THE EFFECTS OF LIMB POSITION AND APPLIED LOAD ON HAND GESTURE CLASSIFICATION ACCURACY USING ELECTROMYOGRAPHY AND FORCE MYOGRAPHY

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ABSTRACT

Modern mechatronic upper limb prostheses are controlled using surface electromyography sensors (EMG) that are typically embedded in the prosthetic socket. However, when the user moves their device in space or interacts with an object, changes in electrode contact pressure can occur that work to the detriment of consistent and effective prosthesis control. Yet, we suggest that these pressure changes offer unique information that can be captured using force myography (FMG) and decoded to help classify intended prosthesis movements. Thus, the goal of this work was to investigate the feasibility of combining FMG with EMG to classify hand grasping movements in an able-bodied cohort and compare this combination to EMG and FMG alone. We hypothesized that FMG will capture complimentary information to the EMG data and when combined, will produce more robust classification accuracies when the user's limb moves in space or grasps objects of varying loads. We used a custom EMG+FMG armband and instructed N=21 participants to grasp objects of different weights at a variety of different positions using 4 different hand grasp movements. The results demonstrated that the average classification accuracy of EMG+FMG was statistically different and of higher classification accuracy when compared to EMG and FMG. It was also found that position and load affect classification accuracy together suggesting that control techniques that adapt to these changes are likely to produce more effective prosthetic control performance.

INTRODUCTION

Modern upper limb prostheses (ULPs) are growing increasingly sophisticated with a variety of clinical and experimental systems offering individually articulating digits to perform a variety of hand movements, grasp force ranges similar to an intact limb, and proportional control of movements [1–3]. Operating these devices most commonly relies on surface electromyography (EMG) to measure residual muscle activity, decode the user's intended movements, and in turn actuate the corresponding prosthetic movement. However, even with these advancements, growing availability of advanced devices, and their increased prescription rates, abandonment rates remain as high as 23-26% [4]. Achieving effective and consistent device control is a major contributing factor [4]. One challenge is the fact that EMG sensors are embedded in the prosthetic socket (PS). When the device is moved or loaded (object interaction) the pressure distribution between the prosthetic socket and the residual limb can dramatically change [5] resulting in varying impedance, potential motion artifacts, and overall inconsistent electrode recordings that collectively work to the detriment of effective and consistent control [6, 7].

While these pressure changes add unwanted variability for EMG control systems, they may also offer unique information about the state of the prosthesis that can be useful for device control. For example, recent studies have recorded patterns of pressure changes inside the PS during residual muscle contractions, which were then classified using machine learning to infer intended prosthesis movements (force myography, FMG) [7–9]. We suggest that the measurement of pressures developed inside the PS may offer complimentary information to augment EMG-based control strategies. Thus, our objective was to investigate the feasibility of combining FMG with EMG to predict hand grasping movements across a variety limb positions and grasped loads. We hypothesized that EMG and FMG would demonstrate variable classification accuracies depending on the limb position and loading conditions and, when fused, EMG+FMG would perform more accurately than either system individually.

METHODS

Participants and Experimental Setup

We recruited N=21 able-bodied participants (14 male and 7 female, average age 24, SD 3.08). Research protocols were approved by the Institutional Review Board at the University of California, Davis and participants provided written informed consent. Participants wore our custom EMG+FMG armband which was comprised of our FMG system (8 Interlink Electronic FSR400 sensors) and our EMG system (8 EMG sensors from our Delsys Trigno EMG system) as shown in Figure 1. The sensors were arranged equidistantly onto a Velcro strap in an alternating sequence before they were tightened onto the muscle bulk of the participants' forearm. Sensor data was collected using two National Instruments USB6210 Data Acquisition Systems, one for the EMG data and one for the FMG data.

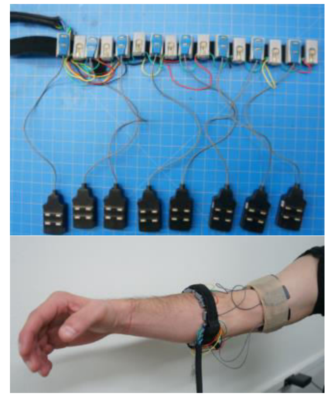

Figure 1: The EMG+FMG armband was comprised of 8 EMG and 8 FMG sensors which were housed in 3D printed casings which attach to the Velcro band.

