

## AFFECTED MUSCLES RETAIN DEXTRIOUS MOTOR CAPABILITIES IN CHILDREN BORN WITH UPPER-LIMB DEFICIENCIES

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### ABSTRACT

Children with Unilateral Congenital Below-Elbow Deficiencies (born without a hand, UCBED) have a high rate of prosthetic abandonment, pointing to unresolved challenges that may be distinct from those faced by adults with limb loss. There is limited knowledge of the motor control these children have over their affected muscles, a highly relevant question for effective dextrous prosthetic control. Our research aims to measure the extent of volitional muscle activation that exists in the residuum when children attempt moving their missing hand, with the goal of creating highly functional pediatric-specific prosthetic devices. In this work, we recruited 28 pediatric UCBED patients across four Shriners Hospital locations. We measured muscle activity using ultrasound imaging and surface electromyography while children attempted 10 missing-hand movements, then used machine learning to analyze the patterns of the affected and unaffected sides. Our algorithms predicted hand movements from residual muscle activity at over 80% accuracy in most cases, and well above chance in all participants. This indicates inherent muscular control which may be leveraged to develop more functional prosthetic devices tailored towards pediatric UCBED patients.

### INTRODUCTION

Approximately 1 in 500 live births will present with an upper limb deficiency, the most common reason for limb absence in children [1]. Children born with a unilateral, congenital, below-elbow deficiency (UCBED) are typically amenable to a prosthesis, but prosthetic abandonment rates for pediatric users reach as high as 45%, compared to approximately 25% for adults with limb loss [2], indicating these devices are not providing the necessary functionality or improved quality of life that the users require [3]. Although there have been significant advancements in dextrous prosthesis development and availability for adults and children, with this increased dexterity comes the need for more sophisticated control systems to pilot the newly available movements. Toward this goal, advanced machine learning-based control systems such as myoelectric pattern recognition approaches have demonstrated significant promise for adult prosthesis users, but have seen limited to no adoption among children born with their limb deficiency [4].

Encouragingly, we have shown in small cohorts of children with UCBED (N= 6-9) that they retain a degree of control over their affected muscles, despite having never actuated a hand before [5-6]. These studies were performed using surface electromyography (sEMG) and the emerging technique of sonomyography (ultrasound imaging) respectively to capture muscle activity. We found that it is possible to decode intended movements of the missing hand from the patterned behavior of the affected muscles using either measurement modality. These results indicate that, like adults with acquired limb absence, these children have a significant potential to benefit from advanced prosthetic control systems.

In the current work, we present our findings from a cohort of N=28 children with UCBED whose data was collected from 4 Shriners Children's Hospital locations across the United States. Participants were asked to attempt simultaneously moving their intact and missing hands into a variety of positions while EMG and ultrasound imaging

recorded the corresponding forearm muscle activity. We hypothesized that, like our prior work, each participant would produce distinct patterns of muscle activity that were unique to each intended hand movement. We further hypothesized that classification accuracies of these patterns would be similar, albeit slightly reduced, when comparing the affected to the unaffected sides. This work provides a deeper understanding of the motor capabilities of children with UCBD and points to the potential for these children to benefit from advanced prosthesis control systems.

## METHODS

**Study Design:** We recruited N=28 pediatric participants (ages 5-20 years old, 16 males and 12 females) with UCBD from 4 Shriners Children's Hospital locations (Northern California, Portland, Greenville, Chicago). Exclusion criteria include those with sensorimotor, cognitive, or developmental differences aside from the absence of an upper limb. All research protocols were approved by the Shriners Hospitals for Children Western Institutional Review Board (WIRB). Participants or their legal guardians provided written, informed consent (and assent as necessary) prior to the study.

