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Age-related deficits in motor learning are associated with altered motor exploration strategies

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Abstract—How is motor learning affected by aging? Although several experimental paradigms have been used to address this question, there has been limited focus on the early phase of motor learning, which involves motor exploration and the need to coordinate multiple degrees of freedom in the body. Here, we examined motor learning in a body-machine interface where we measured both age-related differences in task performance as well as the coordination strategies underlying this performance. Participants (N = 65; age range 18–72 years) wore wireless inertial measurement units on the upper body, and learned to control a cursor on a screen, which was controlled by motions of the trunk. Results showed that, consistent with prior studies, there was an age-related effect on movement time, with middle-aged and older adults taking longer to perform the task than young adults. However, we also found that these changes were associated with limited exploration in older adults. Moreover, when considering data across a majority of the lifespan (including children), longer movement times were associated with greater inefficiency of the coordination pattern, producing more task-irrelevant motion. These results suggest exploration behaviors during motor learning are affected with aging, and highlight the need for different practice strategies with aging. © 2019 IBRO. Published by Elsevier Ltd. All rights reserved.

Key words: motor skill, ageing, variability, redundancy, UCM, PCA.

INTRODUCTION

How does the ability to learn motor skills change with age? Although there is ample evidence that aging affects motor performance at several levels of the motor system including decreased strength, increased motor variability, longer reaction and movement times (Spirduso and MacRae, 1990; Spirduso et al., 2004), the question of how these changes affect the ability to learn motor skills is less well understood. In particular, given that movement rehabilitation is primarily directed at the aging population, it is critical to characterize how motor learning processes are affected with aging.

The large majority of studies that examine motor learning in aging have relied on one of two paradigms- sensorimotor adaptation or sequence learning (Doyon and Benali, 2005; Seidler, 2010; King et al., 2013). Evidence from both paradigms indicates that older adults show deficits in motor learning - in the acquisition of complex sequences, consolidation in sequence learning, and the initial adaptation (Curran, 1997; Buch et al., 2003; Seidler, 2006; Anguera et al., 2012). Although there is an argument that sequence learning is distinct from adaptation because it involves a change in the speed-accuracy tradeoff (Reis et al., 2009; Krakauer and Mazzoni, 2011), the typical tasks used in both paradigms can be categorized as ‘scaling’ tasks (Newell, 1991), because they mainly require modifications of already well-learned movements.

However, the use of scaling tasks to study motor learning raises two critical limitations: first, it largely ignores the early phase of motor learning, i.e., the ‘acquisition’ of a coordination pattern, where qualitative changes may occur (Newell, 1991; Ranganathan and Scheidt, 2016). In one of the few studies examining the acquisition of coordination patterns using novel tasks, older adults were found to have lower performance in learning novel coordination tasks (like juggling and lacrosse) relative to young adults (Voelcker-Rehage and Willimczik, 2006; Voelcker-Rehage, 2008). A second limitation is that even when tasks requiring novel coordination patterns are used, measuring only task performance variables (such as number of successes, speed, accuracy etc.) overlooks the question of ‘how’ the movement itself is organized. This is especially important in light of the fact that because of motor redundancy (or ‘abundance’) (Bernstein, 1967; Latash, 2012), the relation

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Abbreviations: IMU, inertial measurement units; PCA, principal component analysis; UCM, uncontrolled manifold; VAF, variance accounted for.

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between movement strategy and task outcome is a many-to-one relation – i.e. multiple movement strategies can produce the same outcome. The analysis of motor redundancy in well-learned tasks like reaching and prehension have shown differences due to aging throughout the lifespan (Shim et al., 2004; Verrel et al., 2012; Golenia et al., 2018); however these have not been examined during the early learning phase.

