Age-Dependent Upper Limb Myoelectric Control Capability in Typically Developing Children

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Abstract— **Research in EMG-based control of prostheses 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. As a first step to address this gap, experiments were designed to validate and benchmark two experimental protocols that quantify the ability to coordinate forearm muscle contractions in typically developing children. Non-disabled, healthy adults and children participated in our experiments that aimed to measure an individual's ability to use myoelectric control interfaces. In the first experiment, participants performed 8 repetitions of 16 different hand/wrist movements. Using offline classification analysis based on Support Vector Machine, we quantified their ability to consistently produce distinguishable muscle contraction patterns. We demonstrated that children had a smaller number of highly independent movements (can be classified with > 90% accuracy) than adults did. The second experiment measured participants' ability to control the position of a cursor on a 1-DoF virtual slide using proportional EMG control with three different visuomotor gain levels. We found that children had higher failure rates and slower average target acquisitions than adults did, primarily due to longer correction times that did not improve over repetitive practice. We also found that the performance in both experiments was age-dependent in children. The results of this study provide novel insights into the technical and empirical basis to better understand neuromuscular development in children with upper-limb loss.**

Index Terms— **Myoelectric control, pattern recognition, motor development, upper limb, children.**

I. Introduction

THE major cause of upper-limb loss in children is congenital limb reduction [1]. It was estimated that congenital upper limb deficiency occurs in approximately 4 out of every 10,000 birth per year in the United States [2], and similar rates have been reported worldwide [3]. It is desirable to fit terminal devices at an early age for children to increase the acceptance of a prosthesis in their later life [4]–[6]. However, frequent replacement of prostheses to match limb growth across adolescence has been challenging. Over the past decade, thanks to the technological advancement of 3D printing, upper-limb prostheses have become more accessible for these patients to be fitted with low-cost transitional devices [7], [8]. Most pediatric prosthetic hands have simple mechatronics designs with body-powered or simple myoelectric (i.e., using the electric activity of muscle contraction) controllers [9], [10]. This is due to considerations of size, weight, and cost limitations for developing these devices, as well as limited space for attaching surface electrodes to acquire muscle activation signals, i.e. electromyography (EMG). In contrast, more complex muscle contraction patterns can be used to support individual finger movements and a variety of grip types in state-of-the-art hand/wrist prostheses with multiple degrees of freedom (DoF) developed for adults [11]. The differences in the control and use of pediatric and adult upper limb prostheses raise the question about the extent to which children with congenital or early acquired limb reduction can adapt to adult prostheses effectively after they grow into adults. In fact, adults with congenital limb reductions are more likely to wear a passive terminal device than those with acquired limb difference [12]. Some studies suggest that muscle contraction patterns during myoelectric control are less distinguishable in individuals with congenital limb reduction compared to those who had an amputation as an adult [13]–[15]. This is possibly due to difficulties in imagining movements with a limb they never had. Furthermore, it has been shown that differences exist in the neural structure of the motor cortex between individuals with congenital and traumatic limb loss, and patients with congenital limb reduction may not possess sensorimotor representations of the missing limb possibly due to a lack of experience of the movements [16]. However, the patients (and healthy control) in these studies were mostly adults. Therefore, it is unclear the extent to which these findings are related to the neuromuscular development of the affected limbs in children with limb loss. Moreover, it is unclear whether such development can be better facilitated by training programs in relation to the future use of advanced adult prosthetics.

The main objective of the present study is to establish a benchmark protocol to quantify the capacity of myoelectric control in non-disabled developing children, which can be

used as a baseline for future studies with pediatric patients to assess their deficits. Clinically available outcome metrics, such as ACMC [17], SHAP [18], or DASH [19], require users to wear prosthetic hands to evaluate. Although they are valuable assessment tools for functional capabilities, the results are partially determined by the models of the prosthetic devices used in the tests. In contrast, the present study focuses on directly assessing the ability to generate EMG signals for myoelectric control, instead of the functional performance of using a specific terminal device. It is important to emphasize that a better understanding of the neuromuscular capacity underlying myoelectric control can potentially guide the design and selection of terminal devices, which can ultimately improve the outcome of these functional measures.

