overall functionality of an upper-limb myoelectric prosthesis.⁸ Classification error rates have been shown to increase to an average of 35% when attempting grasps in positions different from training data.⁸ Such error rates make tasks such as grasping objects off shelves or from desks exceptionally difficult. Overcoming this hurdle represents an important step towards improving the usability of multi-DoF upper-limb prosthesis and subsequently the quality of life of its users.

Many efforts to address the limb-position effect have actually ignored the limb position entirely. These previous strategies have included limiting the movement of speed of the prosthetic hand when there is a change in classifier decision⁹ and imposing confidence thresholds or majority vote methods to limit the impact of incorrectly predicted active grasps.^{10–13} Others have employed filtering methods of the raw EMG data to make it easier to classify or introduced new features of interest from EMG signals.^{14,15} Hardware

modifications have included utilizing high-definition EMG arrays^{16,17} and evaluating the impact of specific electrode positions.^{18,19} While these results have met with variable success, they have not explored features of the limb position itself that may inform a more robust classifier.

Previous attempts to improve the performance of classification algorithms through incorporating positional data have yielded mixed results.^{4-7,20} These efforts rely primarily on the incorporation of data from accelerometers to augment EMG signal to identify training positions that correspond to the current limb position, and utilize grasp classifiers constructed based on position-specific training data.^{4,5,8} However, this methodology has resulted in a decline in performance when using accelerometer and EMG signals compared to when using EMG alone.²⁰ Position-matching strategies alone do not seem adequate to improve robustness. Therefore, this study was designed to examine specific covariates, including features such as hand height, elbow angle and shoulder angle, as well as a novel 3D training paradigm to generate a more robust classifier to function in multiple positions. The impact of these features on EMG signals was systematically evaluated to determine if inclusion of specific covariates can be used in combination with EMG to improve robustness. Results from limb-position effects for both able-bodied participants and participants with amputation will be compared to determine the usability of control schemes developed with able-bodied participant data as well.

Methods

A. Population

This study was conducted in accordance with protocol approved by the Johns Hopkins University's Institutional Review Board (IRB).

Ten able-bodied participants and two participants with transradial amputation were included in this study. Able-bodied participants had no known neurologic disorders and were ages 23-34. The first participant with amputation (Amp1) was a 63-year-old male seven years status post right upper-limb amputation due to work-related trauma. The second participant with amputations (Amp2) was a 68-year-old female three years status post bilateral upper- and lower-limb amputations secondary to overwhelming sepsis. Both participants with amputation had been using a myoelectric pattern recognition-based prosthesis for over one year. Persons with amputation were tested both while wearing and while not wearing their prostheses.

B. Experimental Procedure

For all able-bodied participants and participants with amputation without their prosthesis, eight channels of raw EMG were obtained through differentially amplifying electrode pairs placed equidistant around the circumference of the forearm. The raw data were amplified by 13E200 MYOBOCK amplifiers (OttoBock, Plymouth, MN) which were modified for remote application and raw EMG acquisition. Following conditioning, the signal was sampled using the NI USB-6009 (National Instruments, Austin, TX) at 1 kHz. A subsequent 20-500 Hz digital bandpass filter and a 60 Hz digital notch filter were applied to the signal. For the

sessions during which the participants with amputation wore their prostheses, eight channels of raw EMG were obtained through differentially amplifying electrode pairs mounted within the rigid socket of their personally owned custom-fitted prosthesis. The signals were amplified using LTI amplifiers (Liberating Technologies Inc., Holliston, WA) and acquired and filtered in the same manner as previously stated. Each individual with amputation conducted the experiment with a bebionic3 hand (RSL Steeper, Leeds) attached yet unactuated to simulate the weight of the arm during real-world use.

Limb-posture information was recorded simultaneously with EMG during all acquisition sessions using a custom network of three 9-axis inertial measurement units (IMUs) (MPU-9150 Nine-Axis MEMS Motion Tracking Device). One sensor was placed on the participant's mid-back overlying the upper thoracic spine; the second sensor was placed on the upper arm; and the final sensor was placed on the forearm. Position data from each sensor were used to generate a virtual representation of the participant's body and limb configuration. This representation was continuously updated in real time and displayed within the experiment's graphical interface (GUI), creating a virtual depiction of the user's full three-dimensional workspace as well as current limb position within that workspace (Figure 1).

