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Understanding Forearm Muscle Coordination in Children

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UNDERSTANDING FOREARM MUSCLE COORDINATION IN CHILDREN

by

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ABSTRACT

A combination of surface electromyography (EMG) and pattern recognition algorithms have led to improvements in the functionality of upper limb prosthetics. This method of control relies on user's ability to repeatedly generate consistent muscle contractions. Research in EMG based control of prosthesis has mainly utilized adult subjects who have fully developed neuromuscular control. Little is known about children's ability to generate consistent EMG signals necessary to control artificial limbs with multiple degrees of freedom. To address this gap, two experiments were designed to validate and benchmark an experimental protocol that quantifies the ability to coordinate forearm muscle contractions in able-bodied children across adolescent ages. Able-bodied, healthy adults (n = 8) and children (n = 9) participated in the first experiment that aimed to measure the subject's ability to produce distinguishable EMG signals. Each subject performed 8 repetitions of 16 different hand/wrist movements. We quantify the number of movement types that can be classified by Support Vector Machine with >90% accuracy. Additional adults (n=8) and children (n=12) were recruited for the second experiment which measured the subjects' ability to control the position of a virtual cursor on a 1-DoF slide using proportional EMG control under three different gain levels. We demonstrated that children had a smaller number of highly independent movements than adults did, due to higher variability. Furthermore, we found that children had higher failure rates and slower average target acquisitions due to increased time-to-target and follow-up correction time. We also found significant correlation between forearm circumference/age and performance. The results of this study provide novel insights into the technical and empirical basis to better understand neuromuscular development in pediatric upper-limb amputees.

This work is dedicated to my family

who supported me through personal hardships and least of all a global pandemic.

And to the future generation of curious engineers and scientists

who seek the advancement of our limited understanding of this world.

ACKNOWLEDGMENTS

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LIST OF ACRONYMS (or) ABBREVIATIONS

DEGREES OF FREEDOM	DoF
ELECTROMYOGRAM	EMG
HIGHLY INDEPENDENT MOVEMENTS	HIMs
LINEAR DISCRIMINANT ANALYSIS	LDA
NONNEGATIVE MATRIX FACTORIZATION	NMF
PATTERN RECOGNITION	PR
ROOT MEAN SQUARE	RMS
SUPPORT VECTOR MACHINE	SVM
VARIANCE ACCOUNTED FOR	VAF

CHAPTER ONE: INTRODUCTION

Background

After the amputation of a limb, a person will have to adapt to a drastic change in their ability to accomplish daily living tasks. Using electromyography (EMG) signals from residual limbs to control a prosthesis can allow for improvements in autonomy for these individuals. There is an estimated 48,000 upper limb amputees that are under the age of 21 in the US [1]. About 2/3s of pediatric limb deficiencies are due to congenital causes [2]. Early adoption of a myoelectric controlled prosthetic device has been shown to increase acceptance rate of the device [3]. Prosthetic devices for children are often limited to simplistic mechatronic systems due to considerations of cost and weight [2]. In contrast, advanced prosthetic devices for adults are able to support multiple degrees of freedom (DoF) and increased functionality, however, rely on the user's ability to generate complex muscle contractions in order to perform efficiently. Some studies have shown that congenital amputees have more difficulty producing distinguishable EMG patterns [4]–[6]. Studies have also found differences in the neural structure of the motor cortex between congenital and traumatic amputees [7]. It is unknown whether children with congenital or early acquired limb reduction are able to adapt to using the more advanced prosthetic device upon entering adulthood as most of the studies previously cited have only examined adults patients and control subjects with fully developed neuromuscular systems. Very little data has been produced on the neuromuscular control abilities of a child amputee or on possible rehabilitation programs that could improve control abilities for use with adult prosthetic devices. In order to address this gap in knowledge, this paper aims to establish and validate an experimental protocol that quantifies that ability to coordinate forearm muscle contraction in able-bodied children across adolescent ages. The two experiments are designed to evaluate the subject's myoelectric control abilities with regard to two types of prosthetic control methods: pattern recognition (PR) and simultaneous proportional control.

PR control leverages a classification algorithm that learns from a labeled "training" data set using a feature vector that condenses some type of characteristics of the signal in order to distinguish between different output classes. The first experiment will test the user's ability to produce distinguishable muscle patterns by performing a series of different hand/wrist movement combinations. The EMG data will then be post-processed and used to train a classifier off-line. The subject's performance will be measured based on the number of movements achieved with a minimum accuracy of 90%. The PR control method is popular it allows for a wider range of functional hand movements to be achieved; however, PR control is limited to one DoF.

In contrast, simultaneous proportional control which has been recently developed, allows for multi-DoF control signals. Using this control method, the user must have the ability to control and scale the magnitude of the muscle activations. The second experiment will assess the subject's ability through a simple target acquisition task. This work will provide the technical and empirical basis to better understand neuromuscular development in pediatric upper-limb amputees. Furthermore, it will inform future studies investigating plasticity of neural mechanisms dictating sensorimotor learning in children, therefore potentially improving the management of pediatric prosthetics/orthotics and rehabilitation protocols.

Hypothesis

The purpose of this study was to quantify able- bodied children's ability to produce adequate EMG signals for control. We hypothesize the children group will have a smaller number of highly independent movements, and there is a correlation between age and classification accuracy. We hypothesize that the children group has on average worse performance with simultaneous proportional control measured by these three metrics, and that performance is positively correlated with age.

CHAPTER TWO: LITERATURE REVIEW

Electromyography

In order to produce any type of body movement, the brain must send an electrical signal to the target muscles via the nervous system. This electrical signal sets off a biochemical pathway that changes the voltage potential of the cell membrane and also causes a physical contraction of the tissue. Larger muscle contraction forces correspond with higher levels of electrical activity [8]. Electromyography is a technique that measures the electrical activity generated during muscle contraction by measuring differences in voltages via electrodes. A minimum of two electrodes are needed; one at the target muscle, another at a ground location usually near the wrist. This technique can be scaled to measure multiple sites concurrently. There are two main methods of electrode placement for collecting EMG signals: Surface contact and intramuscular contact. In surface EMG, the electrodes are placed on the surface of the skin, above the muscle of interest. This method is more common for prosthetic control as it is non-invasive however several important disadvantages to consider. The first one is signal cross talk which occurs when activity from one or more muscles contribute to the recorded signal. For example, an electrode that is placed over a muscle that is not currently active may still record electrical activity from neighboring muscles. A high signal-to-noise ratio is desirable to ensure high fidelity signals. This issue is more prevalent in children due to the smaller forearm circumference sizes, leading to smaller distances between equally spaced electrodes. In the intramuscular approach, a needle is used to attach the electrode at the specific muscle with high precision. This method allows for a higher fidelity signal to be acquired but is used more often in a clinical setting for diagnostic purposes due to the invasive nature [9].

EMG Site Selection

Electromyography has been a popular tool for its diagnostic and biomedical applications, particularly for its ability to generate bio-control signals. By using multiple EMG sites and signal processing techniques, it is possible to represent the muscle contractions into distinct high dimensional data objects and extract the user's motor intent. Several studies have shown that an increase in the number of EMG channels improves classification accuracy for trans-radial amputees but has diminishing returns [8]. Being able to accurately interpret the user's motor intent is vital for any advanced artificial prosthetic system to be successful for use in daily life activities. The placement of the electrode is important and must be located close to the anatomical source. Able-bodied adults are able to produce high fidelity signals however, after an amputation, the muscles are missing, and the control signals are harder to generate. Higher levels of amputations, such as shoulder disarticulation, correspond with a higher degree of difficulty in generate those finer muscle contractions needed for hand and wrist movements. The abilities of EMG signal generation in amputee differs between age at amputation (child vs adult) as well as cause (traumatic vs congenital). Electrodes are usually placed on the forearm of the subject [6].

Muscle Coactivation

Muscle coactivation is the simultaneous activation of opposing muscle groups around a joint. This muscle coactivation provides stability to the surrounding joint. There are many indices that attempt to measure levels of coactivation but one of the more common methods is simply a ratio between the antagonistic and agonistic muscle activations [10].

Neuromuscular Control in Children

From birth until late adolescence, children are in a constant stage of development that involves attempted mastery over daily motor functions, from learning how to maintain balance during their first steps to developing the hand eye coordination needed to strike a baseball with a bat. Several studies have aimed to quantify children's performance in motor tasks using a standardized test known as the Zurich Neuromotor Assessment. This test was used to assess differences in performance in children between several factors such as gender, age and handedness [11]. The findings showed that younger children performed slower than older children and that there was high variability within age groups. Additionally, the complexity of the task correlated with an increase in the age in which performance for that task reached a plateau. Researchers also found that younger children produced more associated movements which are defined as involuntary movements of body parts that are not actively being used during the task [11]. Yet other studies have indicated that there are several neuromotor capabilities that are not yet fully developed at the time of adolescence such as interlimb coordination which also explains a higher amount of associated movements [12]. There is some evidence to support a regression in motor skill around 10-12 years old [11], [13], [14]. There are also cognitive factors to consider.

Pattern Recognition Control

Pattern Recognition (PR) is a common method used in myoelectric control. PR can be used to classify muscle contraction patterns into discrete functional classes which can then be used to control an end-use device. There are many different types of classification algorithms that can be used but all follow the common stages of signal processing which includes data preprocessing, data windowing, feature extraction, and classification. The EMG signals may be subject to preprocessing to remove unwanted interference; the most common sources are power line harmonics and motion artifact due to electrode movement. One disadvantage of this method is that the terminal device always moves at a fixed speed [8]. A critical factor for a successful myoelectric control system is the ability to ensure high classification accuracy as misclassification can lead to adverse outcomes such as unwanted movements or completely failing a task. Our protocol was initially validated using EMG data from the publicly available EMG database (Ninapro), to be used in off-line classification.

