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Children are suboptimal in adapting motor exploration to task dimensionality during motor learning

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ABSTRACT

Motor learning in novel tasks requires exploration to find the appropriate coordination patterns to perform the task. Prior work has shown that compared to adults, children show limited exploration when learning a task that required using upper body movements to control a 2D cursor on a screen. Here, by changing the task dimensionality to 1D, we examined two competing hypotheses: whether children show limited exploration as a general strategy, or whether children are suboptimal in adapting their exploration to task dimensionality. Two groups of children (9- and 12-year olds), and one group of adults learned a virtual task that involved learning to control a cursor on the screen using movements of the upper body. Participants practiced the task for a single session with a total of 232 reaching movements. Results showed that 9-year olds show worse task performance relative to adults, as indicated by higher movement times and path lengths. Analysis of the coordination strategies indicated that both groups of children showed lower variance along the first principal component, suggesting that they had greater exploration than adults which was suboptimal for the 1D task. These results suggest that motor learning in children is characterized not by limited exploration per se, but by a limited adaptability in matching motor exploration to task dimensionality.

1. Introduction

The question of whether children learn motor skills differently from adults has both theoretical and practical significance. Although popular beliefs suggests that children learn faster than adults, a majority of the motor learning studies in a wide variety of tasks actually show that young adults show a learning advantage relative to children [1–6]. However, in many real-world tasks, this comparison between children and adults can be biased in favor of adults due to two reasons– (i) task familiarity – i.e. adults have greater familiarity with most tasks, including knowledge of how to perform them, and (ii) biomechanical factors – adults have bigger bodies, greater speed and strength making it easier for them to achieve a higher task performance level. Therefore, it is critical to minimize the effects of these confounding factors to address the issue of comparing motor learning in children and adults.

One potential way to minimize these two advantages that adults possess is to create novel virtual tasks. Body-machine interfaces [7–9], where movements of the body are used to control an interface like a computer cursor or a robot arm [10–13], provide an ideal way to address this issue. A specific type of body-machine interface that has been used to investigate learning is one where movements of the upper body are mapped on to the control of a computer cursor [14–16]. This task minimizes the task familiarity advantage because the mapping between body movements and cursor movements is not known apriori and the appropriate coordination patterns to solve the task can only be discovered through exploration and practice [17]. Furthermore, the task also minimizes the biomechanical advantage because the movements are based on segment angles (which are independent of limb length and body size), and the mapping can be customized to each individual (e.g., changing the gain) to adjust for differences in speed or strength. Importantly, the body-machine interface not only allows measuring differences in overall task performance (e.g., movement time), but also quantification of the underlying coordination strategies used to perform the task.

In a prior study [14], we used the body-machine paradigm to compare learning in children and adults when learning to control a cursor in 2D. We found that in spite of minimizing such confounds, children showed longer movement times in the 2D cursor control task after learning. Critically, analysis of the coordination strategies revealed that children showed limited exploration of the movement repertoire.

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Movement repertoire was quantified using principal component analysis (PCA), where limited exploration is quantified by a higher relative contribution of variance explained by a single principal component (i.e., exploring along a single movement dimension would result in a very high contribution of variance along PC1 whereas a completely random exploration would result in the variance being roughly equally distributed across all components). Given that a limited movement exploration is potentially suboptimal when learning a 2D task (which requires the participant to explore along two dimensions), the results raise two different hypotheses – (i) children tend to use limited movement exploration as a general strategy when learning novel tasks (similar to 'freezing' degrees of freedom [18]), or (ii) children tend to use motor exploration strategies that are suboptimal for learning the task.

To distinguish these two hypotheses, we used the same task but changed the task dimensionality – i.e. changed the cursor control task from a 2D space to a 1D space. Learning a 1D task requires less motor exploration than a 2D task since the cursor only needs to be moved along one dimension. If children still show lesser exploration in the 1D task relative to adults, then the results would support the first hypothesis that children tend to use limited movement exploration when learning novel tasks. However, if children show greater exploration in the 1D task relative to adults, then the results would support the second hypothesis that that children tend to use motor exploration strategies that are suboptimal for learning the task.