In prosthetic applications, a myoelectric interface extracts intent for moving the terminal device. Simple conventional myoelectric interfaces use on/off or direct control with one or two electrodes and transform EMG signals into one DoF motion. Advanced interfaces that record from electrode arrays can be divided into two main categories: classification-based and regression-based [20]. Many different EMG signal features and pattern recognition algorithms have been tested for the classification of discrete EMG patterns [21]–[26]. Earlier work used each pattern to drive a function module that moves selected joint(s) at a fixed speed (e.g., pinch grasp or wrist rotation), but recent studies showed that proportional joint speed augmentation with 'class activation' in addition to class labels could improve performance [27], [28]. The advantage of classification-based interfaces is that they can afford as many different functions as the number of distinctive muscle contraction patterns one can generate, and more functions can be enabled if one pattern is used for switching between function modules. This is particularly useful to control many DoFs, such as in transhumeral amputees with targeted muscle reinnervation surgeries [29]. A major limitation of classification-based interfaces is the need to sequentially activate multiple functions for more complex tasks, rendering user control unintuitive and slow. This can be partially mitigated by defining more classes that represent functional combinations [30], [31]. However, increasing the number of classes requires more extensive calibration and negatively affects the robustness of the control during real-world use [20]. In contrast, the regression-based controller prioritizes the ability to simultaneously control multiple DoFs [32]–[36]. This approach is more intuitive because the extracted motor intent usually originates from natural hand/wrist movements and function switching is not needed. Moreover, it also naturally extracts the magnitude of muscle contraction for proportional control. Therefore, regression-based interfaces are often called simultaneous and proportional control, which can outperform classification -based control in some scenarios [37]–[39]. However, regression-based interfaces may not support versatile hand postures as classification-based ones do, although novel soft prosthetic hands could compensate for this lack of functional versatility with mechanical adaptivity during grasping [40].

The present study focuses on two important aspects of myoelectric control. First, a user's neuromuscular capacity to support different muscle contraction patterns can determine the functionality he or she can afford to command with a terminal device through a myoelectric interface, especially the advanced ones. Second, real-time myoelectric control critically depends on the capability of the human visuomotor control loop. That is, in the absence of effective proprioceptive feedback, the users must rely on visually monitoring the kinematics of the terminal devices to produce movement commands for completing the tasks. Individuals with slower and more variable visuomotor control are more likely to perform worse in real-time tasks. With the above considerations, we designed two experimental protocols. Experiment 1 quantifies participants' ability to produce consistent and distinguishable muscle contraction patterns using offline classification analysis and dimensionality analysis. Experiment 2 quantifies participants' ability to control a one-dimensional computer cursor in a simple real-time target acquisition task with muscle contractions, in which different levels of visuomotor gains are used to map EMG signals to cursor movement speed.

From birth until late adolescence, children are in a constant stage of maturation that involves attempted mastery over gross and fine 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. Furthermore, children undergo concurrent changes of neuronal and physical structures (e.g., longer muscle length and larger muscle volume), which necessitates relearning previously acquired motor skills as their bodies grow and change. It is well established that there are differences between typically developing children and adults in the ability of motor control [41], such as movement speed, accuracy, and variability [42]–[46]. Children also have different cognitive abilities compared to adults, such as information processing speed [47], [48], spatial working memory [49], and attention [50]–[52]. These differences may lead to differences in motor learning [53]–[55]. Given these factors, it is reasonable to expect that children's ability to use muscle contraction for controlling artificial devices (a novel skill) may be substantially different from adults. Therefore, we hypothesize that typically developing children perform worse in our two experimental tasks compared to adults, but we expect these differences to be smaller in older children.

II. MATERIALS AND METHODS

A. Subjects

A total of 16 adult and 22 children participants enrolled in the study. They all reported normal or corrected-to-normal vision and no history of musculoskeletal or neurological disorders. All participants were naïve to myoelectric control methods. The experimental protocols were approved by the Institutional Review Board at the University of Central Florida (STUDY00001790) in accordance with the Declaration of Helsinki. Informed consent and parental consent were obtained for all participants. Participants were randomly assigned to one of two experiment protocols (see below). The first experiment included 8 adults and 8 children, and the second experiment included 8 adults and 11 children (Table I). Note that we recruited children of a relatively large age range to

TABLE I
SUMMARY OF PARTICIPANT CHARACTERISTICS

	Experiment 1		Experiment 2	
	Adults	Children	Adults	Children
Gender (M/F)	5/3	3/5	4/4	7/4
Age Range (years)	20-41	6-14	21-41	6-13
Height (cm)	174±10	140±9	173±11	137±17
Weight (kg)	75±21	31±11	71±18	35±10
FA Length (cm)	27±3	20±2	26±2	20±3
FA Circumference (cm)	26±3	20±2	25±3	21±2

FA = Dominant Forearm. FA Length was measured from elbow center to wrist center. FA circumference was measured around the largest cross section area.

TABLE II
SUMMARY OF MOVEMENT USED IN EXPERIMENT 1

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

Fig. 1. A. Electrode placement example. B. Experiment 1 data analysis. C. Visual display for Experiment 2. The dashed rectangles represent possible targets. The solid blue area is the starting area. The yellow area is the target for this example trial. The black line is the myoelectric controlled cursor. D. Example raw EMG signals from Experiment 1 (one adult and one child).

investigate the effect of age. 3 children (1 in Experiment 1, 2 in experiment 2) were not able to complete the required experimental tasks due to either technical issues or inability to maintain attention during tasks. Handedness was self-reported (we ask which hand they use for writing and feeding). Most participants were right-handed, and there were one adult and one child who were left-handed in the second experiment.