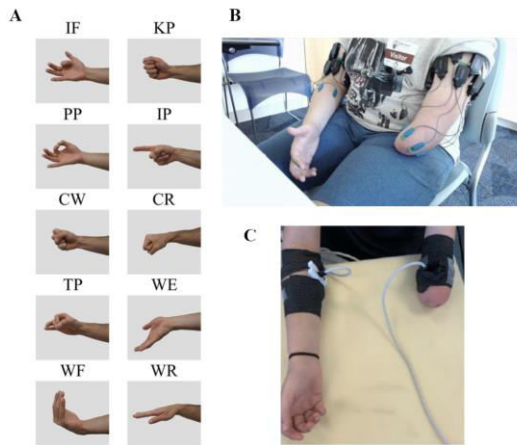


Figure 1: A) Hand grasp configurations used in the experimental procedures B) sEMG sensor placement example C) Ultrasound sensor placement example

We employed ultrasound imaging and sEMG to capture the simultaneous muscle activity of participants affected and unaffected limbs while they attempted different missing-hand movements (Figure 1). Our methodology then used machine learning (ML) algorithms to analyze the consistency of the recorded muscle activity, based either on patterns of electrical activity across sEMG electrodes or the spatiotemporal motion patterns of the muscles. Therefore, participants performed two repetitions of the same experimental paradigm, once while wearing ultrasound sensors, and once while wearing sEMG sensors. Here, they were asked to perform ten different grasp and wrist motions from among the most commonly used grasps in daily living (index flexion (IF), key pinch (KP), pulp pinch (PP), index point (IP), cylindrical wrap (CW), cylindrical wrap wrist rotate (CR), tripod pinch (TP), wrist extension (WE), wrist flexion (WF), and wrist rotation (WR)) [7]. Participants were prompted to begin in a relaxed state, then maintain the

designated position for 3 seconds before returning to a relaxed state. Five to 10 trials worth of data were collected for each hand movement dependent on the child's attention span and reports of mental or physical fatigue.

**Ultrasound setup:** Following our previously established protocol [6], a clinical ultrasound imaging system (Terason uSmart 3200T, Terason, Tetrattech Corporation, Pasadena) with a linear array transducer (16HL7 transducer, Terason, Tetrattech Corporation, Pasadena) was used to capture tissue deformation in the participants' affected and unaffected forearms. The transducers were positioned on the anterior side of each arm, below the elbow, at a location that maximized observed tissue deformation when participants contracted and relaxed their muscles. Image data was sent to a laptop computer through a video capture card (DVI2USB 3.0, Epiphan Systems, Incorporated, Ottawa, CA) at 30 frames per second, and processed in MATLAB (MathWorks, Inc., Natick). Here, the image frames were down-sampled from the raw size of 1048x1048 pixels to 128x128 pixels. The first frame and last five frames of the trial were taken to represent the beginning and final state of the muscles respectively. We calculated the Pearson correlation coefficient between each image frame to the initial muscle state, and used a K-nearest neighbor algorithm to classify the end muscle states of the movement patterns. Leave-one-out cross-validation was used to calculate the classification accuracy and assess the performance of the classifier.

**sEMG setup:** Consistent with our prior work [5], a 16-channel Delsys Trigno surface EMG System (Delsys Inc., Natick) was used to capture affected and unaffected forearm electrical activity. Seven wireless Trigno Mini Sensors were placed on each limb, equally spaced around the circumference of the forearm muscle bulk. sEMG data was sampled at 2000Hz, bandpass filtered at 20-450 Hz, and passed to a National Instruments USB 6210 data acquisition system (National Instruments Corp., Austin), which sampled the data at 6000 Hz and stored it in MATLAB. To examine the accuracy to which hand movements could be classified, we used 60-40 cross-validation analysis with a

Linear Discriminant Analysis classifier that was trained on five sEMG features (correlation coefficient, multi-channel energy ratio, log detector, Hjorth mobility parameter, and integrated absolute value).