Each participant performed five unique hand/wrist configurations, hereafter referred to as “grasps” including: rest, hand open (HO), hand close (HC), wrist pronate (WP) and wrist supinate (WS). Each experimental session began by performing nine repetitions of each grasp presented in random order at a single, neutral position. Following this single-position training, the participant performed random-position training. For training in different positions, the participant was prompted to reach a target point in space as displayed on the GUI and position was confirmed by IMU sensors prior to grasp performance. Once the position was obtained, the participant performed one repetition of all five grasps. In both circumstances, the recording phase of the grasp was maintained for 3 seconds. For position-based experiments, the participant was allowed as much time as necessary to move between positions. Eighty-one random positions were used for all participants except for participant Amp2, who performed grasps in only 54 target locations. Boundaries were calculated by limb length measurements and angular boundaries were $15^\circ \leq \theta \leq 165^\circ$ and $10^\circ \leq \phi \leq 120^\circ$, where θ is defined as the polar angle and ϕ is the azimuthal angle with 0° being the position at which the shoulder is abducted 90° from the anatomical neutral position. User elbow positions were not limited when acquiring target position.

C. Data Processing

All data processing and analysis was performed offline using MATLAB 2014b (Mathworks, Inc., Natick, MA). Time domain (TD) features of the amplified and filtered EMG signals were extracted by imposing a 200 ms moving window with a 175 ms overlap.

The TD features extracted were mean absolute value (MAV), waveform length (WL), signal variance (VAR), slope sign change (SSC) and zero-crossings (ZC) consistent with previous work by Englehart et al.³ Use of these TD features was chosen for comparison to classification accuracies generated in previous literature examining the impact of the limb-position effect.

Consistent with previous research by Scheme et al. that demonstrates the benefits of pooled static training, we performed EMG analysis on the static portions of the grasp. For all participants, the recording phase started 1.5 seconds after prompting to initiate a grasps and continued through the duration of the prompt, to allow subsequent analysis of the static grip portion. Therefore, each grasp was maintained for a total of 4.5 seconds, which included the 1.5 seconds initial phase followed by 3 seconds of recording time.

1) Effect of Limb-Position Covariates on EMG

Covariates included for analysis were elbow angle, the angle between the axis of the forearm and the ground, hand height (relative to the participant's shoulder) and repetition count. Repetition count was included to determine if fatigue was observed during the procedure and to account for temporal variability in classifier robustness, which may modify the influence of positional covariates. The position-specific covariates were calculated from data obtained from the body-mounted IMU network described previously. Initial testing demonstrated that changes in EMG mean-absolute values (MAV) were strongly correlated with changes in other extracted EMG features (WL and VAR). Inclusion of WL and VAR did not significantly improve classification accuracy. Therefore, covariate impact on MAV was examined for the remainder of the covariate testing. The average MAV over the duration of each grasp was computed for each of the eight channels and each repetition. To calculate overall effect, a univariate generalized linear model (GLM) was constructed linking MAV and each positional covariate. The slopes (i.e., the effect coefficient) of the GLM were compiled. The distribution of slopes was tested for a mean of zero (equally positive and negative impacts) using one sample t-tests. Equal variance among the distributions was tested for using Brown-Forsythe tests. A threshold of $p=0.05$ was used when reporting significance. Position-specific covariates with a statistically significant impact on MAV were then incorporated into classification methods constructed in Step 2 to correlate this impact on relevant classification outcomes.

2) Classification

The hand/wrist grasps were classified using Linear Discriminant Analysis (LDA). Six variations on use of training data were explored based on previous literature and position-specific covariate results. The variations on the availability of training data were analyzed across an increasing number of training repetitions available (from 1 to 50). The following methods describe the variations explored.

- i. *Single Position (SP)*: The classifier is trained using data obtained from the single “neutral” position. This methodology is currently the most commonly employed training algorithm and therefore serves as the experimental control to which other methods will be compared.
- ii. *Random Position (RP)*: The classifier is trained based on data from randomly selected positions used in training. Random-position methods accounted for positional covariates not explored in our study and gave insight into a real-world training paradigm that could be utilized without incorporating additional hardware.