B. Experiment Setup

For all experiments, we recorded surface EMG (sEMG) signals with eight electrodes (Trigno Quattro, Delsys Inc) at 2 kHz. Electrodes were placed equidistant radially around the thickest part of the dominant forearm of the participants (Fig. 1A). This represents a dense sampling approach that does not target specific muscles. Although it cannot guarantee the best signal quality for all electrodes, this approach has been commonly used in previous research of myoelectric control [35], [56], [57], because the goal is to acquire a mixture of muscle activity from the underlying recording volume. The lack of muscle specificity can be compensated by pattern classification and regression algorithms. Moreover, such a setup can be implemented in individuals with limb loss whose

underlying muscular structure can be difficult to identify. Experiment control and visual feedback were provided by custom-made LabView programs.

C. Experiment 1 Procedure

In the first experiment, participants were asked to mimic the finger and/or wrist movement displayed on a monitor, using their dominant hand. There were 16 different movements, which were selected from commonly analyzed movements in previous research of myoelectric interfaces (Table II). We prioritized gross movement of the fingers and wrist as well as their combinations. Fine movements of individual fingers were not included because muscle contractions underlying fine finger movements are difficult to produce in individuals with limb loss. Moreover, experiment time was limited to ensure that children remained attentive to the task requirements.

Each movement must be repeated 8 times consecutively with 5 seconds duration and 2 seconds rest intervals. Short breaks between movements were also given to alleviate muscle fatigue and allow children to better maintain focus in subsequent movements. All participants were briefly coached by the experimenter before each movement to ensure that required movement can be executed appropriately.

D. Experiment 1 Data Analysis

The baseline drift and high-frequency noises of the raw sEMG data collected in the first experiment were first removed with a 4-th order Butterworth zero-lag bandpass filter (0.01 Hz – 50 Hz). Because participants were not always able to follow the timing of the experiment perfectly, we also removed periods where the magnitude of muscle activity was below 3 S.D. of the signals collected from resting periods. Two offline analyses were performed as described below (Fig. 1B).

The first analysis was designed to assess how well the participants may operate myoelectric interfaces that are based on pattern classification. We chose to use root mean square (RMS) as the feature and support vector machine (SVM) (Gaussian kernel, 5-fold cross-validation) as the classifier for this analysis. Note that the performance of different features and classifiers may vary across applications. We choose the SVM and RMS combination because they were consistently among the better performing classifiers in comparative studies showing higher offline classification accuracy [58]–[61]. The preprocessed data are segmented with 100 ms windows and we computed the RMS for each segment to create a labeled dataset for each participant. We quantified the 'number of

highly independent movements' for each subject, which was defined as the subset of movement types that can yield greater than 90% classification accuracy. This was obtained through an iterative elimination procedure. Briefly, we started with the entire dataset and removed the movement type that had the lowest classification accuracy. Subsequently, another evaluation was performed with the remaining movement types. This process was repeated until all remaining movement types can be classified with > 90% accuracy. This analysis gives an estimate of the number of movements that could be reliably controlled on a myoelectric hand prosthesis without training [61].

The second analysis assessed the dimensionality of the EMG signals in relation to simultaneous and proportional control. We used non-negative matrix factorization (NMF) [62] to determine the number of DoFs that underlies the sEMG signals collected across all movement types. Briefly, filtered sEMG data was segmented with 100 ms windows and the segmental average of the signals (mean absolute value, MAV) from all movements were concatenated to create a data matrix for each participant. Each sEMG channel was then normalized to have unit variance. The NMF algorithm uses k covariation patterns (synergies) across 8 channels to approximate the normalized sEMG data matrix: $E = W * H$, where W is an 8 by k non-negative matrix representing k synergies for 8 electrodes and H is a k by T non-negative matrix representing the synergy activation coefficients for T samples. Note that k can range from 1 to 8, and typically a larger k can yield a better approximation by capturing more variance of the data matrix [62]. We use the 'variance accounted for' (VAF) metric to determine the appropriate number of k that captures most of the total data variance: $VAF = 100 * (1 - SSE/SST)$, where SSE represents the sum of squared differences between the original data E and reconstructed data $W * H$, and SST represents the sum of the squared original data. The calculation of VAF was done both for all channels (global VAF) as well as within each channel (local VAF). The dimensionality of sEMG signals was defined as the minimum k that achieved a global VAF > 95% and all local VAF > 85%. To avoid convergence to local minima, the NMF algorithm was repeated 20 times for each k to find the best reconstruction. Within each repetition, the data matrix was randomly divided into two subsets: extraction and validation, with 75% and 25% of total samples respectively. The synergy matrix W was computed with NMF using the extraction subset with a given synergy number k, and was fixed to obtain the H of the validation subset for obtaining the global and local VAF. It should be noted that, given the nature of the NMF algorithm, a single dimension (synergy) of the sEMG signal can be only positively activated. This means that two dimensions are usually needed to control one movement DoF, working as agonist and antagonist, e.g., flexion and extension.

Both metrics from the analysis described above, namely the number of highly independent movements and the dimensionality of the sEMG signals, were compared between adults and children using non-parametric Mann-Whitney U Test. Furthermore, we also used correlation analysis to examine the extent to which these metrics can be predicted by age of the child participants.