## RESULTS

All N=28 participants produced ultrasound imaging and sEMG muscle activity data that was classifiable well above chance (10%). In Figure 2, we present results from two participants (age 11 and age 8) demonstrating the spectrum of the highest-performing through lowest-performing classification accuracies found in our sEMG data.

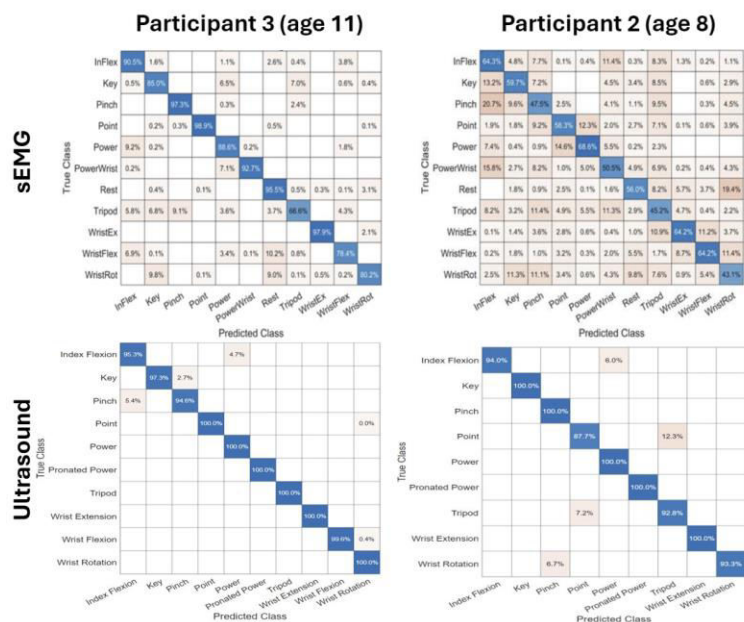


Figure 2: Confusion matrices for sEMG (top) and ultrasound (bottom) classifiers for the affected limbs of two study participants

affected), and  $97.26\% \pm 4.20\%$  (ultrasound, unaffected). Thus, generally, across participants, classification accuracies for the ultrasound data exceed those of the sEMG data. Across our cohort, we observed that classifying muscle activity from the unaffected side resulted in higher classification accuracies; however, even the values for the affected side were far above chance, with the lowest results coming from participant 2's sEMG data at an average  $56.5\% \pm 8.7\%$  accuracy, and the best performance seen in the ultrasound data with accuracies nearing 100%.

## DISCUSSION AND FUTURE DIRECTIONS

The design of effective dextrous prosthetic control systems requires a clear understanding of the motor capabilities of the user and the ability of the user to elicit clear, consistent patterns of muscle activation that can be reliably decoded. The results from the study indicate that children with UCBD have a robust level of motor control over their residual muscles, and that using multiple measurement modalities paired with machine learning, we can decode motor intent from the resulting muscle activity. Here, we found that all N=28 participants were able to elicit consistent patterns of muscle activity that were classifiable well above chance and, in many cases, achieving accuracy values consistent with adult myoelectric pattern recognition literature [8]. Though we must recognize the need for diligence in adapting adult-based techniques to serve the unique conditions a child with UCBD may present, this work emphasizes that children possess innate potential to effectively use ML-based control systems.

It should be noted that most participants had no prior training or experience with myoelectric prosthetics, and all participants did not have any prior experience with motor imagery to practice envisioning and moving their missing hand. Like any motor skill, we suggest moving a missing hand requires learning and training to reach high levels of proficiency. We believe there are exciting possibilities in this population of children to not only amplify their functional abilities with advanced control systems, but also to study human motor learning and development in a truly unique model. For example, most participants' affected muscles did produce consistent and unique patterns of muscle

Participant 3's sEMG data was classified with  $88.3\% \pm 10.0\%$  accuracy and Participant 2's data was classified with  $56.5\% \pm 8.7\%$  accuracy, demonstrating the potential variability across children with UCBD. However, the classification accuracies of the ultrasound data for these same two participants were much higher at  $98.7\% \pm 2.4\%$  and  $96.4\% \pm 4.6\%$ , respectively.