Experimental Procedure

Participants grasped a weighted manipulandum (MPD) using a specific grasp configuration at various positions. This allowed us to examine how EMG, FMG, and their combination are affected by load and limb position. The MPD was loaded with 5 weights, including a no weight condition (the weight of the MPD, 53g), 250g, 500g, 750g, and 1000g. Participants stood in front of a 7-foot-tall shelf and grasped the MPD with 4 different hand grasps: Key, Pulp Pinch, Power and Tripod Pinch [10]. The shelf levels and standing 'zones' were adjusted for participant height such that their arm was fully extended when standing at zone 2 and reaching positions 5-8 (Figure 2a). The participants grasped the MPD using 4 different grasps, at 8 different positions, and under 5 different weights. Each trial consisted of the MPD being placed at one position, in line with the sagittal plane of the subject's dominant arm. They would then be queued to grasp and slightly lift the manipulandum with a specific grasp, hold it for 3 seconds, and then set it down and relax for 4 seconds. This was repeated 3 times at each position prior to moving on to the next randomized position, weight, and grasp combination. Randomization helped ensure that any potential muscle fatigue did not influence experimental results.

Data Analysis

Contraction data was first separated from resting data using time stamps before being parsed together and segmented using a 200ms window and a 50ms time increment [11]. We used the Hudgins' Set to create EMG features [12], the mean absolute value for FMG features [7] and combined both into a single feature vector for EMG+FMG [13]. We used linear discriminant analysis to classify hand grasps using leave-one-out cross validation to train the classifier and calculate classification accuracies. We analysed data in 3 cases: (1) Classification accuracy for a constant position (position 2) and varying weights, (2) classification accuracy for a constant weight (500g) and varying positions, and (3) training the classifier at a neutral position (position 2, no weight, as is done in numerous studies [13-15]) and testing the classifier with data from the most extended and loaded position (position 5, 1000g). We used multiple linear mixed effect models to examine statistical differences in classification accuracies of each modality (EMG vs. FMG vs. EMG+FMG) for each of the 3 cases, using modality as the fixed effect and participant as the random effect.

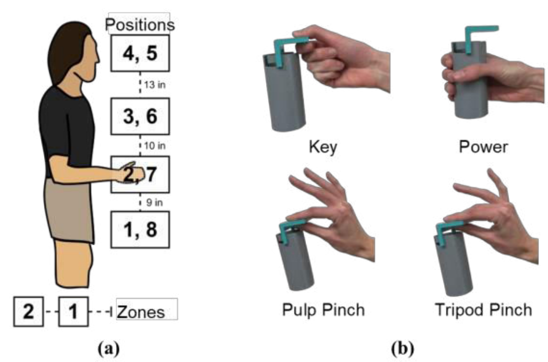

Figure 2: (a) The 8 positions and 2 zones for the test. The participant stood at zone 1 for positions 1-4 and zone 2 for positions 5-8. The participant's elbow was bent at 90º at position 2, between fully extended and bent at positions 1, 3, and 4, and fully extended at positions 5-8. (b) The manipulandum was comprised of two parts such that the weights can be top loaded and held with the 4 grasps.

RESULTS

The first two cases illustrated how varying either the load or position affected classification accuracy for each modality. The results are shown in Figures 3a and 3b, respectively.

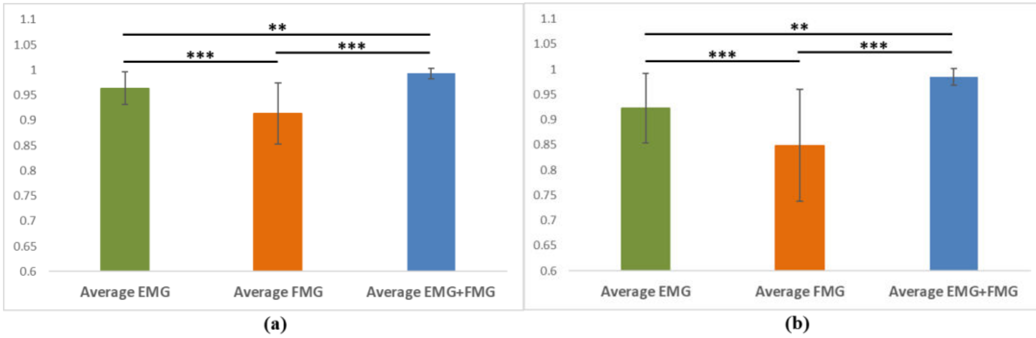

Figure 3. ** (P < 0.01) *** (P < 0.001) (a) Average classification accuracy for case 1 (constant position of position 2 with varying loads). (b) Average classification accuracy for case 2 (constant weight of 500g and varying positions).