E. Experiment 2 Procedure

In the second experiment, participants were tasked to perform a one-dimensional target acquisition task with proportional myoelectric control of cursor speed using flexion and extension of the wrist. This is a Fitts' Law task in which a faster completion time can be considered as a more efficient transmission of information in the visuomotor control loop [63]. Our task is a simpler version of the more complicated 2- or 3-dimensional target acquisition tasks used in prior myoelectric control studies [32], [38], [64], [65], as we focus on the basic visuomotor control ability without considering coordination among multiple DoFs. Specifically, the cursor was presented as a vertical line moving horizontally in the workspace. For each trial, participants must start from the middle of the workspace and acquire a target with a width of 2.5% of the workspace. The cursor must stay within the target for at least 500 ms continuously to acquire the target. The participants were instructed to complete the acquisition as fast as possible. There was a 10-s time limit by which the trial was terminated and considered to be failed. The target was selected to be at one of ten possible locations (Fig. 1C) in a pseudo-random fashion (each location was selected twice within every block of 20 trials).

The myoelectric control signals were extracted from the 8-channel sEMG signals in real-time. Each participant first performed a 15-second calibration session in which they repetitively flexed and extended the wrist of their dominant arm. The first two repetitions must be performed with the highest muscle contraction level in each direction, i.e., maximum voluntary contraction (MVC). The calibration data was segmented with 40 ms windows to build a calibration data matrix with segmental averages. Subsequently, it was used to compute an 8 by 2 synergy matrix W_C with the same NMF algorithm described above (k = 2). As constrained by the calibration task, this approach would yield two vectors in the pseudo inverse W_C^+ that map the sEMG signals to two control signals that represent the neural drive underlying flexion and extension of the wrist. That is $C = K^* W_C^{+*} S$, where S is the 8-channel sEMG signals (averaged per channel with 40 ms window) and K represents a scaling factor to ensure the control signal is 1 for MVC in each direction. To prevent unintended drift in the cursor movement, a threshold was used to eliminate baseline noise. The threshold was set to be roughly 50% higher than the control signal generated when participants were resting for each direction (typically around 0.05). The difference between the portion of control signals above the threshold (c1, c2) was mapped to cursor velocity v with a visuomotor gain k_a as follows: $v = k_a^* (c1-c2)$. This gain was used to regulate the sensitivity of the cursor visual movement to participants' muscle contraction, e.g., a higher gain moves the cursor faster with the same contraction level.

After calibration, participants performed 18 blocks of 20 trials of the target acquisition tasks with necessary rest time between blocks. This consists of three different visuomotor

gain settings (L: 0.1, M: 0.15, and H: 0.2). The rationale for using multiple gain levels is to examine if participants may have different preferences for the sensitivity of the myoelectric control mapping. Note that visuomotor gains in clinical applications are typically determined by trial and error to match individual patient's capability. Participants were assigned to one of two block sequences, both of which implemented consecutive 3 blocks (60 trials) with the same gain. This was designed to allow participants to improve their performance with consistent gain levels. Therefore, the gain setting was either L-M-H-H-M-L or H-M-L-L-M-H to counterbalance the orders across participants. Each gain setting had a total of 6 blocks of trials.

F. Experiment 2 Data Analysis

To quantify the sensorimotor control capability in this task when participants use myoelectric interfaces, we computed four metrics that are commonly used in similar tasks. The first one is simply the Failure Rate defined as the percentage of targets that were not successfully acquired within the 10-s time limit. The second metric is Completion Throughput, which is defined as the ratio between the target's index of difficulty (ID) and target acquisition time. The ID is computed with the Shannon formulation as $\log_2(D/W+1)$ where D and W are target distance and target width, respectively [63]. We considered two components of the acquisition process for the last two metrics. The First Touch Throughput metric focuses on the initial reach, which is defined as the ratio between the target's ID and the time to first enter the target area. The Adjustment Time focuses on the corrective actions if a single attempt did not acquire the target, which is defined as the time between the first entry of target to trial completion. Note that the last three metrics were all evaluated with only successful trials.

For statistical analysis, we first quantified block-to-block learning within the adult and child groups with the Completion Throughput metric using two-way repeated measure ANOVA (3 Gains × 6 blocks), followed by Helmert contrast. Based on the result of this analysis, we grouped trials into early and late stages (first and second three blocks for each gain, respectively). We considered the performance during the late stage to be relatively stable and averaged the blocks for subsequent comparison between adults and children. Mixed two-way ANOVA (2 Age × 3 Gain) was used for these comparisons followed by post-hoc t-tests with Bonferroni corrections. Lastly, we assessed the age dependency in the children group using correlation analysis.