In Figure 3, we use a polar plot to compare accuracies of affected and unaffected limbs for each grasp within the same two participants. Prediction accuracies for the affected limbs were either comparable or slightly diminished compared to the unaffected side, a phenomenon observed across all participants. The average classification accuracies for all 28 participants were  $80.80\% \pm 10.32\%$  (sEMG, affected),  $92.76\% \pm 4.79\%$  (sEMG, unaffected),  $88.27\% \pm 19.25\%$  (ultrasound, affected), and  $97.26\% \pm 4.20\%$  (ultrasound, unaffected).

activation with each attempted missing hand movement. This occurred across all ages of participants which spanned 5-20 years old. Our findings suggest that aspects of hand motor representations are retained despite the child never developing a hand. Further work to understand how affected muscle activity correlates to activity in higher control centers can provide a much deeper understanding of motor development and build up the foundations for effective control of advanced prostheses in this population.

The higher performance seen in the ultrasound data compared to the sEMG is interesting to note. Here, each measurement modality captures different muscular phenomenon: muscular displacement across the depths of the residuum or electrical activation measured at the surface of the skin. We believe there is a strong likelihood that sEMG and ultrasound are identifying distinct yet complementary information in the muscles. Examining fusion techniques or identifying use cases and conditions most amenable to each modality in future work would prove powerful insight to maximizing the classification performance of control systems for children with UCBD. The work presented here is a subset of a large multi-center research effort collecting data from children with UCBD across the United States. Here, the goal is to examine how patient-specific factors such as age, gender, limb characteristics, and prosthetic use may influence their abilities to control affected muscles and the control techniques that may be most amenable to serve patients given these factors. Together this work begins to build the foundations to better understand the muscle motor capabilities of children with UCBD, as well as put down the necessary groundwork that must first be in place to effectively adapt dextrous control techniques for this population.

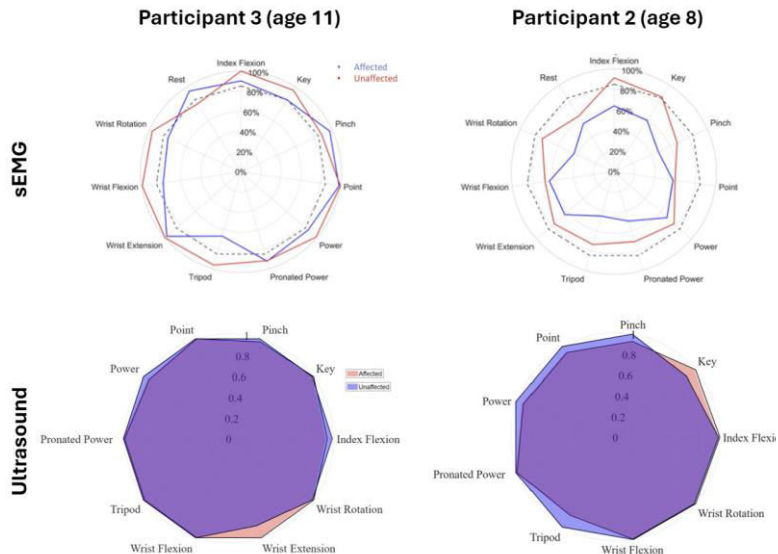


Figure 3: Polar plots for sEMG (top) and ultrasound (bottom) classifiers for both limbs of two study participants

## ACKNOWLEDGEMENTS

This work was supported by the National Science Foundation (2133879), Shriners Children’s Clinical Research Award (79139), and EJW is supported by a NIAMS funded training program in Musculoskeletal Health Research (T32 AR079099) and by NSF NRT Award #2152260. Additional thanks to Josh Siegel.

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