Classifiers & Feature Selection

Many different classification algorithms have been used for myoelectric PR control such as linear discrimination analysis (LDA) [15], random forest [16], support vector machines (SVM) [17], and convolutional neural networks [18]. All approaches to EMG pattern recognition have the fundamental processing stages described earlier. For this study, we decided to examine two classifiers: LDA and SVM. LDA is a popular choice for data classification and dimensionality reduction due to its computational simplicity and comparable performance to other classifiers [9]. This method works by finding a linear combination of features that separate the given data into two or more classes. It is similar to Principal Component Analysis (PCA) which also seeks to explain the variance in the data however the biggest distinction being that PCA does not take into consideration the differences between classes. LDA assumes that the data is normally distributed.

On the other hand, Support vector machines do not make any assumptions about the data and therefore more flexible. SVM works by mapping the original input space into a higher dimensional space and optimizes the hyperplane that separates the classes. This hyperplane is defined using the class data points that are farther away from the center of the group in order to create soft margins which are used to classify new data points [19]. SVM also uses mathematical functions that define a kernel function. SVM was initially meant for binary classification however several adaptations exist that allows for multi-class classification such as one-vs-all or one-vs-one. Both LDA and SVM can provide classification accuracies higher than 90% however SVM generally outperforms LDA [20].

In order make the raw EMG signal useable for classification, a feature-extraction stage is used to increase the information density of the EMG signals. Ideally, the necessary information regarding contraction discrimination should be kept while other irrelevant information is removed [21]. Three common features used in adult prosthetic research are root mean square (RMS), waveform length, and histogram [22]. A combination of features has been found to provide high classification accuracies for certain classifiers [23]. A summary of the commonly used features is provided in the following table.

Table 1:Common Feature Descriptions

Feature	Definition (per channel)
Root Mean Square (RMS)	$\hat{x} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x_t^2}$
Waveform Length (WL)	$\hat{x} = \sum_{t=1}^{T-1} \lvert x_t - x_{t+1} \rvert$
Histogram (HIST)	$\hat{x}_{1:B} = hist(x_{t+1}, B)$
Marginal Discrete Wavelet Transform (mDWT)	$\psi_{l,\tau}(t) = 2^{-\frac{m}{2}}\psi(2^{-1}t - \tau)$

<u>Simultaneous Proportional Control</u>

While PR control has been shown to achieve high classification accuracies, it is difficult to achieve simultaneous control of multiple DoFs (e.g. wrist and finger movements) with discrete classes without also increasing the necessary training. Discrete classes also require motor planning of sequential movements making it difficult for the user to achieve fluid-like motion. Recent research has strived to develop a continuous representation of the user's intent in order to achieve both simultaneous and proportional control. Jiang et al [24] demonstrated that utilizing a method based on nonnegative matrix factorization, it was possible to extract simultaneous multidimensional control signals.

Fitt's Law

Fitt's Law is a model of human performance based on information theory and is often used in virtual environments. Fitt's Law states all human movements convey a certain amount of information over time limited only by the control system. This law also states that there is a trade-off between speed and accuracy. The difficulty of a target acquisition task is defined as the amount of time elapsed in moving cursor to a target is a function of target distance and target width. The Fitt's Law of index of difficultly (ID) is measured in bits and represented in the following equation, where D is the target distance and W is the target width.

$$ID = log_2(\frac{2D}{W})$$

Another important metric is called throughput (TP) which represents the average information generated by a series of movements and is calculated as the average information per movement divided by the movement time (MT).

$$TP = \frac{ID}{MT}$$

The metrics provided by Fitt's Laws have been shown to be sufficient for evaluating EMG control systems using target aquation tests.

Non-negative Matrix Factorization and Muscle Synergies

Non-negative matrix factorization is a method that factorizes a non-negative input matrix V into two matrices, W and H. Generally, the cost function used in non-negative matrix factorization is non analytical and thus must be approximated numerically. This method reduces the dimensionality of the feature space and is able to represent non-negative data quite well [25], making it a great tool for extract muscle synergies in EMG data. Under the muscle synergy framework, it is useful to think of W as a *n* by *k* matrix that represents k synergies and n number of electrodes. Additionally, H is k by T matrix that represents the synergy activation coefficients for T samples. A higher number of k synergies corresponds with a more accurate approximation of V. There are many methods that can be used to determine the minimum number of k synergies needed to explain the majority of variance in the data. In this study, the 'variance accounted for' (VAF) is defined in the following equation, where SSE is the sum of squared differences between the approximated and exact EMG data and SST is the sum of squared original EMG data.

$$VAF = 100 * (1 - \frac{SSE}{SST})$$

In order to avoid settling at a local minimum, the NMF algorithm must be applied multiple times. Direct subject to subject comparison of muscle synergies is possible if the electrodes are placed at precise anatomical locations [26]–[28]. This method has been commonly used in studies that examine muscle synergies [29]–[31]

Evaluation of Control Systems

PR control systems are commonly assessed offline which does provide useful information but can lack details about how the system would perform in real time. Furthermore, classification accuracy cannot be used to evaluate non-PR control methods. Virtual environments are used in place of existing functional tests as they are more adequate for objective evaluations [32]. This also eliminates the need for an actual prosthetic device. Several studies have used virtual tasks to quantify performance, showing that differences can exist between offline and online evaluations [33]. The Target Achievement Control (TAC) test is the model that will be the basis for the second experiment and is based on Fitts' law for human motor control [34], [35]. This target acquisition test was adapted for 1D target task. For actual prosthetic device performance, the best evaluation metric involves direct control of the device to accomplish daily living tasks. These functional tasks are more representative of actual performance [35].

CHAPTER THREE: METHODOLOGY

Subjects

Eight healthy adults (5 males, 3 females, 29±8.3 years) and nine healthy children (4 males, 5 females, 8.4±2.5 years) successfully completed the first experimental procedure. Eight healthy adults (4 males, 4 females, 28±7.5) and thirteen healthy children (8 males, 5 females,9.2±2.3) where recruited for the second experimental procedure. Two subjects from the children's group were not able to successfully complete the procedure and the resulting data was excluded from analysis. This research was approved by the University of Central Florida.

Table 2: Subject Characteristics From Experiment 1

Subject ID	Gender	Age	Handedness	arm length (cm)	forearm circumference (cm)	Ht (cm)	Wt (kg)	Completion
A1	m	27	r	28	29	182	80	y
A2	m	37	r	26	29	184	95	y
A3	m	37	r	30	29	182	107	y
A4	m	20	r	28	29	177	80	y
A5	f	20	r	25	21	165	54	y
A6	m	22	r	29	27	183	79	y
A7	f	29	r	25	23.25	160	54.4	y
A8	f	41	r	22.5	22.75	63	49.9	y
C1	f	10	r	22	18	145	24.94	y
C2	f	14	r	24.5	23.5	157.5	56.24	y
C3	m	7	r	18	17.5	131	24.9	y
C4	m	6	r	19.5	21	124.5	32.6	y
C5	f	9	r	18	20	134	31.9	y
C6	f	9	r	21	18.5	143	32	y
C7	f	7	r	19.5	20.5	133	23	y
C8	m	8	r	20	20	142	28	y
C9	m	6	r	19	18	131	25	y

Table 3: Subject Characteristics From Experiment 2

Subject ID	Gender	Age	Handedness	arm length (cm)	forearm circumference (cm)	Ht (cm)	Wt (kg)	Completion
A1	m	27	r	28	29	182	80	y
A2	m	37	r	26	29	184	95	y
A3	f	29	r	25	23.25	160	54.4	y
A4	m	22	l	29	27	183	79	y
A5	m	21	r	26.5	27.5	182	91	y
A6	f	41	r	22.5	22.75	63	49.9	y
A7	f	21	r	25	21	165	54	y
A8	f	26	r	23	23.5	162	65	y
C1	m	13	r	24	23	163	48	y
C2	f	11	r	21	23	155	52	y
C3	m	7	l	18	21.5	126	27	y
C4	m	7	r	21	19.5	137	29	y
C5	m	10	r	20	20	151	36	y
C6	f	12	r	24	29	163	64	n
C7	m	8	r	19	21	123	30	y
C8	m	8	r	18	21	131	32	n
C9	f	7	r	17	20	123	27	y
C10	m	6	r	17	18	121	26	y
C11	f	9	r	20	18.5	130	24	y
C12	f	12	r	25.5	23.5	160	49	y
C13	m	9	r	22	17.5	122	41	y

Equipment Set Up

The same equipment set up was used in both experimental protocols. Electrode placement was selected based on the literature review. Eight sEMG electrodes (Trigno Quatro, Delsys Inc) were placed equidistant radially around the thickest part of the subjects dominant forearm. The electrode placement was mirrored between right and left handed subjects to provide consistency during data analysis. The sampling rate of the sEMG was 2kHz, using 2 sets of Delsys Trigno Quattro sensors (4 mini electrodes each). Data acquisition and experimental protocol was developed using the LabVIEW software. PR algorithms require sizeable window sizes in order to extract valuable data from the features. A window size of 250 ms was selected as this has been shown to provide an acceptable tradeoff between classification accuracy and time. The feature selected was root mean square (RMS) which has been shown to be a popular feature in adult prosthesis studies.