III. RESULTS

A. Experiment 1: Number of Highly Independent Movements

In the first experiment, participants performed 16 different types of hand/wrist movements (Table I). We first quantified the accuracy of an offline SVM-based classifier to assess the participants' ability to produce distinguishable EMG patterns. With all movement types, the classification accuracy was significantly higher in adults (59.2±7.3%) than in children
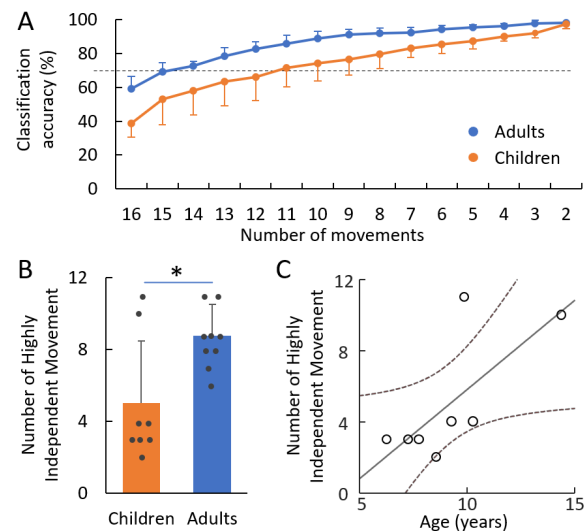
Fig. 2. Offline classification of movement types. A. Classification accuracy following iterative elimination process. The horizontal dashed line represents 90% accuracy. B. Comparing number of highly independent movements between children and adults. Black dots are individual samples. C. Effect of age on highly independent movements in children. The solid and dashed lines are linear regression and its 95% confidence interval.

(38.6±7.9%; p<0.001). As we iteratively eliminated movement types with low accuracy, the classification accuracy in the adult group remained to be better than the child group (Fig. 2A).

The number of highly independent movements, defined as the subset of movement types that affords >90% classification accuracy, was significantly larger in adults (8.7±1.8) than in children (5.0±3.5). This was confirmed by the Mann-Whitney U Test (p = 0.044; Fig. 2B). Furthermore, we also examined the age dependency of this metric in children. Spearman's correlation analysis revealed a significant positive correlation ($\rho = 0.736$, p = 0.045; Fig. 2C).

B. Experiment 1: Dimensionality of the sEMG Signals

We also examined the dimensionality of the sEMG signals created by the repetition of 16 movements. While the classification approach in the previous section quantifies the number of discrete EMG patterns one can produce, the NMF approach identifies the number of major directions of variation from the collected sEMG data. We found no difference in the dimensionality estimation between children (4.4 ± 0.5) and adults (4.0 ± 0.9). This suggests that four major synergies can explain ~95% of the total variance of the muscle activity generated to perform the 16 hand/wrist movements. We also did not find age to correlate with the dimensionality in children.

To further explore the distribution of the signal variation, we performed 4-dimensional NMF with all participants of each age group. The resulting channel weight vectors were pooled within-group, and four clusters were subsequently defined with the k-means method. Each cluster can be considered to represent a major EMG co-variation pattern. It can be observed
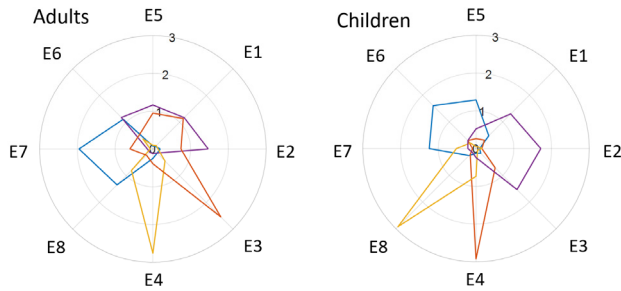
Fig. 3. Distribution of EMG signals across eight electrodes surrounding forearm circumference. The concentric circles represent the value of coefficients of eight electrode channels (E1 − E8), i.e., weighting in co-variation patterns. Electrodes 1 and 5 were always placed at the ventral side (mostly flexors), and electrodes 4 and 8 were always placed at the dorsal side (mostly extensors). Each color represents the mean of a cluster of the coefficient vectors extracted with four-dimensional NMF.

Fig. 4. Block-to-block learning of myoelectric control. Three gain conditions were averaged for each participant. The asterisks represent significant Helmert contrast ($p < 0.05$) comparing the corresponding block to the average of following blocks.

that the distributions of the estimated variance directions around the circumference of the forearm were qualitatively similar between children and adults, representing the bidirectional activation of two major DoFs (Fig. 3). The orientation difference may be caused by small differences in electrode placements.

C. Experiment 2: Differences Between Children and Adults in Real-Time Myoelectric Control

In the second experiment, participants controlled a cursor to acquire targets in a 1-dimensional workspace. There were three different visuomotor gain levels, with the highest one moving the cursor twice as fast as the lowest one when the same level of muscle contraction was produced. Each gain level was used in six blocks of 120 trials. We first evaluated whether participants learned to improve their performance, i.e., increasing trial Completion Throughput, as more trials of the same gain were repeated. Interestingly, we found that adults improved their performance across blocks, much more than children did. Specifically, the adults increased their throughput by approximately 15% comparing the last and first blocks, whereas the child participants only increased by approximately 7% (Fig. 4). This was confirmed by statistical analysis. For the adult group, two-way ANOVA revealed a significant Block effect ($p = 0.001$), but no significant Gain effect nor interactions. The Helmert contrast suggested that the improvement reached a plateau after the third block. In contrast, no significant effect was found in children, and the contrast suggested that there was no improvement beyond the first block. Based on these results, we decided to focus on the comparison between adults and children during the last three blocks of trials by taking the average of these blocks.