2. Materials and methods

2.1. Participants

A total of 54 participants took part in this study from three different age groups: (i) a 9-year old group (8–10 year olds, $n = 15$, age 9.60 ± 0.75 years, 8 females), (ii) a 12-year old group (11–13 year olds, $n = 13$, age 12.20 ± 0.98 years, 4 females) and (iii) an adult group ($n = 26$, age 21.46 ± 1.76 years, 15 females). These age groups were based on our prior study in which children from these age groups showed age differences in their task performance [14]. Children were paid $10 for their participation and all adults were college students who received extra course credit for their participation. Informed consent (including parental consent when needed) was obtained prior to participation and all procedures were approved by the Michigan State University Human Research Protection Program.

2.2. Experimental setup

The experimental design and procedures were similar to our prior studies [14,15] and are summarized below. The main difference is the change in the dimensionality in the task; the current study only required participants to control the cursor in 1D (moving left/right) instead of in 2D in prior studies.

Participants sat in a chair in front of a 23″ (58.4 cm) computer screen and were instructed to move their upper body to control a cursor on the computer screen. They wore a customized vest that was securely strapped using Velcro straps under their arms and around the torso. Four wireless inertial measurement units (IMUs) (3-space, YEI Technology, Ohio, USA) were attached to the vest using Velcro hooks at the anterior and posterior ends of the acromioclavicular joint on both the left and right sides of the body (Fig. 1). All four sensors were placed at 45° to the long axis of the body and captured scapular movements: retraction, protraction, elevation and depression. We only used the signals corresponding to the roll and pitch angles from each IMU sensor, resulting in an 8-D signal (4 IMU sensors × 2 signals/ sensor).

2.3. Mapping body motions to cursor position

We used a linear mapping to transform the 8-dimensional body space (h) into the 1-D task space. The mapping was given by $p = A\ h + p_0$, which p was the cursor position, A refers to the map and p_0 is an offset term [10]. In order to determine map A, we used a calibration procedure similar to previous studies [10,12]. During the calibration, participants performed free exploratory movements for 60 s, where they were asked to explore all different motions using their upper body while maintaining a comfortable range of motion. Thereafter, we performed PCA on this calibration data and extracted the first principal components. The coefficients of the first principal component were scaled by a gain factor, equal to the reciprocal of the square root of the first eigen value, which was then used to form the 1 × 8 vector A. The offset p_0 was set so that the average body posture during calibration (close to the resting posture) resulted in the cursor being in the center of the computer screen.

As mentioned in the introduction, there are two important features of this task: (i) the IMU signals captured only angles in the upper body (i.e., shoulder and torso), and therefore the developmental differences in the length of body segments (such as arm length) did not influence the task, (ii) the map was customized to each individual to ensure that the range of motion and sensor placement had minimal influence on the participants' ability to perform the task.

2.4. Cursor control task

Participants performed a virtual center out reaching task in 1D, where they controlled a cursor on the computer screen using their upper body movements. They moved the cursor from the home position ($r =$ 0.8 cm, in the center) to one of a number of 'targets' (of the same radius) presented in X-direction only, and returned back to the home position. Each trial started when the home position showed up for 500 ms followed by the presentation of a peripheral target. Participants were instructed to move the cursor to the target as fast and as close to the center of the target as possible. The task was completed when the participant was able to hold the cursor within the target for 500 ms; after