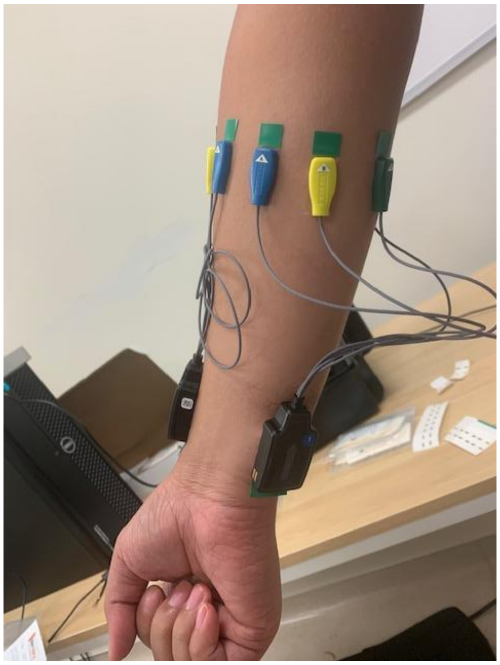

Figure 1: Picture of Electrode Setup

Figure 2: Delsys EMG Sensors and Base

Experimental Procedure 1

Eight healthy adults and nine healthy children successfully completed this experimental procedure. Parental informed consent was acquired for each child participant. During data acquisition, participants were asked to mimic the hand-wrist movement displayed on a monitor, using their dominant hand. The subject was briefly coached before each movement on how to properly execute the movement. The experiment included 8 repetitions of 16 different hand-wrist movements. Each repetition was held for 5 s with a rest period of 2 s in between repetitions, with short breaks between movements to alleviate muscle fatigue as needed. The 16 movement were selected from commonly analyzed movements in current EMG research as describe in Table 3.

Table 4: Movement Summary

Movements		
1.closed fist	7.wrist supination	13.wrist supination w/closed fist
2.extend all fingers	8.wrist pronation	14.wrist pronation w/closed fist
3.wrist flexion	9.wrist flexion w/closed fist	15.wrist flexion & supination
4.wrist extension	10.wrist extension w/ closed first	16.wrist flexion & pronation
5.wrist abduction	11.wrist abduction w/ closed fist	
6.wrist adduction	12.wrist adduction w/closed fist	

<u>**Experimental Procedure 2**</u>

Subjects were tasked using their wrist extension/flexion to control and move an on-screen cursor to a random target on 1-dimensional slide, as quickly as possible as shown in the following Figure 3. The target had a fixed width of 0.5 units.

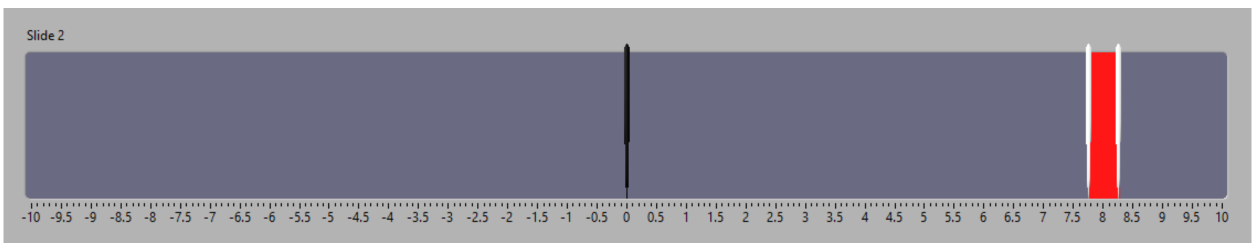

Figure 3:Slider Task

This experiment included a calibration phase followed by the testing phase. During calibration phase, 15 seconds of EMG data associated with repetitive wrist flexion/extension movement is acquired. Using the MATLAB function, nnmf, where the first input is the EMG data and the second input is 2 because we are interested in the matrix coefficients that separate the into raw EMG signal into two control signals. Because the first set of coefficients could correspond with either extension or flexion movement, it is sometimes necessary to invert the control signal so that from a right-handed perspective, extension corresponds with cursor movement to the right and flexion corresponds with moving the cursor to the left (reversed for left-handed subjects). After the coefficients are acquired and applied to the signal, the subject is asked to try to control a sample cursor and inversion of the control signal is applied as necessary. In order to reduce unintended drift in the cursor movement, the subject is asked to assume a rest position with minimal EMG activity. A resting threshold that is roughly 50% higher than the average resting EMG amplitude for each channel is established. EMG signals below this threshold will not contribute to the movement of the cursor. If the average resting EMG amplitude was around 0.1, recalibration was suggested. In the testing phase, the test variable consisted of 3 different gain settings (low, medium, high). Each gain setting had 3 runs consisting of 20 targets each. If the target was not reached within 10 s, it was counted as a failure. The gains were tested in two different orders: 1. Low, medium, high, high medium, low and 2. High, medium, low, low, medium, high. Each subject was randomly assigned one of these orders in order to make sure that there was no learning bias in the final data. Performance was measured through several common metrics used to evaluate subject performance using proportional control systems as described in Table 4.

Table 5: Metrics Summary

Metric	**Description**
Completion Throughput	The time needed to complete target acquisition normalized by the target's index of difficulty (ID) using Fitts' Law
First Touch Throughput	The time needed to first reach a target normalized by the target's ID using Fitts' Law
Adjustment Time	The amount of time necessary to complete target acquisition after the first moment the cursor is within target range.
Completion Rate	The percentage of targets reached within the allowed time

Data Analysis

EMG Signal Processing

The raw EMG signals collected from each movement repetition are processed using MATLAB. The EMG signal is zero-meaned and rectified and then passed through a zero phase digital filter using the filtfilt function and the transfer function coefficients of a 4-th order Butterworth filter with normalized cutoff frequency 0.01 Hz. In order to decrease variability in the signal and increase classification accuracy of the algorithm, the portions of the EMG signal associated with muscle contraction ramp-up and periods of inactivity were removed. Additionally, samples that lied 3 standard deviations above the mean were removed. The remaining EMG data was then partitioned further into windows consisting of 80 samples each and the RMS feature was calculated for each window.

Highly Independent Movements

Data from repetitions 1,3,4,6,8 were used to train the SVM model while data from repetitions 2,5, and 7 were used for testing. The SVM model is based off of a learner template with a gaussian kernel function and standardization set to true. Standardization is used to center and scale each column of the input data by the column mean and standard deviation. After training and testing, a confusion matrix was generated with all the movements and their error rates. The movement with the lowest accuracy was removed from the training and testing datasets and the SVM model was retrained with data from the remaining movements. This process was repeated until all remaining movements had a minimum classification accuracy of 90%. After the algorithm classifies the data for the first time, the movement with the lowest accuracy is removed and the algorithm is retrained using only the remaining movements. This process is repeated until all remaining movements have a minimum classification accuracy of 90%. The number of HIMs gives an idea on the number of movements that could be generated using a prosthetic hand for that specific user with minimal training [26].

Dimensionality Analysis

The processed EMG data for each movement is partitioned into windows consisting of 250 samples and are appended to a matrix that contains the data from all movements. Each of the 8 channels are then normalized by dividing by the standard deviation of each column. The data is then randomly separated into a training and validation set (80% and 20% respectively). Using the training set, the nnmf algorithm is used to produce W and H matrices. The variance accounted for as defined earlier (See Literature Review) is calculated both globally and locally (per EMG channel). This procedure is repeated for k synergies ranging from 1 to 6 in order to find the smallest k that results in a minimum global VAF of 95% and local VAF of 85%. The nnmf algorithm is repeated 20 times for each k synergy in order to minimize the chance of converging to a local minimum. Once the average minimum k synergies are found, the synergy weights will be graphed on a polar plot. Figure 4 shows the orientation of the polar plot (from the right-hand perspective) where flexion and extension correspond with 0 and 180 degrees respectively. Similarly, abduction and adduction correspond with 90 and 270 degrees respectively. Because electrode placements are mirrored in left-handed subjects, these four movements will still correspond to the same polar directions.

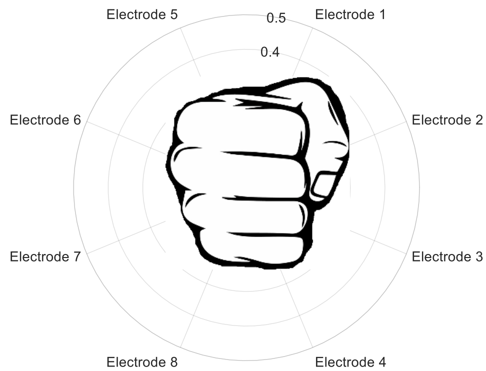

Figure 4: Polar Plot Orientation

Statistics

A simple linear regression was used to determine if there was a correlation between the number of HIMs and subject's age. The failure rate was calculated for each subject and a correlation between age was conducted. If the subject had a greater than 50% failure rate, the data was considered unusable. From the children's group, the data from subject 6 and 8 was excluded. The successful trails were used to calculate the parameters shown in the following Table. Fitt's law was used to determine the difficulty index of each target. A two-way mixed ANOVA test was conducted for each performance metric. A two tailed paired test was further applied if interaction between factors was significant.

CHAPTER FOUR: FINDINGS AND DISCCUSSION

Experiment 1 Results

As stated in the previous sections, forearm circumference is an important factor in prosthesis control. Subject 4's results were not included as the exhibited loss of attention to the task while near the end of the experiment, resulting in only one movement being classified as highly independent. This result was excluded as it does not have any practical implications as any random movement could achieve high classification accuracy if that movement was the only one being trained. First, we began by identifying a simple correlation between forearm circumference and the subject's age as shown in Figure 5. As expected, a significant linear relationship was found (R^2=0.51, p=0.038).