A key phenomenon that is critical to learning these novel redundant tasks is motor exploration. Here, we use the term motor exploration in its broad context of being able to use different coordination patterns in the movement repertoire. Essentially, because of the high dimensionality afforded by the large number of degrees of freedom, participants have to actively engage in searching this high-dimensional space to settle on an appropriate task-relevant coordination solution. These exploratory movements (also called 'search strategies') have been quantified but have predominantly used lower-dimensional or non-redundant tasks (Krinskii and Shik, 1964; Newell et al., 1989; McDonald et al., 1995). In particular, when considering exploration in the context of aging, there is evidence in other domains such as foraging behavior and object recognition that aging is associated with reduced exploration (Mata et al., 2013; Brandstatt and Voss, 2014), and may be associated with specific neurobiological changes involving dopaminergic function (Düzel et al., 2010). Therefore, there is a critical need to examine if and how aging affects motor exploration and the acquisition of novel coordination patterns in tasks with redundancy.

In this study, we used an experimental paradigm called a body-machine interface to examine the effect of aging on motor learning and coordination. A body-machine interface transforms body motions to the control of a machine (Casadio et al., 2012) - specifically in this case, the interface transformed movements of the shoulder and torso to the motion of a cursor on a screen (Lee et al., 2016, 2018). In addition to being a novel task that required motor exploration to find a new coordination pattern, the task was also designed to have redundancy, which meant that multiple coordination strategies could be used to achieve the task goal. Using this paradigm, our primary goal was to examine the effect of aging on short-term learning (i.e. changes in performance measured within a single session of practice). In addition to the primary focus on aging, we also examined data on children from a prior study (Lee et al., 2018) to provide a developmental account of motor learning and coordination over a large majority of the lifespan.

EXPERIMENTAL PROCEDURES

Participants

Participants had no reported history of neurological or orthopedic impairments, and were divided into three groups based on age: 18-35 yr (n = 24, 11 females, mean age: 26 ± 6 years). 36-50 yr (n = 19, 12 females, mean age: 44 ± 5 years) and greater than 50yr (n = 22, 11 females, mean age: 58 ± 6 years). Participants received $10 or extra course credit for their participation in the study. All participants provided informed consent prior to participation, and procedures were approved by the IRB at Michigan State University.

The data from children and young adults are from a prior study that focused on learning in children (Lee et al., 2018) – these included 25 children (thirteen 9-yr olds and twelve 12-yr olds), and 20 adults (19 young adults and 1 middle aged adult).

EXPERIMENTAL SETUP AND DESIGN

The experimental methods and procedures were identical to our prior study (Lee et al., 2018) and are briefly summarized below (Fig. 1a).

Participants sat in front of a 23" (58.4 cm) computer monitor and were instructed to move their upper body to control a screen cursor. Four wireless inertial measurement units (IMUs) (3-space, YEI Technology, Ohio U.S.A) were attached to the anterior and posterior end of the acromioclavicular joint on both the left and right sides of the body. 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 x 2 signals/sensor) which constituted the 'body space'.

Mapping body motions to cursor position

We used a linear mapping to convert the 8-dimensional body space (**h**) into the 2-D task space, which was the cursor position (**p**). The mapping used was given by $\mathbf{p} = \mathbf{A}\,\mathbf{h} + \mathbf{p_0}$. where **A** refers to the map and $\mathbf{p_0}$ is an offset term. To determine the map **A**, we used a calibration procedure similar to previous studies (Farshchiansadegh et al., 2014). During the calibration, participants performed free exploratory movements for 60 s where they were asked to explore different motions that they could perform with the upper body, while maintaining a comfortable range of motion. We then performed principal component analysis (PCA) on the calibration data and extracted the first two components. These two vectors of component coefficients were scaled by a gain factor (which was equal to the reciprocal of the square root of the respective Eigen value) to make the movements along both axes comparable in difficulty, and formed the two rows of the matrix **A**. The offset $\mathbf{p_0}$ was set so that the average posture during calibration (which was close to the resting posture) resulted in the cursor being in the center of the computer screen. This procedure allowed the task to be customized to each individual, minimizing both sensor placement variations, and any variations due to biomechanical effects like range of motion.