For both cases, EMG+FMG was found to be the most accurate sensing modality while FMG alone was found to be the least accurate. Each sensing modality yielded an average classification accuracy of greater than 90% except for FMG in case 2 (84.9%, SD=11.1%). It was also found that each modality was statistically different from one another, as shown by Figures 3a and b. Furthermore, it was found that position and weight demonstrated an effect on EMG and FMG as shown by statistically different accuracies (P < 0.05) when comparing cases 1 and 2 while EMG+FMG was not affected (P > 0.05), indicating that the fusion of the two modalities may be more robust to these conditions.

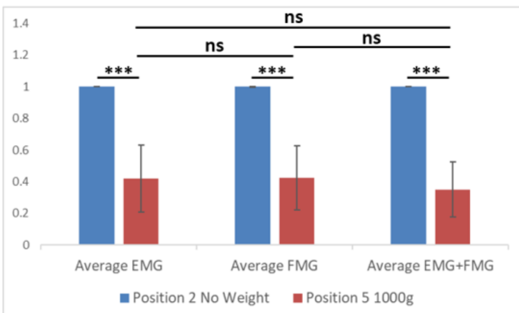

Figure 4: *** (P < 0.001) ns (P > 0.05) Case 3: Average classification accuracies at the neutral position (position 2 no weight) and at the extended and loaded position (position 5 1000g) after being trained at the neutral position.

For case 3, we first graphed the average classification accuracy of the classifier at the neutral position. We then trained the classifier at this neutral position and tested the classifier with data from the most extended and loaded position, illustrated in Figure 4. As shown, there are significant differences between the classification accuracies of the neutral and extended positions. Furthermore, there was no significant difference between each modality's classification accuracies at the extended and loaded position.

DISCUSSION AND FUTURE DIRECTIONS

We found that that position and grasped load affect classification accuracy muscle measurement modalities (EMG, FMG, EMG+FMG). As illustrated by the results of case 1 and 2, EMG outperformed FMG in both cases and yielded higher classification accuracies when the load and position was varied. This may have been a result of little change of radial muscle forces across the range of loads and positions, or alternatively large variability in these radial forces. Thus, it may be useful in the future to classify hand gestures under multiple combinations of varying weight and position to further define the nature of these relationships. Furthermore, as shown by the results of cases 1 and 2, the combination of EMG and FMG yields statistically different and nominally greater classification accuracies than either EMG or FMG could individually produce. This suggests that FMG produces complimentary information that can be paired with EMG data to more accurately classify hand gestures during varying position and loading conditions. Further, when comparing the results of the same modality across cases, accuracies for cases 1 and 2 for EMG and FMG were found to be statistically different whereas EMG+FMG demonstrated no difference. This indicates that the combination of the two provide a more robust classification accuracy during changes in position and load than the two modalities separated.

The results from case 3 further illustrate the effect of limb position and loading on classification accuracy for each modality. As shown in Figure 4, when the classifiers are trained and tested at the neutral position, as is typically done for ULPs, the classification accuracy of the four hand gestures approaches 100%. However, when trained in the neutral position and then tested in the extended and loaded position, the average classification of each modality decreases to 35-40%. Furthermore, these classification accuracies were found to be not statistically different from each other (P > 0.05), illustrating that each modality performed equally poorly when tested at the extended position. While the extended position was the most different from the neutral position, this illustrates the fact that limb position and loading can work to the detriment of classification accuracies. As current ULPs are usually trained at a neutral position, the addition of weight and position would vastly decrease the effectiveness of the users control system. Furthermore, current literature does not provide a reliable consensus on if the combination of EMG and FMG adds any statistical value for hand gesture classification [13, 16, 17]. However, in our work, we demonstrated that when the limb is moved to various positions and loaded, as is more representative of real-world object manipulation, the addition of FMG adds significant improvements to current EMG classification systems. Thus, designing and implementing a control system that implements these combinations can account for or adapt to position and loading changes could aid in more effective device control.

The long-term goal of this work is to implement an EMG+FMG sensing system inside of ULPs for the purpose of more robust control. While this experiment begins to provide feasibility data to further explore this topic, future work is ongoing to investigate how combinations of position and load affect classification accuracy of grasping patterns along with how well the modalities can accurately classify positions and applied loads. This future work will illustrate the robustness of each sensing modality along with what conditions each sensing modality may be best suited to perform under. We further aim to begin to examine how in-socket prosthesis applications of our approaches may change relative to our able-bodied dataset and examine efficient machine learning training practices that incorporate and accommodate for position and grasped weight combinations.

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