Overall, children failed much more than adults (Fig. 5A), but the failure rates were similar across three gain levels. This was confirmed by a significant Group effect ($p = 0.007$) and no Gain effect or interactions when comparing Failure Rate. The large variation in the children group was mainly caused by one participant (7 years old boy), but excluding this participant does not change the results. Within successful trials, children took more time to acquire the targets, leading to smaller
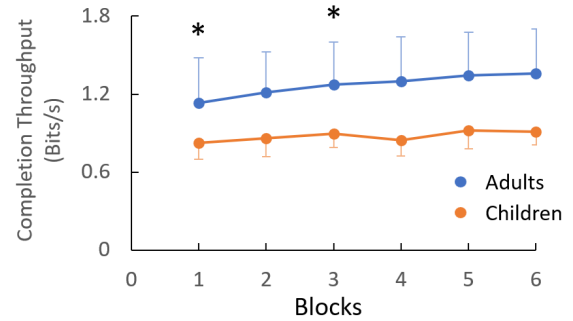
Completion Throughput than adults had (Fig. 5B). Statistical analysis revealed significant effects of both Gain and Group ($p = 0.008$ and $p = 0.001$, respectively) with no interaction. Post hoc paired t-tests found significant differences between Low gain and Medium gain as well as High gain levels ($p < 0.001$ and $p = 0.011$, respectively), but Medium and High gains were indifferent. A close examination of the individuals revealed that 5 adults and 4 children had the best performance with the High gain, whereas 3 adults and 5 children did the best with the Medium gain.

We break down the target acquisition process into the initial reach to the target and adjustment time. The First Touch Throughput was similar between children and adults, both showing faster movement with higher gains (Fig. 5C). Statistical analysis confirmed this observation with only a significant effect of Gain ($p = 0.002$), not Group nor interaction. Post hoc comparisons revealed that Low gain was significantly slower than both Medium and High gains ($p < 0.001$). For adjustment time, children took much longer to correct than adults did if they were not able to stay in the target area after first entry (Fig. 5D). Two-way ANOVA revealed a significant interaction ($p = 0.047$). Post hoc comparisons showed that adults had significantly smaller adjustment time than children ($p < 0.001$). Moreover, the gain levels had different effects. Specifically, adults had the longest adjustment time for High gain ($p < 0.003$) and the other two were not different. In contrast, children had the smallest adjustment time for Low gain ($p < 0.001$), and the Medium and High gains were not different.

D. Experiment 2: Age-Related Effect on Real-Time Myoelectric Control in Children

We evaluated the extent to which age may predict children's ability to use proportional myoelectric interfaces. For Completion Throughput, all three visuomotor gain levels were positively correlated with age (Fig. 6A). Pearson's correlation coefficients for Low, Medium, and High gains were 0.790 0.848, and 0.790 ($p = 0.004$, 0.001, 0.004), respectively. This indicates that children could attain target acquisition goals faster as they grow older. We found that age does not predict the First Touch Throughput, instead, the improvement
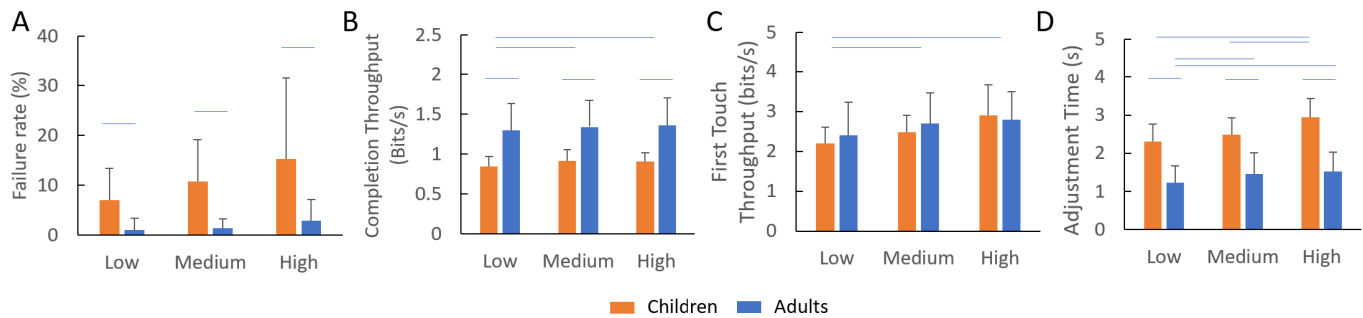
Fig. 5. Capability of Myoelectric control per visuomotor gain level during the last three blocks of trials (mean ± S.D.). A. Completion rate. B. Completion throughput. C. First touch throughput. D. Adjustment time. The blue bars at the top indicate significant differences.
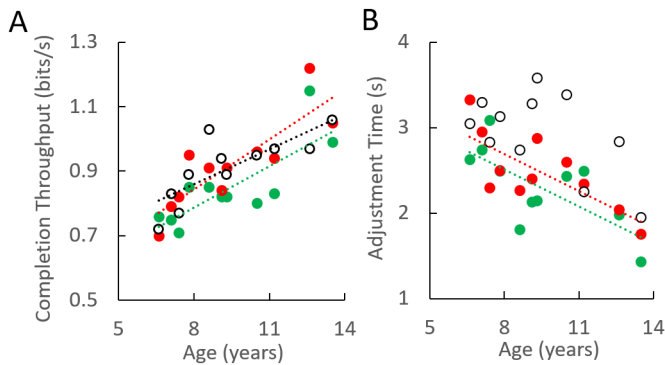