Cursor control task

Participants had to move their shoulders and torso in order to control a cursor on the computer screen to perform a virtual center-out reaching task. Participants moved the cursor from the home position (r = 2.2 cm, in the center) to one of a number of peripheral 'targets' (of same radius) presented at a distance of 11.5 cm, and then returned back to the home position. The peripheral targets were presented in a random

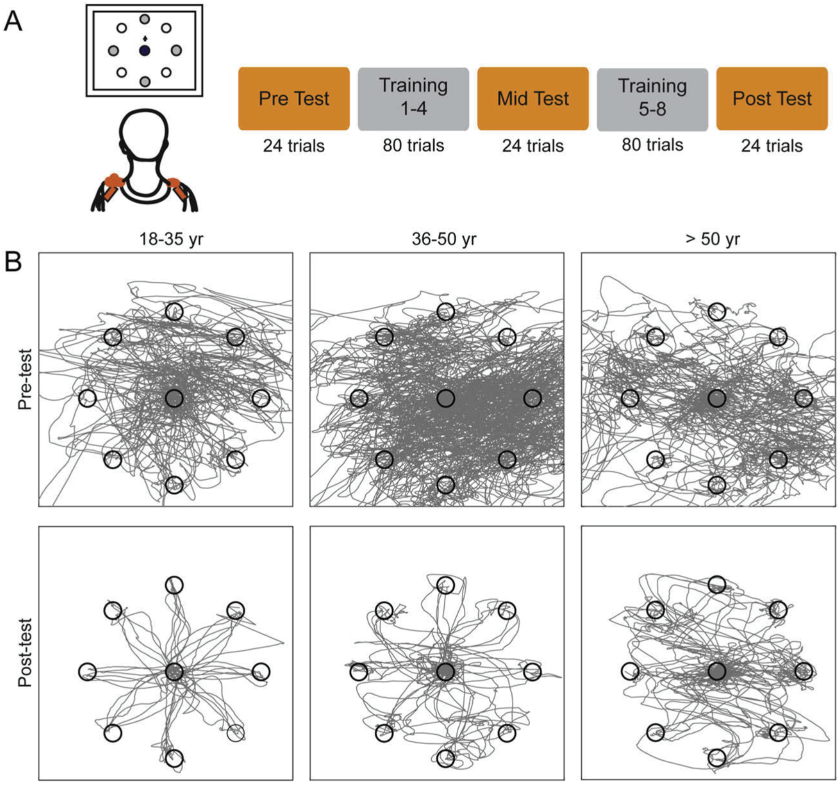

Fig. 1. (a) Schematic of experimental setup and protocol. Participants learned to move a screen cursor to different virtual targets on a screen using motions of the shoulder and torso. The main comparison in this study involved young, middle-aged and older adults. Data from 9-yr and 12-yr old children groups (shown in dotted boxes) were from a prior study (Lee et al., 2018) and were only used for a comparative analysis on learning over the lifespan (b) Sample trajectories from a single participant in the three adult groups in the pre- and post-tests.

sequence. Each trial started when the home position showed up for 500ms 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 also required the participant to keep the cursor inside of the target circle for 500ms before they returned to the home position. Each trial terminated only when the target was reached, and upon reaching the target and returning to the home position, the subsequent target was presented.

Participants performed two types of blocks: there were 8 ‘training’ blocks in which they reached for 4 peripheral targets in the cardinal directions 5 times each (for a total of 20 trials), and 3 ‘test’ blocks (pre-, mid- and post- test) in which they reached for 8 peripheral targets 3 times (for a total of 24 trials). The sequence in which these blocks were performed were: pre-test, training blocks 1-4, mid-test, training blocks 5-8 and the post-test at the end (Fig. 1a). Within each block, targets were presented in pseudorandom order with the constraint that all targets had to be presented before a target could repeat. The total of 232 trials were performed in a single experimental session lasting typically 45-90 min.

Direct comparisons between groups were focused on the test blocks. The test blocks included the 4 targets in the cardinal directions (similar to the training blocks), but also involved 4 targets placed along diagonal directions (i.e. at 45 degrees above and below the horizontal). These additional targets were designed to test whether the learning in the training sessions generalized to unpracticed directions. We chose to use an immediate post-test (rather than a delayed test) to get a measure of the ‘within-session’ learning and avoid the confounding influence of consolidation on learning, which are known to be affected by age (Hornung et al., 2005; Harand et al., 2012; Pace-Schott and Spencer, 2013).