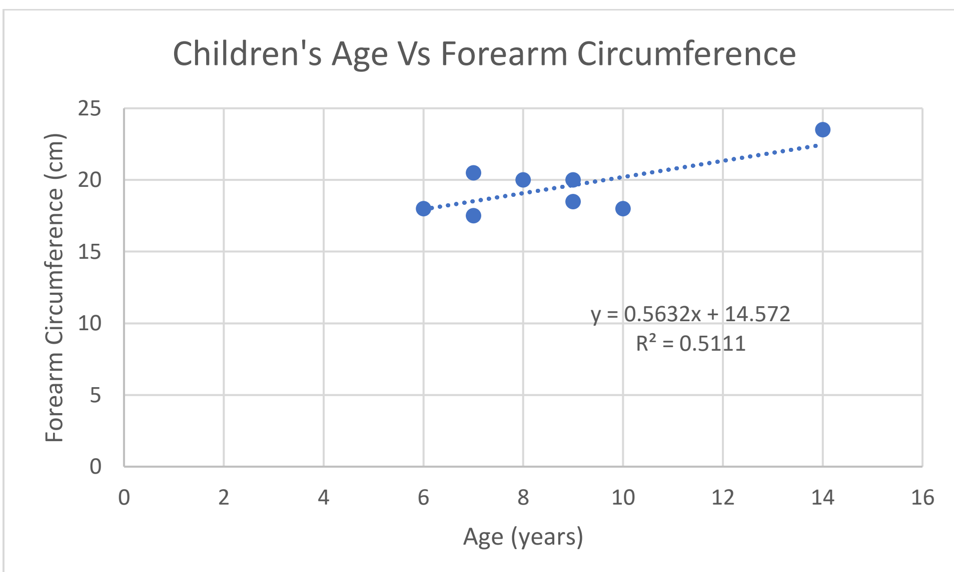

Figure 5: Correlation Between Child's Age and Forearm Circumference

The younger children subjects had the smallest forearm circumference with a linearly increase with age. Maximum forearm circumference is eventually reached in adulthood and does not continue to increase with age. A stronger linear relationship (R^2.=0.576, p=0.002) could be achieved by only examining subjects below the age of 25 years.

As hypothesized, children in general (t = 0.045) achieved fewer HIMs (mean: 5.625 ± 3.54) than adults (mean: 8.8±1.7). Figure 6 shows the correlation between child subject's age and the number of HIMs (p = 0.05345). Here it is important to discussion the distinction between the way HIMs are generated in this study as opposed to previous studies [36]. While HIMs are generally characterized by high classification accuracy (>90%), previous studies created hierarchical cluster trees using the Mahalanobis distances of each movement to make statistically meaningful separation between movements. In our study, we took a more practical approach by defining HIMs around the classification algorithm being used (in this case SVM), which gives a better idea on how a child might perform using a prothesis with this control method. Future studies should be conducted to measure which specific movements are the most separable within children, which can help guide training programs.

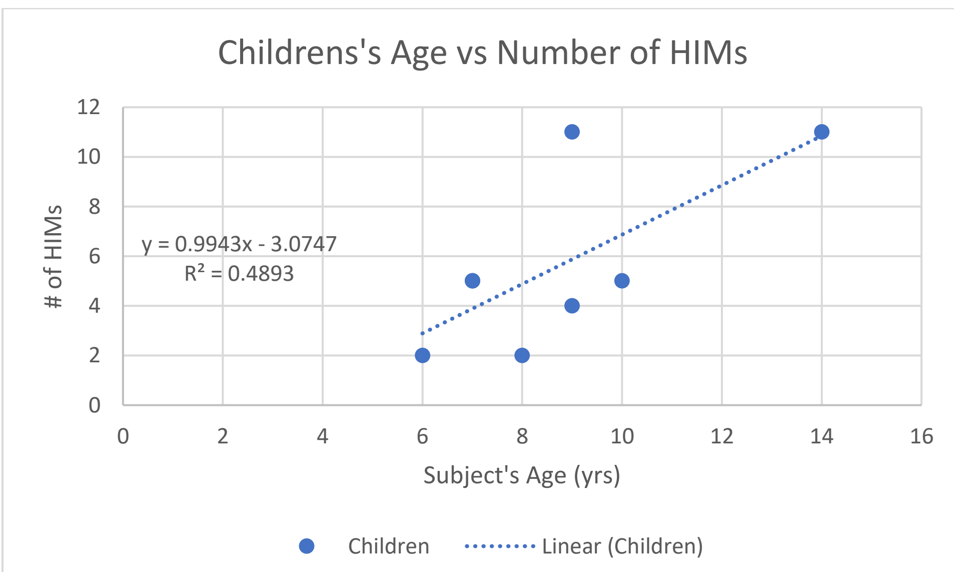

Figure 6: Correlation Between HIMs and Child's Age

Cluster analysis showed that children subjects had higher within cluster sum of squares than adults.

Additionally, we investigated the relationship between children's forearm circumference and the number of HIMs generated. Figure 7 shows a linear correlation between the two factors however this result was not found to be significant (p = 0.11). There are many factors that can cause a large variation in forearm circumference within children such as nutrition, genetics, physical fitness, etc. A larger sample size with a wider range of adolescent ages is suggested in order to provide a more definitive answer to whether a correlation exists among children.

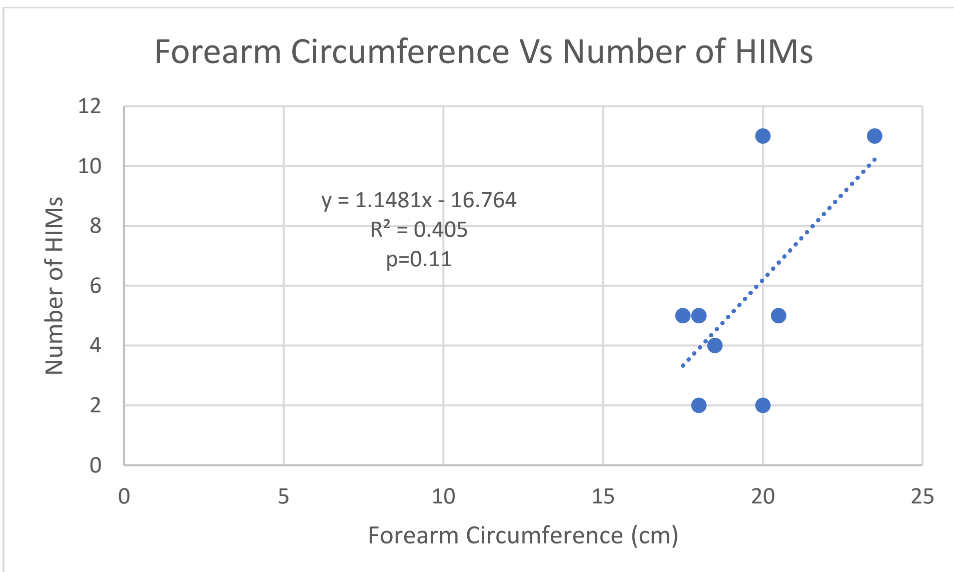

Figure 7: Correlation Between Forearm Circumference and Number of HIMs

Studies have shown that in trans-radial amputees, the remaining forearm percentage is an important clinical parameter that affects prosthesis usage [22]. The results shown in Figures 6 and 7 support the assumption that forearm circumference increases as children go through normal neuromuscular development stage, and that the offline performance of current pattern rely on the user's ability to generate distinct muscle activation patterns which is correlated with the user's age. Similar to what other studies have found, we saw high variability within the children age group. This could support the idea that classification performance is not solely limited by the circumference of the forearm and that children could be trained to achieve better performance, although younger children would likely require more training than older children.

Qualitive observations of subjects' performance indicated that younger children often had difficulty maintaining focus on the task before nearing completion, resulting in higher levels of inactivity and variability in the EMG recordings. These findings support the idea that children do not reach full development until about the age of puberty or about 14 years of age [11] and also suggest that psychological factors must be considered. One subject (9 y.o) performed exceptionally well, achieving a total of 11 HIMs, adding support to the findings of high variability in performance within age groups. A lower overall number of HIMs indicates that children may have some difficultly controlling prosthetic devices designed for adults. We did not find a strong correlation in the adult group as they all performed similarly, regardless of age.

Using NMF analysis, we found that there was no significant difference ($t = 0.78$) between the average number of minimum synergies to explain the majority of the variance for both adults (4 ± 1.07) and children (4.125 ± 0.35). Thus, a total of number of 4 synergies was chosen to visualize the groups of electrodes responsible for most of the movements. Figure 8 and 9 shows the relationship between the VAF and number of synergies for adults and children respectively.

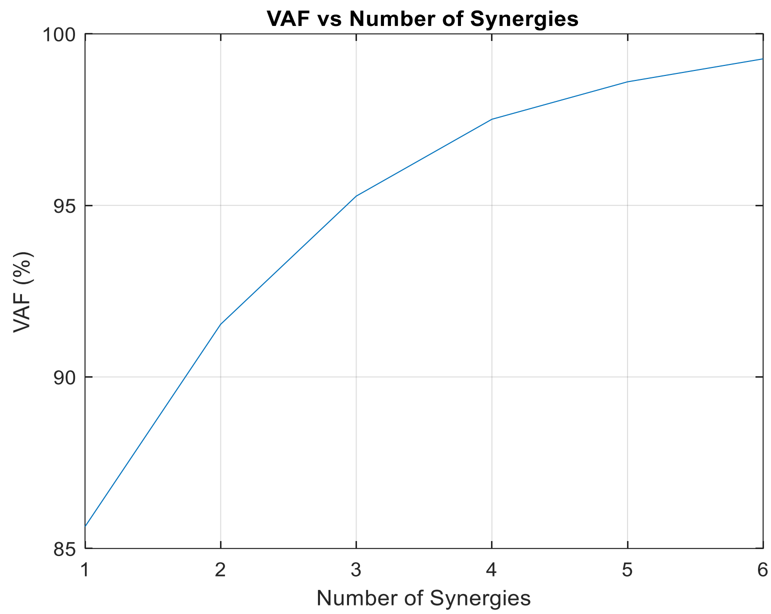

Figure 8:Variance Accounted For Vs Number of Synergies (Adults)