- iii. *Nearest Position (NP)*: Hand height position was determined to have significant impact on MAV in covariate analysis. In initial analysis, hand height impact differed slightly based on x and y coordinates. Therefore, additional positional information with x and y coordinates was also incorporated. In this method, a local classifier is trained for each position using the data from m nearest locations evaluated during training, where $m \in \{1,5,10\}$.
- iv. *Nearest Elbow Angle (NE)*: The nearest elbow-angle was determined to be a covariate with the greatest variance during training in step 1. Therefore, a classifier was trained using m training repetitions performed at the nearest elbow angle to the position being tested, where $m \in \{1,5,10\}$.

The following two methods were incorporated to explore the impact of position on classification predictions:

- v. *Majority of Votes (MV)*: Individual classifiers are trained on the data from each location visited during the training protocol. Unlike the majority vote methods used in previous literature, the majority of votes methods here were constructed based on the instantaneous voting from each individual classifier, instead of based on inputs from previous times. For a given test sample, that grasp is selected as the predicted grasp which receives the majority of the predictions from individual classifiers.
- vi. *Weighted Posterior (WP)*: Similar to the majority of votes, individual classifiers are trained on the data from each location visited during the training protocol. However, in this model, votes are weighted according to Euclidean distance from the test point. This algorithm is shown in equations 1 through 4 where N is the number of grasp classes (in this case 5), and M is the number of individual classifiers created. The weights, $\mathbf{d}$, are multiplied by the matrix P yielding the weighted posterior estimates of the data belonging to each class $\mathbf{p}^*$. The class with the maximum weighted posterior is selected as the predicted class $\hat{g}$.

$$\mathbf{d}=(d_1 \dots d_M) \quad (1)$$

$$P=\begin{pmatrix} p_{1,1} & \cdots & p_{1,N} \\ \vdots & \ddots & \vdots \\ p_{M,1} & \cdots & p_{M,N} \end{pmatrix} \quad (2)$$

$$\mathbf{p}^*=\mathbf{d}P=(p_1^* \cdots p_N^*) \quad (3)$$

$$\hat{g} = \text{argmax}(\mathbf{p}^*) \quad (4)$$

Fifty repetitions were randomly selected from all available (81 in most cases, 54 for Amp2 with prosthesis) as test repetitions, allowing for cross validation of each method. In each case, classification error was computed by dividing the number of samples misclassified by the total number of testing samples without the application of a sliding majority vote filter or other misclassification rejection methods.

D. Statistical Analysis

Classification accuracies for each method were compared in a pair-wise comparison to SP using two-tailed t-tests. Bonferroni correction was used to account for multiple comparisons. SP was chosen as the comparator as it currently serves as the standard of care and therefore represents the benchmark to which novel classification methods must be compared. Multi-way Analysis of Variance (ANOVA) for comparison of group means was also conducted for multiple group comparisons between all classification methods, which allowed for multiple analysis corrections for statistical significance via the Tukey-Kramer correction.

Results

Each participant was able to complete all trials within 45 minutes. The initial data acquisition was completed by performing the 5 grasps once in each of the 81 positions. Each grasp was maintained for 4.5 seconds, which included a non-recorded stage of 1.5 seconds and then 3 seconds of recording. Unlimited time was given for each participant to reach the desired location. This resulted in a total of 81 positions performing 5 grasps in each position, for a total of 4.5 seconds per grasp, for a total recording time of 30.375 minutes. During experimentation, each position was obtained in approximately 5 seconds or less, given a total movement time of 6.67 minutes. Therefore, the total testing time for each participant was less than 45 minutes, including attachment time for the IMU sensor array.

1. Analysis of Positional Covariates

Initial evaluation of positional covariates demonstrated approximately linear relationship for all covariates examined, prompting subsequent analysis for these linear relationships only. For all participants, the distribution of slopes corresponding to repetition number had means equal to zero, providing sufficient evidence that fatigue did not occur. Elbow angle was the covariate for which the distribution had the largest variance for participants with amputation and able-bodied participants (variance 0.25, $p < 0.001$ in pair-wise comparisons). Additional covariates were analyzed in comparison to the variance obtained for elbow angle and each had significantly lower variance except hand height in persons with amputation. Hand height was also the only distribution with non-zero mean, demonstrating increases in the MAV of EMG signal as the hand height increased regardless of the grasp being performed.