Fig. 6. Age related effect on real-time myoelectric control in children. A. Completion Throughput. B. Adjustment Time. The dashed lines represent significant correlation.

was mainly due to the greater ability to adjust after missing the targets. For Adjustment Time, we found that Low and Medium gains showed significant negative correlations with age (Fig. 6B), with Pearson's correlation coefficients being -0.704 and -0.745 ($p = 0.016$ and 0.009), respectively. No significant correlation was found for the High gain level.

IV. Discussion

The present study compared typically developing children with young adults regarding the ability to use myoelectric interfaces. The first experiment focused on the extent to which participants can produce different EMG patterns with their forearm muscles, whereas the second experiment focused on participants' ability to use muscle contraction as control signals in a real-time visuomotor task. The results generally supported our hypothesis that children have less myoelectric control capability than adults, and the capability improved as their neuromuscular systems develop with age. We discuss our findings with respect to the broad literature about motor control in children and clinical relevance below.

A. Generation of EMG Patterns: Variance and Consistency

In the first experiment, we found that the classification accuracy of different hand and/or wrist movement was lower for children in general and improved with age (Fig. 2). In contrast, the dimensionality analysis suggests that more than 95% variance of the sEMG signals associated with these movements can be explained similarly in both children and adults with

four major co-variation patterns. These two results indicate that the main cause underlying the less accurate classification with children was their lack of consistency for reproducing the same movement type, rather than not being able to produce different movement types. This is consistent with previous research that demonstrated higher movement variability in children and that the variability reduces with age [42], [46], [66], [67]. There are two potential causes of high movement variability in children. First, physiological constraints may arise from the developing neuromotor system. For instance, the nervous system is inherently noisy [68], and the signal-to-noise ratio could be lower in children due to immaturity in neural transmission, population coding, or inexperience in redundancy resolution [69]. Furthermore, children have limited capability to maintain attention [50]–[52], thus they may be more likely to be distracted in our experiments even though we tried to help them keep the focus on the task by giving breaks and verbal encouragement.

Another theory argues that movement variability may reflect a process implemented by the nervous system to explore different motor actions to benefit motor learning [70]. A related theoretical framework for motor development is the Neuronal Group Selection Theory (NGST) [71]–[73], which proposes that motor development reorganizes and selects variable neuronal repertoires through exposure to various tasks and environments. This theory has been used to explain the cortical activities in children with congenital upper limb deficits [74]. Therefore, it is possible that children may rely on this exploration process more than adults as they need to adapt to the constantly changing body mass and dimension. Although the present study cannot distinguish the two causes of motor variability (i.e., inherent constraints or intentional exploration) in our task, both mechanisms could likely be at play. It has been shown that movement variability could be reduced after extensive practice of novel motor skills in children, suggesting a task-specific reduction of intentional variability [69]. To quantify the contribution of the above two mechanisms of variability, future studies will examine the extent to which classification accuracy can be improved after practicing different movement types.

B. Real-Time Myoelectric Control in Children

In the second experiment, we investigated children's ability, in comparison to adults, to control a simple 1-DoF cursor with

a proportional myoelectric interface. As expected, children performed worse with more failures and longer time to acquire the targets. Surprisingly, we found that children benefited much less from consecutive practice than adults, showing little overall improvements across blocks (Fig. 4). Previous research has demonstrated that children could significantly improve movement speed in simple drawing and reaching tasks after repetitive practice [43], [75]. Moreover, children can also learn some complex novel motor skills at similar rates at adults, such as adapting to force field [69] and visuomotor rotation [76], as well as acquiring visuomotor mapping between torso movement and a 2-DoF cursor [45]. We speculate that the lack of significant learning effect in our task was caused by one unique feature of myoelectric control, namely the velocity-based EMG-to-movement mapping which is commonly used in myoelectric control of prostheses. Regardless of the task complexity, previous research of motor control in children mostly used tasks that are operated by natural movement, where the state of the muscles can be mapped to a single location in space. In contrast, velocity-based mapping in myoelectric control has inherent position ambiguity, i.e., the end-effect can be at any location for the same muscle state. Therefore, velocity-based control could be particularly challenging for the children's nervous systems to make predictions about the consequences of their actions, an ability that is not fully developed in children compared to adults [43]. Consequently, children may need significantly more practice to master velocity-based myoelectric control.