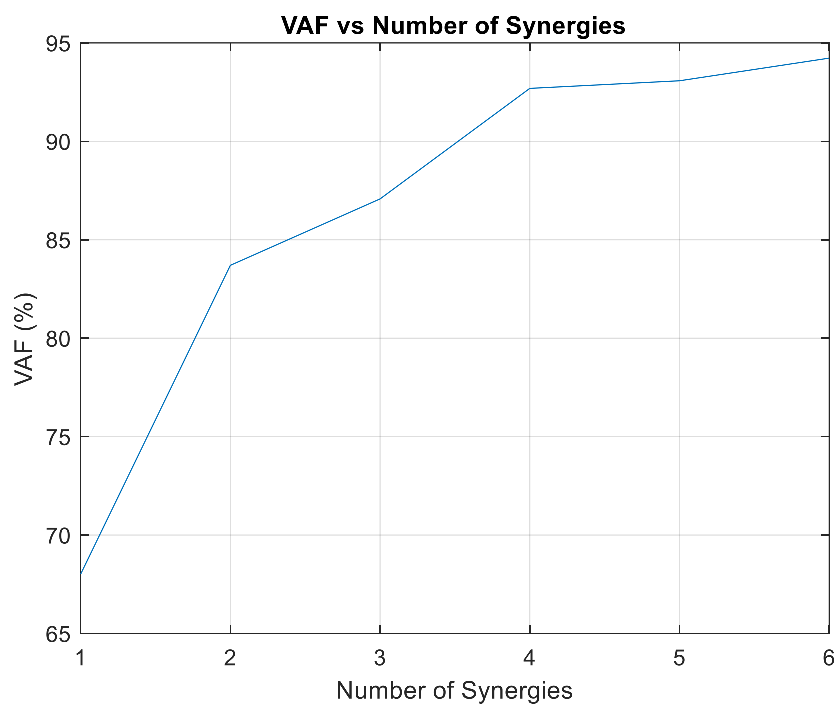

Figure 9:Variance Accounted For Vs Number of Synergies (Children)

Even children who had achieved a low number of HIMs showed similar synergy results. Thus, using four synergies, the average weights were calculated, and corresponding electrode locations were graphed on a polar plot shown in the following figure. Each synergy can be thought of corresponding to flexion, extension, abduction and adduction. The fact that there is no difference between age groups suggests that children already possess a control space of the same order as adults.

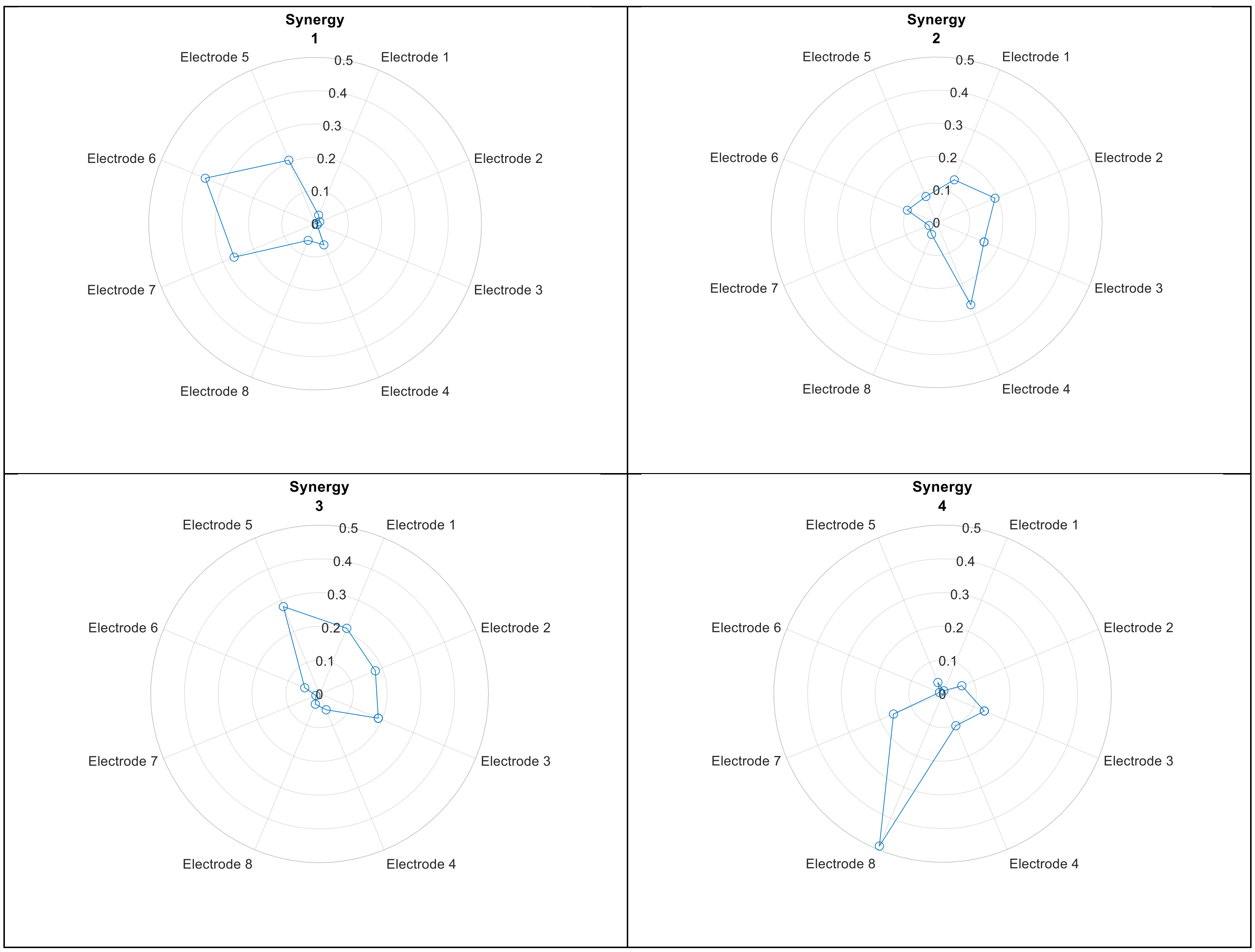

Figure 10: Synergies-Adults

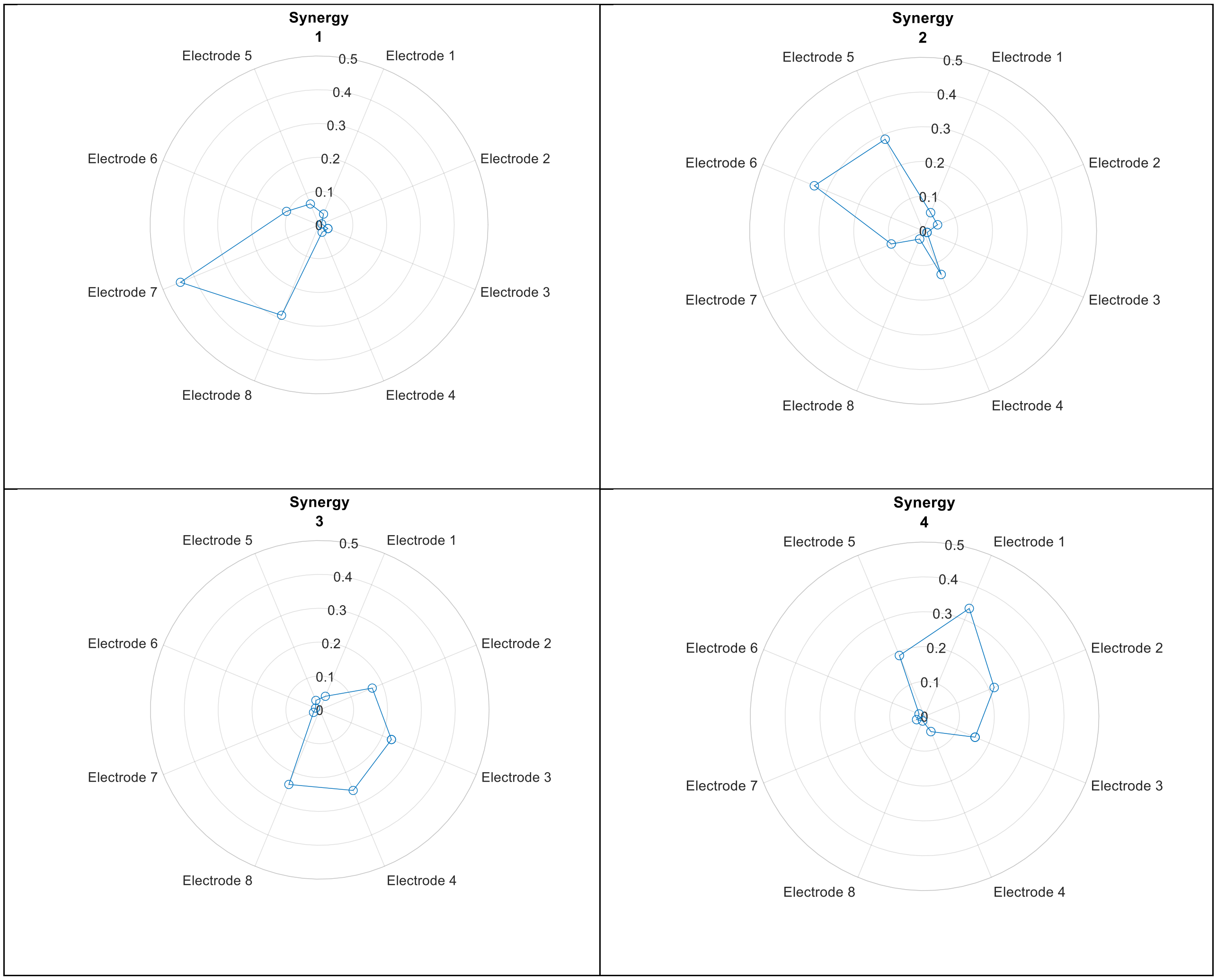

Figure 11: Synergies-Children

Under the assumption of four synergies, the polar plots indicate that there are four very distinguishable groups of electrodes contributing to the majority of the variance. Although not exact, the synergies have similar locations between adults and children. The four directions correspond with the approximate anatomical locations of muscles that are used for extension, flexion, abduction, and adduction. One of the common critiques of the muscle synergy framework is that it demonstrates limitations of the task as opposed to actual groupings of muscle [37]. In other studies, subjects performed over 40 different tasks and the average number of muscle synergies was 6 . Thus, it stands to reason that the synergy results from this experiment could be attributed to the reduced number of movements in the task, resulting in less overall task complexity. A reduced movement set was selected for this experiment in order to accommodate the average attention span of a child as experimentation. Further studies utilizing anatomical positioning of electrodes can provide more information on the exact muscles involved in each synergy. Knowing each muscle's contribution to a synergy as well as understanding how each muscle contribution changes throughout the development stage of the child would be of great benefit for developing training programs for upper limb prosthetic control.