2. Classification

Including increasing numbers of training repetitions resulted in statistically significant decreases in classification error for nearly all classification algorithms for able-bodied participants (Figure 2). One exception to this pattern occurred with including greater than 15 training positions in the NE classifier, for which classification error increased. All classification methods outperformed SP for able-bodied once five training positions were included (Figure 2) ($p < 0.001$ for all pairwise comparisons). NP and NE classifiers each demonstrated classification rates of 9.5% at five repetitions. RP classification resulted in 9.46% accuracy at five repetitions and outperformed single position classification (9.46% vs 15.67%, $p < 0.001$). Comparisons between RP, NP, and NE classification methods did not reveal any statistically significant differences.

For participants wearing their prostheses, classification accuracy improved with additional training data for all classifiers except SP. For Amp1, SP classification resulted in classification error that leveled near 40% after three training sets, with no improvement seen after incorporating more training repetitions (Figure 3). NP and NE classification resulted in significantly lower classification error than SP and remained between 3.5-3.7 % (with prosthesis) after four training repetitions ($p < 0.001$). For Amp2, SP classification error rates remained between 24.39-24.93% after just one training repetition and was not improved with additional repetitions (Figure 4). NP and NE classification with prosthesis averaged near 9.3% and was significantly lower after including five repetitions ($p < 0.001$). For both participants with amputation, RP classification rates performed statistically equivalent to NP and NE methods (at five repetitions, Amp1: 3.77% $p = 0.39$, Amp2: 9.32% $p = 0.063$).

Majority vote and weighted posterior calculations necessarily required three training repetitions before becoming viable classification strategies but subsequently demonstrated a similar pattern of rapid decline in classification error with increased numbers of training repetitions as seen with other classification methods. However, MV and WP methods performed worse than RP, NE, or NP methods and similar to the SP method when incorporating five repetitions in any of the test cohorts (combined: 12.16 and 15.33, MV and WP, $p < 0.001$ for RP, NE and NP comparisons). Both WP and MV method classification accuracies were significantly better than SP after seven training repetitions were included. Results were compared to a 10% error rate threshold as this rate reflected the highest possible classification error to maintain the system's utility for prosthetic control and therefore represented a reasonable baseline which we would expect algorithms to outperform.¹

For participants with amputation participants, classification error differed depending on whether or not they had donned their prosthesis for the experiment (Figures 3 and 4). For Amp1, without his prosthesis, classification from training based on the SP method performed similarly to RP for all number of repetitions available for training ($p > 0.05$ for all comparisons). Upon wearing his prosthesis to complete the experiment, classification error for the SP method significantly increased despite the number of training repetitions included. Classification error with RP method while wearing the prosthesis was also significantly higher though dropped below 10% after three repetitions. RP classification continued to demonstrate improvement until four training repetitions were included at which

point classification error did not significantly reduce significantly with inclusion of additional repetitions. While wearing his prosthesis, RP also outperformed MV and WP methods until approximately 25 repetitions were included in the training set (five repetition accuracy 3.77% vs 13.11 % MV and 16.19 % WP, $p<0.001$). RP, NP and NE methods performed similar for all training repetition numbers tested. Participant Amp2 also demonstrated similar patterns of higher classification errors with the SP classifier when donning the prosthesis (Figure 4). Again, classification errors for the other methods were higher when the prosthesis was worn, but the discrepancy between the two states was lower than that for Amp1. For both participants with amputation, SP classification while wearing the prosthesis resulted in classification error rates significantly higher than the useable range (Amp1: 39.10-40.97%, Amp2: 23.76-24.92%).

Discussion

Current advanced myoelectric prosthetic control schemes are based on EMG signal patterns obtained during training sessions. However, if testing occurs outside of the position in which training took place (i.e., reaching to a new location), the algorithms often fail suggesting a lack of robustness to positional variation. As such, the motivation for this research was to improve robustness by incorporating position-specific covariates into classifier algorithms and to thus inform training paradigms for prosthetic users. Initial examination sought to identify the relationship between three position-specific covariates (elbow angle, forearm angle, and hand height) and one temporal covariate (repetition number), providing a potential target for subsequent classifier construction to improve robustness of prosthesis control. In doing so, specific positional elements of the limb, such as hand height, elbow angle, and forearm-ground angle, were extracted and analyzed for their impact on the MAV of the EMG signal.