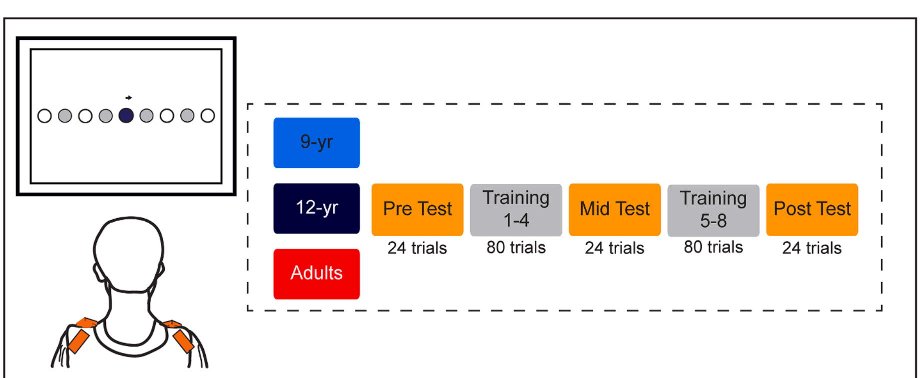

Fig. 1. Schematic of experimental setup. Participants wore 4 IMUs on the upper body and controlled a 1D cursor on the screen that could only move along the horizontal direction. Targets were placed along this horizontal dimension. Three groups of participants (9-year olds, 12-year olds, and adults) learned this task over a single practice session. Each practice session consisted of 3 test blocks (pre-test, mid-test and post-test) and 8 training blocks. The training and test blocks differed in the number of unique targets used in the block (4 for training and 8 for test).

which they had to return back to the home position. This was followed by the presentation of the next target.

There were two types of blocks: training blocks and test blocks. The main difference between them was that the training blocks used a set of 4 targets, whereas the test block used a set of 8 targets (4 that were part of the training blocks and 4 new targets) to probe if learning generalized beyond training. During each of the 8 training blocks, participants reached for 4 targets in the X-direction (2 on either side of home position) located at a distance of: 8.2 cm and 16.4 cm from the center. Targets were presented 5 times each – for a total of 20 trials per each training block. During each of the 3 test blocks (pre-, mid- and post-test), participants reached for 8 targets in the X-direction (4 on either side of home position) located at a distance of: 4.1 cm, 8.2 cm, 12.3 cm and 16.4 cm from the center. Targets were presented 3 times each – for a total of 24 trials per each test block. The sequence of these blocks is shown in Fig. 1. In each block, targets were presented in a pseudo-random order with a constraint that all targets were presented before a target could repeat. A total of 232 trials were performed overall and the entire study typically lasted for 45 – 90 min. Rest breaks were provided in between blocks when participants requested them.

In our original experimental design, the 1D task was followed by a 2D task (to examine if there were age differences in the transfer from 1D to 2D task) – however, because the children could not complete the two tasks in a single session, the 2D task was not analyzed further and is not presented here.

2.5. Data analysis

Data analyses were similar to our previous study [14] but adapted to the 1D task. All analyses were performed only on the outward movements – i.e. when the participant moved from the home target toward the peripheral targets. We selected only the outward movements because the return movement to the home target involved coming back to the same initial posture, which was generally easier to do (and therefore required less exploration than the outward movements). We divided the data analysis metrics into two categories: task performance and coordination.

2.6. Task performance

We quantified task performance using two measures - the movement time, and the normalized path length (which measured the straightness of the path taken). The cursor control task was designed so that each trial stopped only when the target was reached, at which point the subsequent target was presented. We used movement time as the primary measure of task performance (spatial accuracy was controlled for because all reaches eventually reached the target). Also, because the task was only 1D, cursor movements were always in straight lines-however, the path lengths could change if there were direction reversals. Therefore, the normalized path length provided an index of how well participants controlled the cursor.

The two measures were computed as follows. Movement time was calculated from the time that the cursor left the home target to the time that it reached and stayed inside the target for the subsequent 500 ms. Normalized path length between two targets was defined as the actual distance traveled by the cursor divided by the straight-line distance between the targets (i.e. reaching to a target without any direction reversals would result in a normalized path length of 1).

2.7. Coordination

For assessing the coordination of the upper body, we used principal components analysis (PCA) [19]. Because the task is 1D, participants only needed to learn a single coordination pattern to perform the task, although the redundancy in the task allows them more if they wanted to explore different ways of performing the task. We therefore analyzed the time series of the 8 signals in each block using PCA and computed the percent of variance accounted for (VAF) by the first principal component (PC1) to investigate the degree of exploration in their body movements when learning the task. We used the covariance matrix to perform the PCA, which preserves the amplitude information in the signals.