Experiment 2 Results

In the second experiment, the mean failure rate among children per gain test (15%±5.2%) was significantly higher than the adult group (1%±0.5%). For both groups, an increase in gain level had a significant ($p = 0.001$) increase in failure rate.

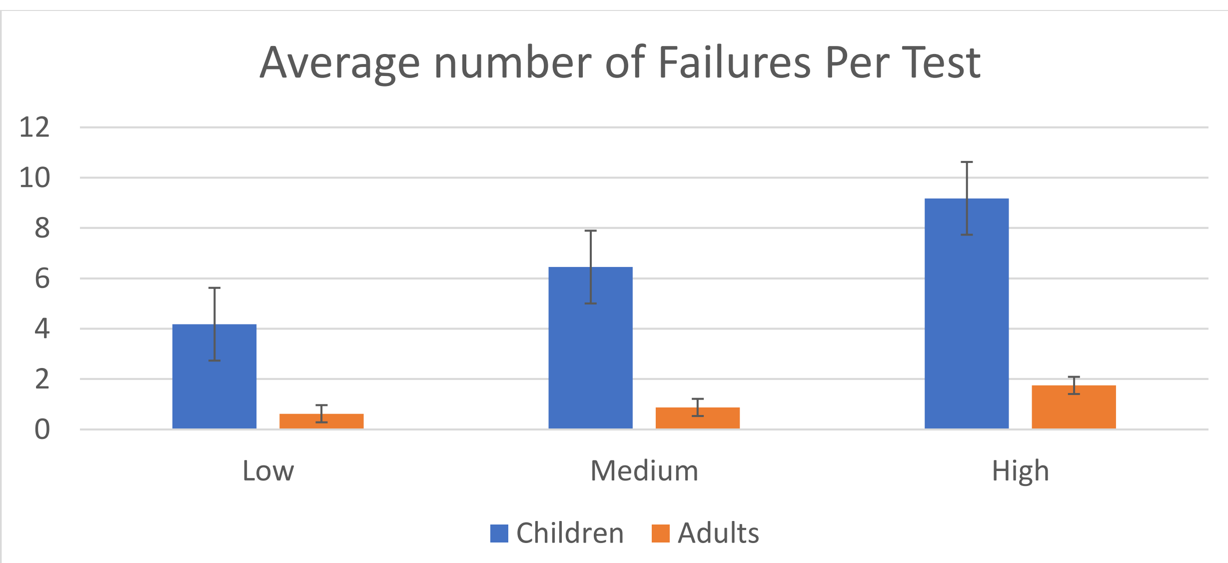

Figure 12: Average Number of Failures per Test

In order examine learning within subject groups, we compared the completion throughput between the first three and last three tests. Figure 13 shows that on average, the completion throughput for adults increases through each test with a significant difference between the first and second half (t = 0.001). However, children did not show a significant difference in average completion throughput between the first and second half (t = 0.12). Therefore, for the following metrics reported, only data from the second half is considered as it provides a more accurate description of expected performance.

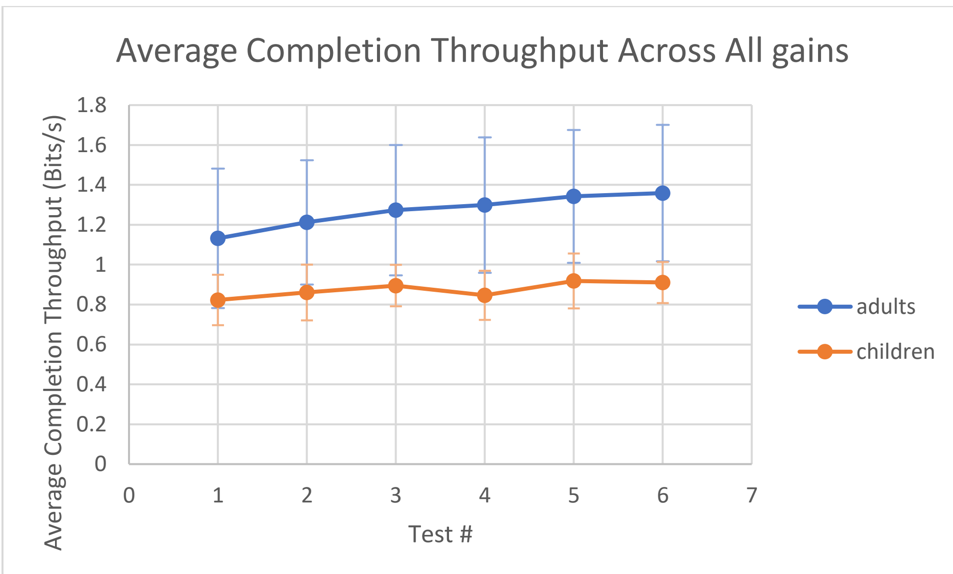

Figure 13: Average Completion Throughput

The Average Completion Throughput (Figure 14) indicates the information transmission rate in order to complete the target acquisition. In evaluating target acquisition performance between targets of different distances, completion time is not a sufficient metric as near-by targets should have expected completions times less than targets located at greater distances. Completion throughput is a metric that scales the completion time with the target distance in order to achieve a more comparable metric between different targets. Here we observed a significant difference in both gain and age factors (p = 0.004 and p = 0.001 respectively) with no interaction between factors (p = 0.732). Thus we conducted a post hoc 2-tailed paired T-test and found no significant difference between the Medium and High gain for both groups.

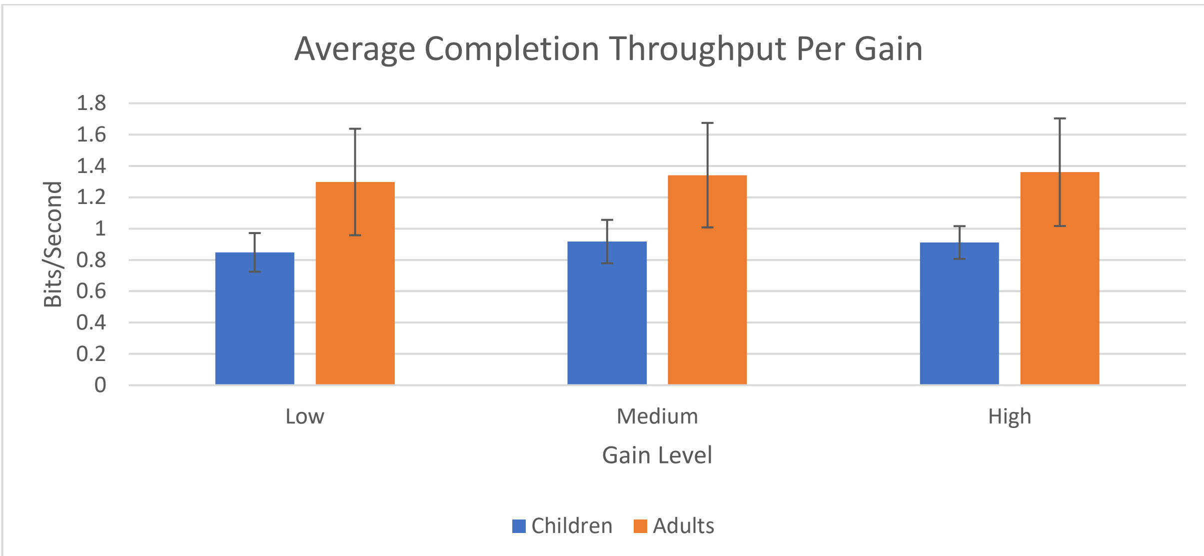

Figure 14: Average Completion Throughput Per Gain

The mean adjustment time between groups is shown in Figure 15. For this metric, it was found that a marginally significant interaction between age and gain level existed (p=0.047). Thus, 3 two-tailed paired T tests were conducted for each age group (Low Vs Medium, Medium Vs High, Low Vs High). Between children subjects, there was significant difference between High and Medium gain (t = 0.0027) and High and Low gain (t = 0.0026), with no significant difference between Low and Medium (t=0.183). In the adult group, there was a significant difference in adjustment time between Low and Medium gain (t = 0.0026) and Low and High gain (t=0.0002), with no significant difference between the Medium and High gain (t=0.326).