DATA ANALYSIS

All analyses were performed only on the outward movements – i.e. when the participant moved from the home position toward the peripheral targets. We divided the data analysis metrics into two categories: task performance and coordination.

Task performance

Movement Time

Based on the fact that our protocol required participants to reach the target before the next target was presented (i.e. spatial error is ~ 0), and all targets were equidistant from the home position, we quantified task performance using the movement time. Movement time was calculated from the time that the cursor left the home position to the time that it reached and stayed inside the target for the subsequent 500 ms. The return movement from the target to the home position was not analyzed.

Coordination

Principal component analysis

For assessing the coordination of the upper body, we used PCA with the covariance matrix. We ran PCA on the time series of the 8 signals in each block computed the percent of variance accounted for (VAF) by the first two principal components (since the task was two dimensional).

To analyze the degree of motor exploration, we used the relative distribution of variance along the first 2 PCs. We quantified this exploration using an aspect ratio – i.e. the square root of the ratio of VAF in PC2 to PC1 – a smaller aspect ratio indicates greater reliance on PC1, and hence limited exploration.

Task-irrelevant motion

Because the principal components analysis described above depend only on the movement data (and not its relation to the task mapping), we performed a second analysis that focused specifically on the redundancy in the task. We computed the efficiency of the coordination pattern used by measuring the ‘task-irrelevant’ or ‘self-motion’ (i.e. motion of the body that results in no motion of the cursor) during a given block.

To compute this, we considered the entire motion in the body space (i.e. the 8-D space) in a given block (i.e. all 24 trials combined) and split this overall variability into task space component, and a null space components (Ranganathan et al., 2013). To compare these numbers across individuals and groups, we obtained a ‘normalized’ null space motion measure by dividing the null space variability by the task space variability. A greater normalized null space motion indicates a more inefficient coordination pattern.