Of the four covariates tested, two yielded statistically significant impacts on EMG signals. Elbow angle was found to yield a distribution of MAV values of largest variance while maintaining a distribution mean of zero. We posit that this represents a strong combination of positive and negative impacts, indicating a strong influence of elbow angle on position-related EMG signals and possibly implicating its role as a mediator of the “limb-position effect.” Additionally, hand height was also identified as an important covariate as it demonstrated an overall positively centered distribution, reflecting increased MAV at higher hand heights. Physiologically, this makes intuitive sense as increased limb height likely represents an increased strain on the muscles of the forearm to support the weight of the hand. This is especially true when rotation around the shoulder, rather than the elbow, is responsible for most change in the hand height, as was seen for most of the participants in this experiment. It is noted that most positions within this experiment were far enough in front of the participant that elbow angle was flexed less than 90 degrees. In the circumstances when elbow angle is flexed greater than 90 degrees, the moment arm of the arm would actually decrease and this phenomenon may not be observed. When persons with amputation removed their prosthesis for testing, hand height no longer exhibited this positive trend, which helps support this hypothesis. The positive trend was re-demonstrated when the prosthesis was worn during experimentation. After identifying the impacts of elbow angle

and hand height, these covariates were used for classifier construction, as we believed their inclusion would improve the robustness of the overall algorithm.

The identification of these covariates drove the process of classifier algorithm construction in the subsequent analysis. Training at a single position and testing in multiple other positions confirmed the detrimental impact to performance caused by the “limb-position effect” and yielded classification errors consistently outside of the usable classification error threshold of 10% proposed by Scheme et al. in both able-bodied participants and participants with amputation. Incorporating either nearest elbow angle or nearest position into a classifier significantly improved classification accuracy in both able-bodied participants and participants with amputation donning their prosthesis. However, the feasibility of obtaining position-specific information outside of the clinical or laboratory setting is a reasonable concern for current prosthetic users. Most prosthetic devices are not designed to record positional information. As such, random-position training methods were also tested. Interestingly, classifier construction based on random-position training data consistently outperformed the single position-based classifier and performed comparable to position-covariate based classifiers. These results outline a method of training that can be realized by persons with amputation currently using a myoelectric prosthesis without the requirement for additional hardware.

These results suggest a fully realizable training paradigm for current prosthetic users. In this study, we have demonstrated that incorporating data from random-position training dramatically decreases classification error when testing in multiple locations. Consistent with previous work from Scheme et al., we have demonstrated that pooling data into an aggregate classifier results in the most robust classifier within our tested algorithms.²¹ The reason for this improvement is speculative but may represent a covariate that is not adequately explored within this research. Supporting this hypothesis, “weighting” the classifier by the nearest position or elbow angle (the two tracked covariates) did not outperform RP classification. While this finding warrants additional “real-world” testing to evaluate its impact on robustness in the user's natural environment, it is nonetheless encouraging and informative to see these in-lab results. Furthermore, maximum benefits in classification accuracy were observed to occur within five training repetitions, representing a training duration that could be acceptable among prosthetic users. This strategy also obviates the need for complex position tracking systems to improve classification accuracy.

Inclusion of position specific covariates also outperformed traditional, single position training and classification methods. The incorporation of position-specific covariates can and should extend beyond simple nearest x, y, and z Euclidean coordinates. Multiple factors beyond position alone can influence EMG signal, such as we have demonstrated with elbow angle, and therefore their inclusion into an “informed” classifier improves performance. This should motivate the search for additional covariates not traditionally considered in classifier design. In this regard, the random-position training method likely incorporates variables not explicitly studied in this research. This motivates the continued search for additional covariates, as well as the impact of these covariates on features of EMG signals other than MAV that are incorporated into training algorithms, such as WL and VAR.