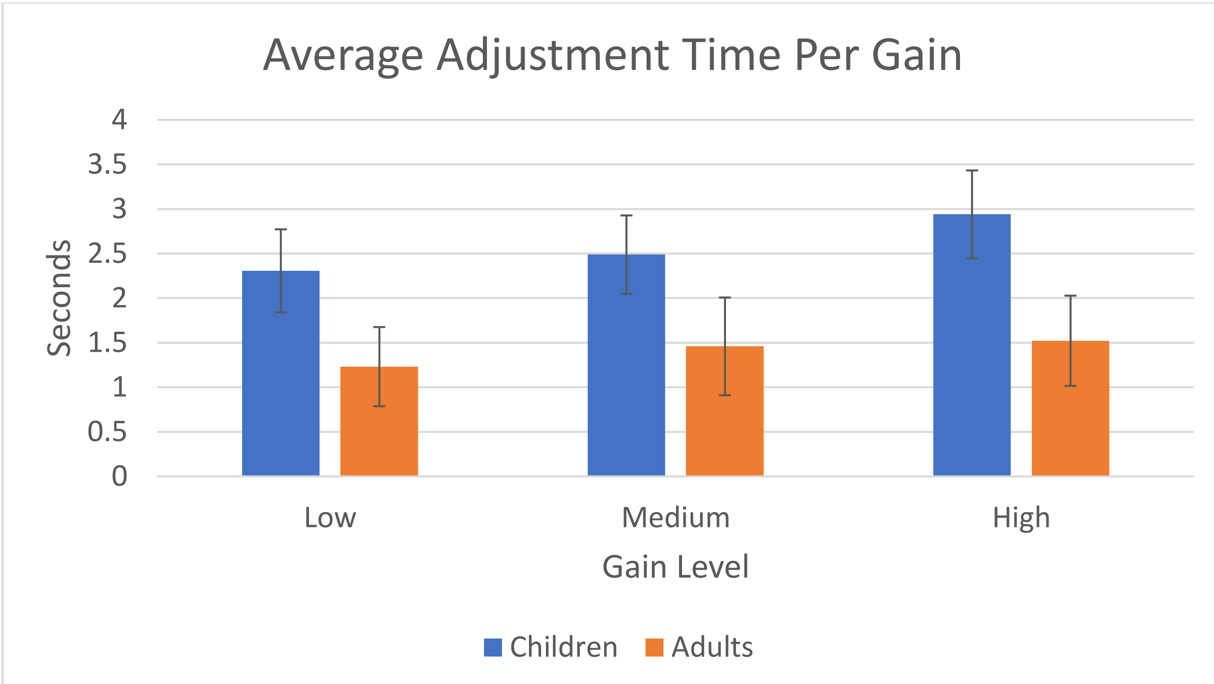

Figure 15: Average Adjustment Time Per Gain

Although not recorded, it is suspected that children on average had higher levels of co-contractions which could be quantified by taking the minimum magnitude between the left and right control signals. High levels of co-contraction will increase the minimum magnitude between these control signals. Co-contractions could also be a reason that the children subjects on average had longer adjustment times.

Comparing the First Touch Throughput in Figure 16, no significant difference between age groups was found ($p = 0.154$), indicating that children had a similar reaction speed to adults per gain. Additionally, 2-tailed paired T-tests between gains showed that there was no significant difference between Medium and High gains ($p = 0.107$) but Low was significantly different than both Medium and High ($p = 0.006$, $p = 0.007$ respectively).

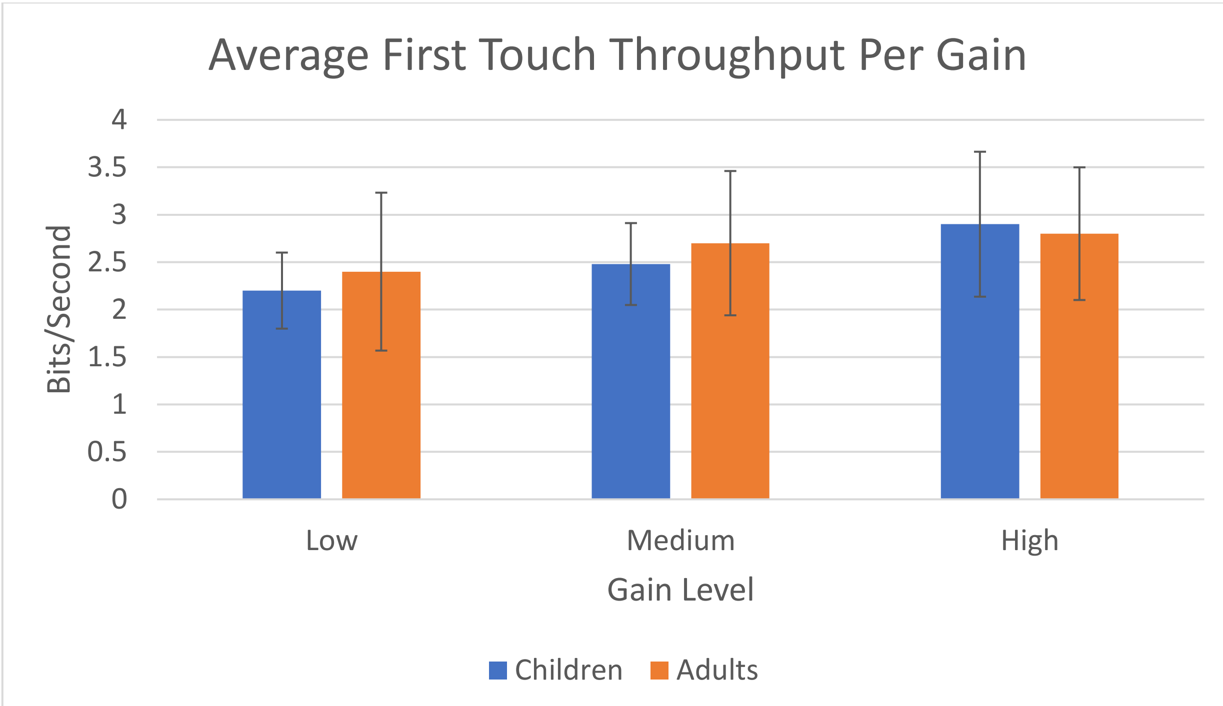

Figure 16: Average First Touch Throughput Per Gain

Due to the significant differences that were detected between some of the gain levels, an examination of the relationship between the children's age and completion throughput between each of the three gain levels was conducted, as shown in Figure 17. A significant positive correlation was found between age and completion throughput (Low: p=0.007, Medium: p=0.026, High: p=0.004).

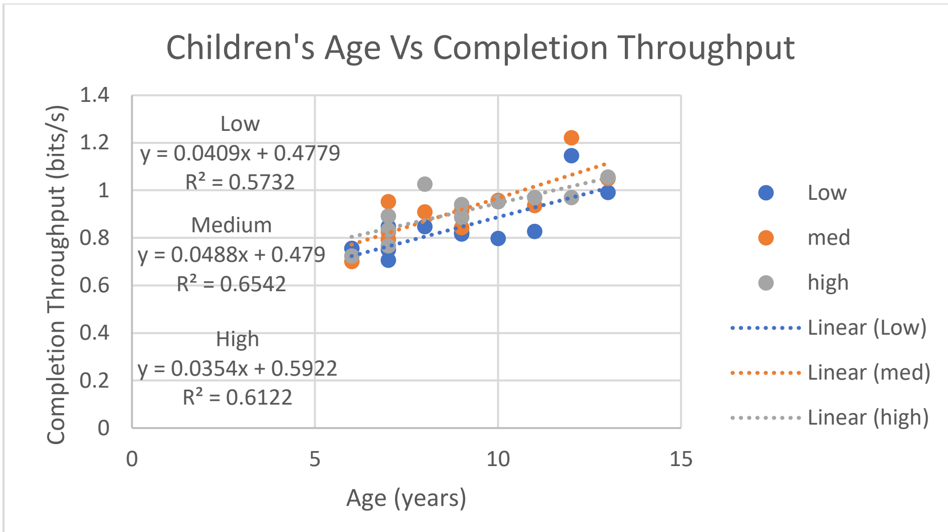

Figure 17:Correlation Between Children's' Age and Completion Throughput

Similarly, the relationship between forearm circumference and completion throughput was examined in Figure 18. A significant positive correlation was found within the low and medium gain levels ($p = 0.047$ & $p = 0.034$ respectively) however no significant relationship was found when examining the high gain level ($p = 0.158$).

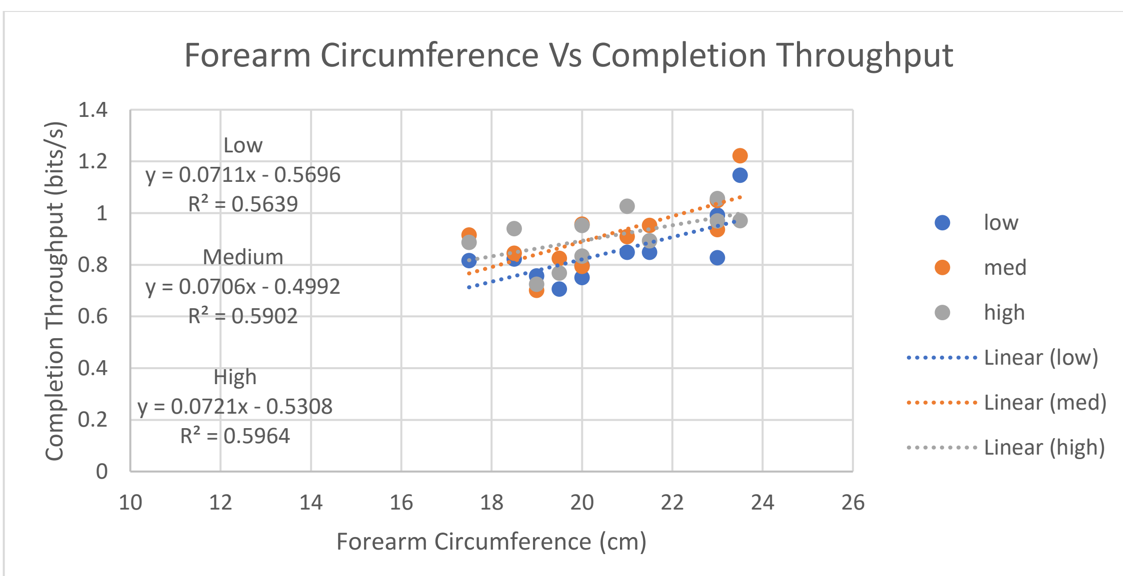

Figure 18:Correlation Between Forearm Circumference and Completion Throughput

Additionally, a significant negative correlation was found between age and adjustment time at low and medium gains shown in Figure 19 (Low: $p = 0.02$, Medium: $p = 0.011$, High: $p=0.077$).