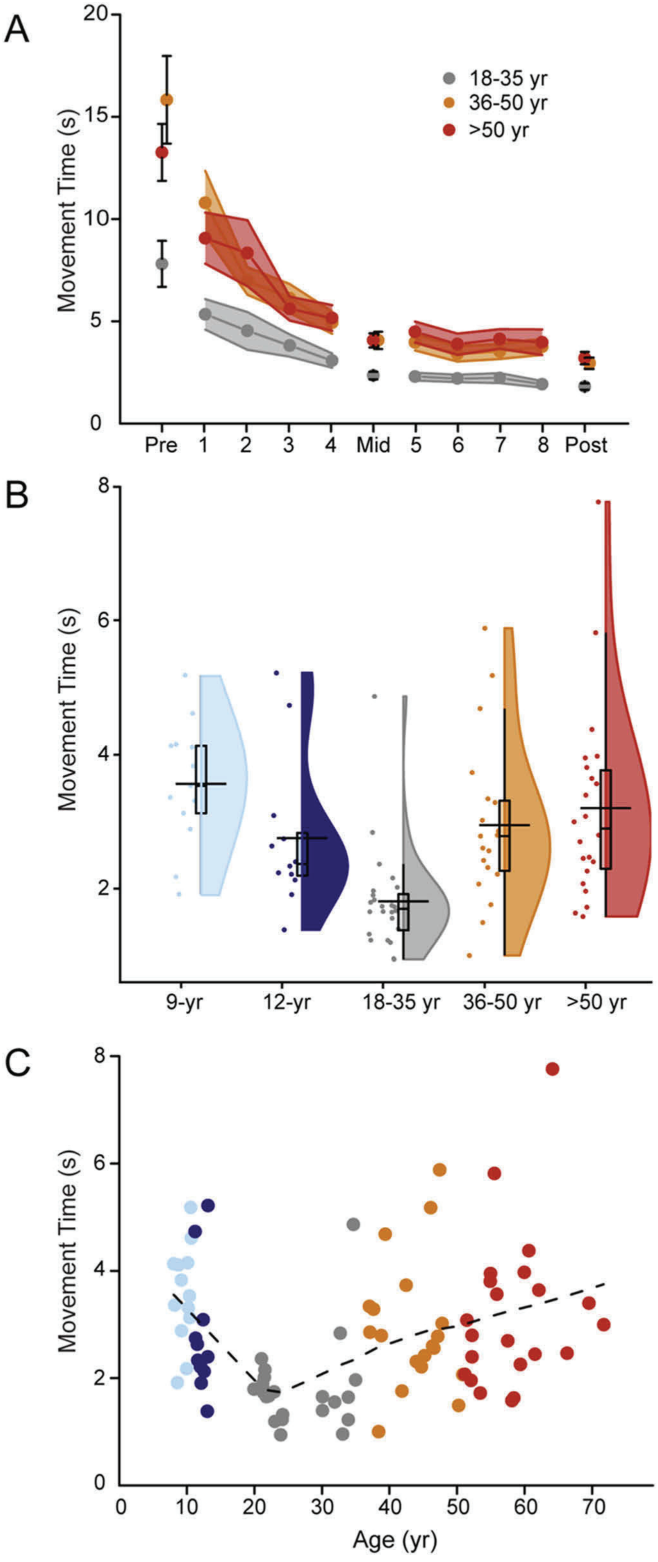

Fig. 2. (a) Movement time as a function of practice in the adult groups. (b) Raincloud plot showing individual distribution of movement times in the post-test across the lifespan (including children). Movement times tend to show a U-shaped trend with young adults having the fastest times in the post-test. (c) Movement time as a function of actual age, showing a rapid improvement until young adulthood and a slower decline into the 50s–60s. The dotted trendline was generated by a LOWESS fit. Raincloud plots were generated using a web version https://gabrifc.shinyapps.io/raincloudplots (Allen et al., 2018). Data from children and young adults were published in a prior study (Lee et al., 2018)

It is important to note two points regarding the null space motion metric – first, this measure (and the interpretation) of task and null space variability is different from typical analyses using the uncontrolled manifold (Scholz and Schöner, 1999), where the null and task space variance are usually considered with respect to only a single target. The latter measure of null space variability examines ‘flexibility’ in exploiting redundancy -i.e. how many different ways could they perform the solution, where increased null space variability (relative to the task space variability) is an index of greater flexibility. In our case, the null space motion measures the amount of body motion that had no impact on the motion of the cursor – therefore, a smaller null space motion indicates that participants reduced ‘wasted’ body motions. We did not perform the analysis with respect to a single target because of the small number of trials to each target (only 3/target in the test blocks). Second, because the current measure of null space motion is computed across all targets, it is possible that biomechanical constraints also affect this measure (i.e., it may not be possible to have zero null space motion because biomechanical constraints require motion in the null space) – therefore, the focus is on the comparison of this measure between groups (rather than the absolute values themselves).

Coordination-Task performance relation

Finally, we examined association between the coordination measures and the task performance. For this analysis, we combined our current data with a prior data set on 9-yr and 12-yr old children (Lee et al., 2018) to examine this relation over the entire lifespan. Here we examined the correlation between (i) movement time and exploration, where the exploration metric was represented by the aspect ratio (square root of the ratio of VAF in PC2 to VAF in PC1), and (ii) movement time and the inefficiency of the coordination pattern, where the inefficiency metric was represented by the normalized null space motion

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 rationale for this was that the test phases consisted of all 8 targets and was more representative of their learning at the task (however, all training data is included in the Figures). The dependent variables were analyzed using a 3 x 3 (Block x Group) repeated measures ANOVA. Block (Pre-test, mid-test, post-test) was the within-subjects factor, whereas Group (young, middle, older adult) was the between-subjects factor. Violations of sphericity were corrected using the Greenhouse-Geisser factor when applicable. To minimize the number of comparisons, post-hoc comparisons for group were restricted to comparison with the young adult as the control group. Significance levels were set at $P < .05$.

RESULTS

Sample trajectories in the pre- and post-test from an individual in each group are shown in Fig. 1b.