A closer examination of the target acquisition behavior revealed that children and adults could be equally fast as to generate the initial movement to move the cursor towards the target (Fig. 5C). The main problem children faced was the lesser ability to make corrections if they could not stay in the target after first entry (Fig. 5D), and older children were better than younger ones (Fig. 6B). In a novel visuomotor task like ours, it is critically important to predict the cursor movement and start to reduce muscle contraction level to prevent overshooting the target. It has been documented that younger children may rely more on feedback, particularly the slow visual feedback loop, than feedforward motor planning to in visuomotor tasks [43]. As a result, younger children could exhibit a more separated sequence of submovements during the corrective portion of goal-directed reaching tasks [77]. Therefore, our results are consistent with these studies, and further suggest that children, especially the younger ones, are inherently constrained by their neuromotor control capability to support fine motor actions through myoelectric interfaces.

C. Clinical Implications

The main objective of the present study was to validate the experimental protocol and provide baseline data from typically developing children for future investigations in children with upper limb loss. The motor development of the affected limb in children with congenital limb reduction or early amputation remains unknown. An animal study with cats showed that early suppression of limb motor experience during the period of motor development can lead to defective development of the corticospinal tract and a prehension deficit in maturity

[78]. In humans, it has been shown that the threshold to activate muscle cortical representation via transcranial magnetic stimulation was higher for the affected limb in adults with congenital limb loss, showing an opposite hemispheric asymmetry compared to traumatic amputees [16]. This indicates that motor experience was important to reduce inter-hemisphere inhibition during motor development, and may explain the diminished ability of adults with congenital limb loss to use classification-based myoelectric interfaces [15]. A recent study comparing children with limb reduction and age-matched typically developing children showed that they have similar performance to use body-powered hand prostheses in gross motor tasks (i.e., Box and Block Test). However, imaging data acquired by functional near-infrared spectroscopy showed distinct cortical activity patterns. Children with limb reduction showed significant activation of the motor cortex ipsilateral to the impaired limb, indicating a possible compensation to the underdeveloped contralateral hemisphere [74]. These findings suggest appropriate motor practice with the impaired limb in developing children is critically important to the maturation of the neuromotor control system to prepare for the use of advanced myoelectric interfaces in adulthood. It is expected that children without motor training would perform worse in our experimental tasks than what we reported here with typically developing children.

Our findings also have several other important clinical implications. First, the offline analysis in the first experiment suggested that regression-based controllers may be a better option than classification-based ones for children. This is because the relatively low classification accuracy and a small number of independent movements diminish the advantage of functional flexibility in classification-based interfaces. In contrast, regression-based interfaces could be more robust to motor variability in children. Second, the visuomotor gain of myoelectric interfaces should be carefully selected to match the capability of the individual user because the optimal gain could vary between users, and children may generally prefer a smaller gain than adults. Lastly, given the challenge for children to improve real-time myoelectric control, it is important to develop training programs that are engaging to enhance motor skill learning, which may be achieved through virtual reality and gamification [79].

D. Limitations and Future Directions

The present study only used eight electrodes for recording. This may be sufficient to measure from non-disabled individuals consistently, but it could be challenging to produce comparable data from individuals with limb loss. Moreover, the current setup may not be able to capture fine details of the muscle activations (i.e., individual finger movement) that could support higher classification accuracy and more DoFs. In future studies with both individuals with limb loss and non-disabled controls, we will use high-density EMG arrays to provide better spatial resolution to quantify the myoelectric control capability. Another methodological limitation is that we did not quantitatively ensure that true wrist MVC was performed during calibration. This could lead to unaccounted variability in the visuomotor mapping for the target acquisition

task. Furthermore, the present study focused on simple 1-DoF real-time control. While the results provide important insights into the fundamental neuromotor control capacity in children, the real-world functional tasks often require the activation of multiple DoFs (either sequentially or simultaneously) that may have higher cognitive demand. In future studies, we will extend our target acquisition experiment to multi-DoF space to investigate the real-time myoelectric control capacity in more complex tasks. Lastly, this study was designed to obtain baseline measures of myoelectric control capabilities with non-disabled children. In future studies that enroll children with limb loss, we expect to see large deviations from our baseline measures due to variations in the characteristics of the patients (e.g., level and type of limb reduction).

V. CONCLUSION

To our best knowledge, the present study is the first to quantify children's myoelectric control capability. We found that, similar to other motor skills, typically developing children increase their myoelectric control as they grow older, and their capability is limited by motor variability and reliance on feedback control mechanisms. An important finding is that myoelectric control, commonly based on mapping EMG signals to the velocity of the end-effector, presents a major challenge for children to improve over repetitive practice. Overall, our results represent the initial step towards better understanding of the neuromotor development in children with limb loss.

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