In addition, to examine the change in the PCs themselves, we computed an angle (using the subspace command in MATLAB) between PC1 in each block relative to the task map (i.e., the PC1 in the calibration block). This measure allowed us to examine how much change occurred in the coordination pattern occurred with practice and if they were significantly different between groups.

2.8. Statistical analysis

To examine changes with learning, we analyzed only the pre-test, mid-test and post-test (i.e. the training blocks were not included for statistical analysis). The dependent variables were analyzed using a 3 $\times$ 3 (Block $\times$ Group) repeated measures ANOVA. Block (Pre-test, mid-test, post-test) was the within-subjects factor, whereas Group (9-yr,12-yr, adult) was the between-subjects factor. Violations of sphericity were corrected using the Greenhouse-Geisser factor when applicable. Post-hoc comparisons for group were examined using Tukey's correction. Significance levels were set at $p < .05$.

3. Results

Data from one 9-year old participant was excluded from analysis because of extremely high movement times in 6 out of the 9 blocks (greater than the 1.5* IQR from the upper quartile for the group, where IQR is the interquartile range).

3.1. Task performance

All groups decreased movement time with practice as indicated by a significant main effect of block, $F(1.15, 57.39) = 40.27$, $p < .001$ (Fig. 2A), with movement times decreasing significantly from pre-test to mid-test, but not significantly between mid-test and post-test. There was also an age-related effect indicated by a significant main effect of group, $F(2, 50) = 7.60$, $p = .001$. Post hoc analysis of the main effect of group showed that adults had shorter movement time than 9-year olds ($p < .001$). The difference between 9-year olds and 12-year olds ($p = .083$), and the difference between adults and 12-year olds ($p = .65$) was not significant. The block $\times$ group interaction was not significant, $F(2.30, 57.39) = 2.09$, $p = .127$.

The correlation between the movement time and the normalized path length was high throughout practice ($r = 0.93$ in the pre-test and $r = 0.74$ in the post-test). So, the results from the normalized path length (Fig. 2B) showed a similar pattern. All age groups showed smaller path lengths (i.e. lesser movement reversals) with practice as indicated by a main effect of block, $F(1.03, 51.69) = 12.24$, $p < .001$, with path lengths decreasing significantly from pre-test to mid-test, but not significantly between mid-test and post-test. There was also age-related effect indicated by a significant main effect of group, $F(2, 50) = 4.52$, $p = .016$. Post hoc analysis of this main effect showed that adults showed significantly shorter path lengths than 9-year olds ($p = .012$). The difference between 9-year olds and 12-year olds ($p = .152$), and the difference between adults and 12-year olds ($p = .716$) was not significant. The block $\times$ group interaction was not significant, $F(2.07, 51.69) = 1.34$, $p = .272$.

3.2. Coordination

Similar to the movement performance, all groups changed coordination strategy with practice as indicated by a significant main effect of block. For the VAF-PC1, there was main effect of block, $F(1.58, 79.01) = 13.97$, $p < .001$ (Fig. 3A), with the variance increasing significantly from