Task performance

Movement Time

There was a significant main effect of block, (F(1.05,64.94) = 118.15, $P < .001$), a main effect of group (F(2,62) = 10.25, $P < .001$) , which was mediated by a significant block × group interaction (F(2.10,64.94) = 5.12, $P = .008$) (Fig. 2a). Post-hoc comparisons showed that in both the pre- and post-tests, the young adults had shorter movement times than the middle-aged and older adults (all P's between < .001 and .023) but this difference was larger in the pre-test relative to the post-test. The movement time in the post-test across a majority of the lifespan (i.e. 9–72 yr) is shown as a function of group (Fig. 2b), and actual age (Fig. 2c). The comparison of movement times across the pre-test, mid-test and post-test is also shown in Table 1.

Coordination

VAF PC1

There was a significant main effect of block (F(1.76,109.01) = 5.81, $P = .006$) and a main effect of group (F(2,62) = 9.65, $P < .001$) (Fig. 3a). The interaction was not significant (F (3.52,109.01) = .50. $P = .715$). Post-hoc comparisons showed that the VAF PC1 in the young group was significantly lower compared to the older adults group ($P < .001$), but not the middle aged group.

VAF PC2

There was a significant main effect of block (F(1.74,107.82) = 6.54, $P = .003$) (Fig. 3b). The main effect of group (F(2,62) = 1.75, $P = .181$) and the interaction (F(3.48,107.82) = .53, $P = .689$) were not significant.

Table 1. Movement times (in seconds) in pre-, mid- and post- tests for the age groups. Values are presented as mean (SD).

Age group	Pre-test	Mid-test	Post-test
9 yr	13.56 (6.93)	3.75 (1.09)	3.56 (0.92)
12 yr	10.61 (4.69)	3.70 (1.62)	2.75 (1.13)
18 35 yr	7.81 (5.51)	2.35 (0.93)	1.81 (0.78)
36-50 yr	15.83 (9.36)	4.07 (1.50)	2.95 (1.23)
>50 yr	13.26 (6.54)	4.07 (2.00)	3.20 (1.45)

Coordination-Task performance relation

There was a negative correlation between movement time and aspect ratio in the post-test (r = -0.22, $P = .035$) (Fig. 4a), and a positive correlation between movement time and the normalized null space motion (r = 0.44, $P < .001$) (Fig. 4b). In addition, there was also a negative correlation between the aspect ratio and the normalized null space motion in the post-test (r = -0.64, $P < .001$).

DISCUSSION

The goal of the study was to examine the effect of aging on the acquisition of novel coordination patterns during short-term motor learning (i.e. change in performance measured within a single session of practice). In addition to measuring changes in task performance with learning across age groups, we also examined changes in coordination strategies. Our results showed that (i) there were clear age-related differences in task performance after practice; both middle-aged and older adults took a longer time to complete the task, (ii) older adults showed more limited exploration of their movement repertoire, (iii) across the lifespan (i.e. from 9 to 72 years), deficits in task performance were associated with limited exploration and the use of inefficient coordination patterns.

In terms of task performance, the U-shaped trend with age (with the shortest movement times occurring in young