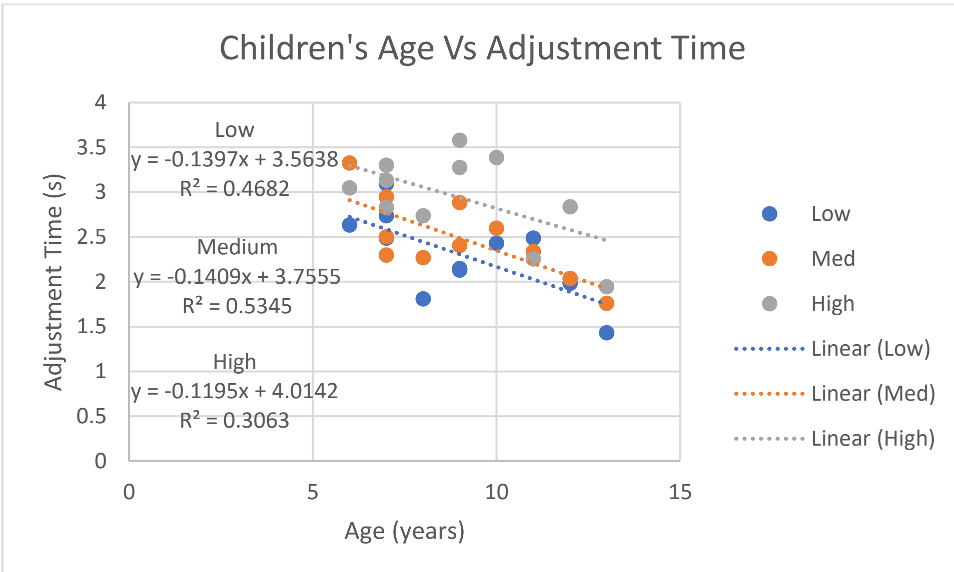

Figure 19:Correlation Between Children's Age and Adjustment Time

Similarly, the relationship between forearm circumference and adjustment time was examined in Figure 20. No significant relationship was found for the low gain setting and adjustment time ($p = 0.25$) however there was a significant negative correlation for both medium and high gain levels ($p = 0.018$ and 0.006 respectively). The correlation results suggest that age is better indicator of performance than forearm circumference even though both factors are dependent on each other.

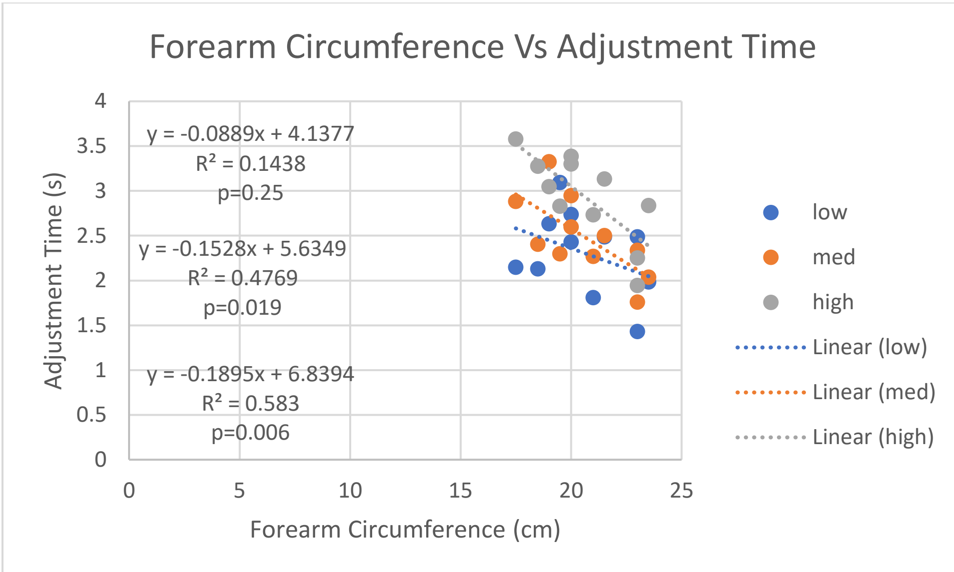

Figure 20:Correlation Between Forearm Circumference and Adjustment Time

Overall, these results match expected results from the current state of research in this field. The subjects from the children group have shown to have a similar overall meta-dimension control similar to adults. This is not surprising as children are expected to control their muscles in a manner not overtly different than adults. However, the biggest difference was in fine motor control. Children overall had higher adjustment times than adults, contributing to lower throughput. The low and medium gains had lower failure rates as well as lower adjustment times. Another surprising result was the lack of learning and improvement shown in children. It was thought that children would have a higher improvement than adults between the first and second half of the experiment, however this is not the case. Adults showed a plateau in throughput in the last three trials and with a minimum number of failures. Further testing is required in order to quantify a child's ability to adapt to proportional control systems with training. There are many cognitive factors that could be explored further to account for the higher variance in children's performance. It remains to be examined whether children can be trained to perform better or are they limited by their neuromuscular development or cognitive function. Regression based control may be a better option for children due to similar level of dimensionality with use of a soft adaptive hand as independent finger posture is not possible [38]. It's important to note that variability is not just a symptom of noise within the signal. In general, children might have more variability in their motor control thus they prefer smaller speed. Because of the high inter-subject variability, is very appliable in functional applications to have an automatic gain tuning so that it can increase that user's performance. It is possible to develop an automatic gain updater that adjusts the gain in reaction to the extent and frequency that the user exhibits overshot or undershoot during target acquisition.

CHAPTER FIVE: CONCLUSION

From our studies, we were able to quantify the EMG performance of children performing abstract tasks, using several different metrics, and comparing the results to adults. As hypothesized, children performed worse on several metrics such as lower number of HIMs and slower completion times. The children did perform similarly to adults in regard to the dimensionality of the EMG space for the muscle contractions produced. This suggests that the children in this experiment have similar capability of producing distinct muscle contractions while performing a range of hand movements, compared to adults. However, the lack of consistency during repeated movements led to poor training data and classification accuracy. One improvement to the first experimental protocol would be to introduce some form of feedback to the user. Visual feedback could provide the user with a sense of their performance so that they can perform more consistently. Haptic feedback has been shown to provide enhanced control in prosthetic devices [39]. In the protocol validation stage, SVM produced more highly independent movements than LDA and was thus selected for the final protocol. Both methods resulted in different movement types to be classified as highly independent. A thorough investigation into which classifiers and features are best suited for adolescent subjects is suggested.

The lack of learning observed in children during the second experiment suggests that children may have difficultly using simultaneous proportional control systems and that longer training periods will be required. Adult subjects showed improvement in both adjustment time and completion throughput in the second half. The classic tradeoff between speed and accuracy must be consider especially for children. Overall, a low to medium sensitivity gain setting is suggested as this resulted in the lowest number of failures and does not sacrifice on overall throughput. The fact that children had longer adjustment times and lower number of HIMs supports the idea that children struggle at reproducing repeatable EMG control signals. The reason that children display more co-contractions than adults could be attributed to the muscle mass and the immature neuromuscular control that they possess. Increased EMG crosstalk could also be a contributing factor in the observed co-contractions. In target acquisition performance tasks, co-contractions were found to increase with smaller target sizes [40]. Studies have shown that subjects are able to reduce the amount of co-contractions with enough training time. If co-contractions could be reduced via physical training or through data processing and filtering, performance in both PR and SP methods could be improved. In general, children performed worse than adults in utilizing both PR and SP control systems. Further studies should examine if it is possible for children to be trained to control prosthetics devices developed for adult users. It remains to be known how children would have performed in a 2D or 3D target acquisition test.

Personal observations and comments from several participants suggest that a more visually stimulating graphical interface could help increase the focus of younger children. While performing tasks, loss of focus was found to be the biggest source of variability among children. It is known that younger children have shorter attention spans than older children and adults which contributed to errors in the final results which is why both experiments were designed to have an average completion time of 60 mins. The majority of children subjects also indicated that they played some type of video game at home. Feedback during the first experiment was non-existent as subjects had no indication on how they were doing, while subjects in the second experiment received real time visual feedback on the placement of the cursor. Future work and training programs could adapt the protocol to introduce game like features. Additional studies could be adapted to examine performance in functional tasks vs abstract tasks. Recently, the effect of exercise gaming, or exergaming, has been applied to the rehabilitation of amputee patients [41]. A review of studies showed overall, exergaming did improve outcomes and was feasible for prosthetic training, however, due to differences in clinical parameters such as amputation level, results were varied. Due to all the nuances between individuals that affect prosthetic performance, it would be very beneficial to develop prosthetic devices that learn the intrinsic characteristics of the individual users instead of having the user learn the prosthetic system. The next step would be to quantify the performance of congenital and traumatic limb loss adolescent amputees and able-bodied children over a longer training period.

Overall, this study provided quantitative measures on the performance of able-bodied children in controlling modern myoelectric control systems and the results suggest that control and rehabilitation programs must be specifically designed for children with these differences in mind.

APPENDIX: IRB APPROVAL LETTER

UCF

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

APPROVAL

October 1, 2020

Dear Qiushi Fu:

On 10/1/2020, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title:	Understanding forearm muscle coordination in children
Investigators:	Qiushi Fu and Miguel Gonzalez
IRB ID:	STUDY00001790
Funding:	Name: University of Central Florida Research Foundation, Inc.
Grant ID:	
IND, IDE, or HDE:	None
Documents Reviewed:	• Consent_Adult_092220.pdf, Category: Consent Form; • Consent_Children_092220.pdf, Category: Consent Form; • COVID-19_Study_Specific_Safety_Plan.docx, Category: Other; • Edinburgh-Handedness-Inventory-short-form.pdf, Category: Survey / Questionnaire; • flyer_emg_children.docx, Category: Recruitment Materials; • IRB video sample.mp4, Category: Other; • Protocol_093020.docx, Category: IRB Protocol; • Subject_InfoSheet_pediatricEMG.xlsx, Category: Other; • Supplement_background_0803.docx, Category: Other;

The IRB approved the protocol from 10/1/2020.

In conducting this protocol, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. Guidance on submitting Modifications and a Continuing Review or Administrative Check-in are detailed in the manual. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Adrienne Showman
Designated Reviewer

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