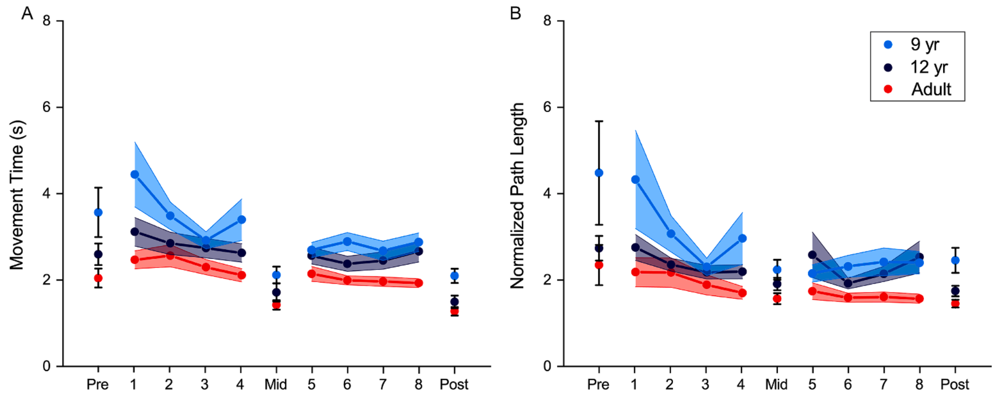

Fig. 2. Task performance across all groups. (A) Movement time, and (B) Normalized path length. Both movement times and path lengths decreased with practice, but adults showed shorter movement times and smaller path lengths than 9-year olds. Error bars indicate 1 SE.

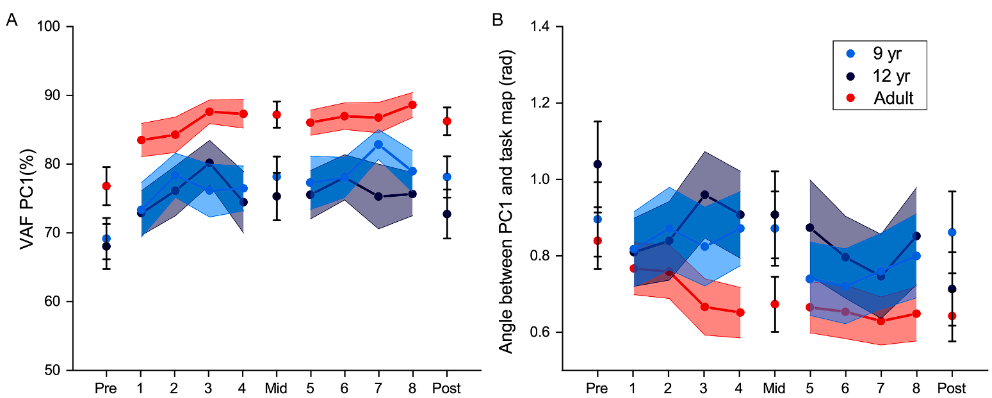

Fig. 3. Coordination across all groups. (A) VAF accounted by the first principal component across all groups. VAF PC1 increased with practice in groups. Children (both 9-year and 12-year olds) showed smaller VAF-PC1, indicating that they were suboptimal in channeling their exploration to match the dimensionality of the 1D task. (B) Angle between first principal component and the task map. All groups decreased the angle with practice indicating greater alignment with the task. Error bars indicate 1 SE.

pre-test to mid-test, but not significantly between mid-test and post-test. There was also a significant main effect of group, $F(2, 50) = 8.07$, $p < 0.001$. Post hoc analysis of the main effect of group indicated that adults had higher VAF- PC1 than the 9-year olds ($p = .023$) and 12- year olds ($p = .002$). The block × group interaction was not significant, $F(3.16, 79.01) = 0.35$, $p = .802$.

When comparing the angles that PC1 in each block made with the task map, we found that angles decreased with practice, becoming more 'aligned' with the task map. There was a main effect of block, $F(1.32, 65.95) = 9.73$, $p = .001$ (Fig. 3B), with angles decreasing significantly from pre-test to mid-test, but not significantly between mid-test and post-test. There was no significant main effect of group $F(2, 50) = 1.25$, $p = 0.294$ or group × block interaction, $F(2.64, 65.95) = 1.50$, $p = 0.227$.

3.3. Calibration analysis

To rule out the possibility that differences in age groups were due to any systematic differences in the 'free exploration' movements of the calibration phase, we examined if there were any systematic differences in the principal components between age groups during calibration.

In terms of the variance accounted for by PC1, there was no statistically significant difference between age groups, $F(2, 50) = 0.448$, $p = 0.642$.