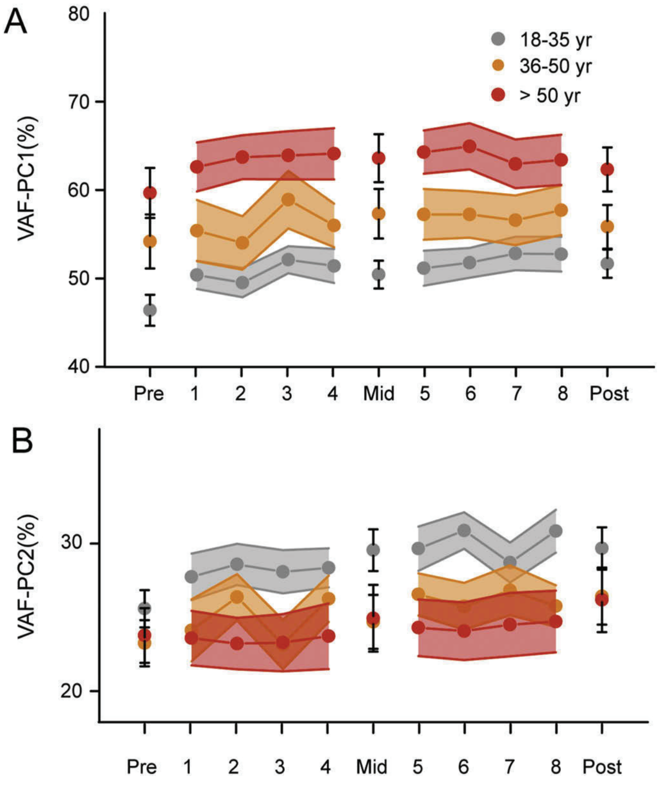

Fig. 3. Percent of variance accounted for (VAF) as a function of practice in (a) PC1, and (b) PC2. Older adults showed a much higher VAF in PC1, indicating a more limited exploration of the movement repertoire during the task.

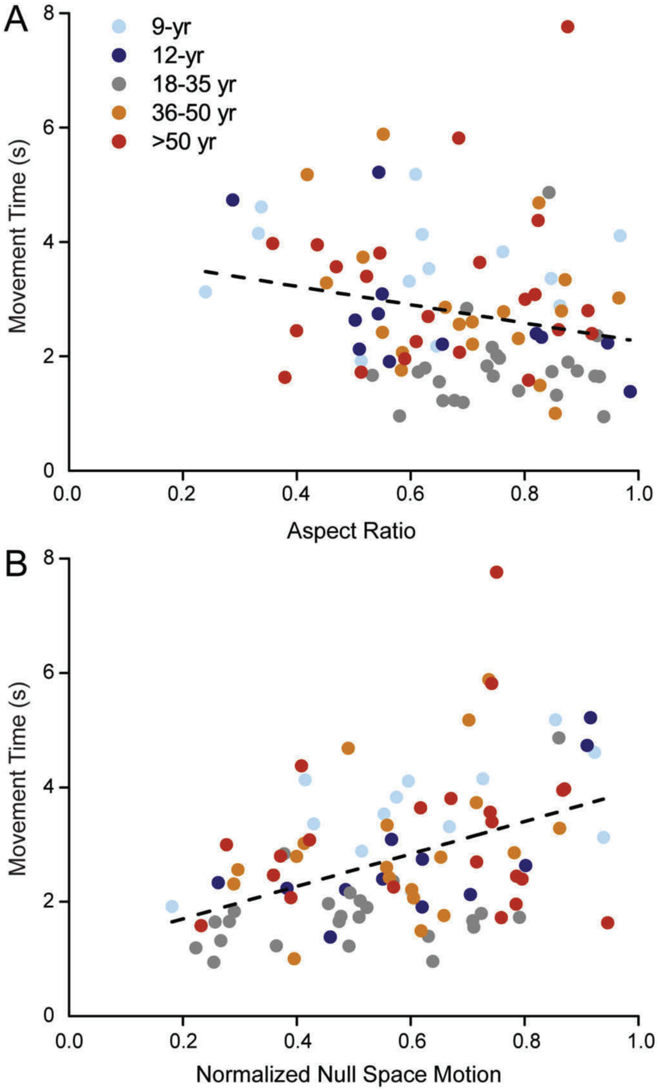

Fig. 4. Scatter plots showing the relationship between: (a) movement time and the aspect ratio, and (b) movement time and the normalized null space motion, across the lifespan. The aspect ratio, a measure of exploration of the movement repertoire, was correlated negatively with movement time (indicating that limited exploration was associated with longer movement times), On the other hand, the null space motion, a measure of the ‘efficiency’ of the coordination pattern, was correlated positively with movement time (a more inefficient coordination pattern was associated with longer movement times). Data from children and young adults were published in a prior study (Lee et al., 2018).