Our results also highlight the differences in training individuals with amputation with and without wearing their prostheses. Indeed, the results of testing individuals with amputation while wearing their prosthesis is consistent with results seen with able-bodied participants, and consistent with the hypothesis suggested by Geng et al. that “EMG signals acquired for an intact limb are more affected by limb-position variation.”²² We clarify this statement by suggesting that EMG signals acquired for a prosthesis-weighted limb are more affected by limb-position variation (than a non-prosthesis weighted limb). When tested without their prostheses, classification error rates for participants with amputation were dramatically lower than rates when they were wearing their prostheses. If testing were only conducted in the setting without the prosthesis, in which classification error appeared to have no reduction when training in multiple positions, lack of perceived benefit in classification error rates may shift the user's acceptance of longer training times or additional hardware. This may have an affect on virtual training paradigms conducted without the user wearing his or her prosthesis. Finally, the wide disparity between classification error between testing with and without a prosthesis may highlight the effect of socket fit, in addition to position-specific factors, impacting classification error warranting further study. Data collection without the prosthesis was performed using a standalone electrode array as opposed to the in-socket electrode array used for collection when the prosthesis was worn. Interestingly, the classification error of one of the participants with amputation, Amp1, was not significantly different across the various classification strategies explored when not wearing his prosthesis. This lack of variability differed from the results of the second person with amputation. One factor that may have led to this phenomenon may be the extensive training history of Amp1, who has been using a pattern recognition-based prosthesis for several years and has a take-home pattern recognition training program. In the home setting, Amp1's training is completed in a virtual environment which may be similar to the training without the prosthesis performed in this study's experimental protocol.

This work has some limitations. First, the dynamic portion of the grasp (transitioning from one grasp to another) was not evaluated nor was data collected or analyzed while the limb was moving. It has been shown that training while moving the limb, known as dynamic training, yields lower classification error than pooled static training when testing on data from dynamic movements.²¹ The same study also shows, however, that pooled static training yields lower classification error than dynamic training when testing on data from static postures. We suggest that for pattern recognition-based prosthesis control methods, classification accuracy should be optimized for static postures, as has been the focus of this work. Additionally, the use of classification error as the sole outcome measure justifies consideration. Indeed, classification error may not be the ultimate indicator of prosthesis utility.^{23,24} Future incorporation of actual or online task-based testing will enhance this study's objective of exploring the benefits of position-specific or random-position classifiers on prosthesis functionality. Indeed, this step is vitally necessary to determine the applicability of these results within a more generalized training paradigm, and is the focus of our ongoing research. Next, covariates were analyzed according to their impact on EMG MAV alone. Additional analysis on features such as VAR and WL may have demonstrated dissimilar relationships to what our study demonstrated. Despite low classification error rates with RP methods, analysis of additional covariates may have yielded position-specific

covariates with improved accuracy. Finally, while our results do show a clear indication that the inclusion of position-specific covariates improves classification accuracy, we acknowledge that the inclusion of more participants with amputation may contribute to the generalization of our findings.

Conclusion

Incorporating position-specific covariates into myoelectric classification algorithms can dramatically improve robustness and classification accuracy when using the prosthesis in the user's entire workspace. In our analysis, elbow angle and hand height significantly impact the MAV of EMG signals when grasps are performed in different positions. When these two covariates are included in classifier algorithm construction based on multiple positions, classification error rates decrease to previously accepted thresholds for usability (less than 10%), and prosthetic robustness is improved over single-position training methods. In these methods, classification error rates stabilized at 10% for able-bodied and near 7% for individuals with amputation when at least 5 training repetitions were used. As position tracking hardware becomes smaller and can be implemented into socket designs, incorporating position-specific information into classifier algorithms can dramatically reduce the limb-position effect. Importantly, training based on data from random positions performed equally as well as covariate-specific information and is immediately implementable on currently available commercial hardware. Current prosthesis users can benefit from an improvement in the robustness of their prosthesis control through training in multiple positions even without the use of additional position-tracking. These results offer a potentially immediate improvement to the limb-position effect in current prosthetic users through training performed in multiple, random positions.

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Figure 1.

An illustration of the experimental procedure with the participant viewing the large GUI in front of them. The framework on the left represents the participant's body and is shown to the participant in real time. Once the participant's hand or projected hand (individual with amputation) is within 3~cm of the randomly-prompted target position, the participant performs the cued grasps shown to them on the right.

Figure 2.

Average classification error for all able-bodied participants resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean. X axis is nonlinear to include allowing closer examination of low repetition number classifier performance. For MV and WP strategies, at least two data points were required to allow for a majority voting strategy. For NP and NE strategies, the results are indicated for 5 nearest positions, and thus results are reported after 5 training repetitions are included. Offsets are included to visualize overlapping error bars.

Figure 3.

Average classification error for Amp1 resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean. Offsets are included to visualize overlapping error bars. Offsets are included to visualize overlapping error bars.

Figure 4.

Average classification error for Amp2 resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean. Offsets are included to visualize overlapping error bars. Offsets are included to visualize overlapping error bars.