To compare the principal components across groups, we used a bootstrap analysis. In each iteration, we picked PC1 from a random adult and compared the similarity to (i) another randomly chosen adult, (ii) a randomly chosen 12-year old, and (iii) a randomly chosen 9-year old. The similarity between the PCs was computed using the subspace command in MATLAB (if vectors are more similar, the subspace angle is closer to zero). We repeated this analysis for 100 iterations and used a one-way ANOVA to examine the angles in the adult-adult comparison relative to the adult-12 year old and the adult-9 year old comparisons. The assumption was that if there are significant differences between groups during the calibration phase, then the angles should be smaller (indicative of greater similarity) in the adult-adult group compared to those across groups. We found no evidence of a group effect, $F(2,297) = 0.509$, $p = 0.602$, again indicating that there were no systematic age differences in the free exploration phase.

4. Discussion

The goal of this study was to examine motor learning in children using a body-machine interface. Based on prior work that found age-related differences in exploration, we used a 1D task to distinguish between two hypotheses - (i) children tend to use limited movement exploration as a general strategy when learning novel tasks, or (ii) children tend to use motor exploration strategies that are suboptimal for learning the task. Overall, our results support the second hypothesis that motor exploration strategies in children are suboptimal for learning the task.

From a task performance standpoint, our results showed that despite the reduced complexity of the 1D task, movement times were longer in 9-year olds relative to adults. These differences were generally present throughout learning and are consistent with a number of other studies on learning in children showing slower performance [14,20,21]. However, it is important to note that in our case, the differences in movement times were not simply a consequence of speed differences between children and adults because the analysis of path length also indicated that the children made more movement reversals.

The coordination strategies provided further insight into how the task was performed. In the 1D task, VAF - PC1 increased with practice, indicating that participants learned to restrict the exploration along the one dimension required to perform the task. There was also greater alignment between PC1 and the task map indicating that all participants were learning to explore (on average) along the relevant dimension. However, even though the 1D task required simply variation along a single dimension (i.e. a single coordination pattern), children (both 9- and 12-year olds) show lower VAF-PC1 than adults, indicating that they were performing greater exploration. These results are in striking contrast to the 2D task, where children tended to have higher VAF-PC1 (i.e. lower exploration) than adults [14].

This suggests that adults were able to adapt their exploration based on the task demands – they increased their exploration to perform the 2D task and decreased their exploration to perform the 1D task. Children, however, were not able to do this successfully – they showed limited exploration in the 2D task, and in the 1D task tested in this study, they were not able to sufficiently channel their exploration along a single dimension. Although we do not have a measure of whether these exploration strategies were 'intentional' or not, one potential explanation for children having lower VAF-PC1 in the 1D task may be due to the fact that children are more typically variable than adults [22]. This 'noise' could have prevented children from reducing the variability along other dimensions as much as the adults did. One limitation is that our measure of exploration measured VAF PC1 as a % of the total variance– so, while this measure is sensitive to 'overall' exploration along other principal components (increasing variance along other principal components would reflect as a decrease in terms of the percentage of VAF PC1), it is not sensitive to certain types of 'compensatory' exploration along these higher dimensions (for e.g., if an increase in exploration along PC3 is associated with a decrease in exploration along PC2). However, given that our task is 1D and that our results show that VAF-PC1 is close to 80%, we believe that this metric captures the major changes in exploration.

Taken together, these results show that children have difficulty adapting their movement exploration to that required by the task. These results are consistent with the hypothesis from Vaillancourt and Newell [23] that the dimensional change in motor learning is influenced by the task demands. Although the original hypothesis was based on older adults and used a different measure of motor output (i.e. dynamical degrees of freedom [24]), their results showed a very similar pattern where older adults had difficulty both in increasing dynamical degrees of freedom in a constant force production task, and in reducing degrees of freedom in the sinusoidal force production task. Our results extend these findings to children by showing that children (like older adults) have a limited ability to adapt their exploration to the task demands.

In conclusion, our results add to the evidence that there is a clear developmental trend to motor exploration during learning, but that this trend needs to be considered in the context of task demands. Using practice strategies that directly manipulate exploration may be critical next steps to determine if exploration can facilitate motor learning in children when learning novel tasks.

CRediT authorship contribution statement

Mei-Hua Lee: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Priya Patel:** Investigation, Writing – original draft, Writing – review & editing. **Rajiv Ranganathan:** Methodology, Formal analysis, Writing – review & editing.

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