adults) is consistent with other studies on learning of complex tasks across the lifespan (Voelcker-Rehage and Willimczik, 2006). Although this pattern of findings may be expected in tasks dominated by biomechanical factors such as speed or strength, it was interesting to observe the same pattern in the current task, which was not only novel, but calibrated to each individual’s movement repertoire to minimize the influence of these biomechanical factors. It is important to note that the term ‘U-shaped’ here is used only in the sense that there is an age of optimal performance in the middle, and does not indicate a symmetrical rate of improvement and decline in performance (Newell and Morrison, 2016). In fact, as seen in Fig. 2c, when performance is plotted against actual age, the shape is clearly asymmetrical with rapid improvements in childhood, and a much slower deterioration with advancing age. One potential explanation for longer movement times in older adults is that it was simply a performance-related difference – either due to general ‘age-related slowing’ (Birren, 1974), or as a compensatory strategy for an altered speed-accuracy tradeoff (Welford et al., 1969). However, one of the novel contributions of our study is to show that while these factors may be important for task performance, they cannot account for age-related changes in coordination strategies employed during learning.

First, the exploration, as measured through PCA, showed much higher relative variances along the first principal component in older adults compared to young adults. In other words, older adults, similar to young children, show limited exploration of their movement repertoire and mostly explored along a single dominant coordination pattern. These results highlight that even though older adults may be more variable in their performance, they may actually limit exploration along potentially habitual patterns of coordination (de Rugy et al., 2012; Ranganathan et al., 2014); analogous to Bernstein’s ‘freezing degrees of freedom’(Bernstein, 1967). This strategy was also potentially maladaptive for task performance, as indicated by the negative correlation between the movement time and the variance aspect ratio, consistent with our prior work (Lee et al., 2018).

Second, the limited exploration was also associated with efficiency of the coordination pattern, which had a strong association with task performance – i.e. across all age groups, participants with longer movement times were not only associated with limited exploration, but also chose more ‘inefficient’ coordination patterns, creating greater task-irrelevant motion. These results are consistent with an interpretation that motor exploration is important for learning (Davids et al., 2006; Ranganathan and Newell, 2013), and that limited exploration could potentially lead to suboptimal coordination patterns.

Although our experiment was not explicitly designed as a test of a specific hypothesis, our results are consistent with the ‘loss of complexity’ hypothesis in aging (Lipsitz and Goldberger, 1992). Originally based on physiological processes (such as cardiovascular control), the loss of complexity hypothesis proposes that aging leads to either a loss or impairment of functional components and/or altered coupling between these components which then leads to impaired adaptability to physiologic stress. In the context of motor control, this impaired adaptability has also been shown as a reduction ‘functional’ degrees of freedom in tasks requiring the control of force and posture (Newell et al., 2006), but with the additional caveat that the task and environment play a critical role in the observed complexity (Vaillancourt and Newell, 2002). Our current results further extend these ideas to motor learning by showing that reduced tendency for motor exploration in older adults could also be viewed as a signature of a reduction in adaptability.

There are a number of limitations to the current study. First, while we observed group differences, there was a large degree of inter-individual variability in both children and middle-aged/ older adults. Although some of this increased variability is likely inherent to these populations, this variability could have also been increased by the novelty of the task, and the fact that the mapping between body motion and cursor motion in the task was based on participants' initial free exploration. Second, the correlations across the lifespan (i.e. between task performance and exploration and task-irrelevant motion) were somewhat weak to moderate (-0.22 and 0.44). However, we think that these correlations are expected to be somewhat small given the large age range involved (9 to 72 years) and the extent to which other age-related factors (e.g., motivation, use of cognitive strategies) have an influence motor learning. Finally, our measure of exploration examines only the relative 'amount' of variance in the two principal components, but does not examine the temporal 'structure' of this variability (Newell and Slifkin, 1998), which could potentially distinguish active exploration from motor noise (Therrien et al., 2015). This distinction has been used to show that learning depends on a balance between these two sources of variability; however, they have been restricted to models where variability is constrained to a single task parameter (e.g., reach angle). Extending these concepts to high-dimensional redundant tasks will be an important step towards a greater understanding of motor exploration.

Overall, we found that across a large majority of the lifespan, motor learning is characterized by changes not only in task performance, but in exploration of movement repertoire. Although motor exploration has been examined in well-learned tasks in the context of reinforcement learning (Wu et al., 2014), exploration in high dimensional spaces with many degrees of freedom (like the task examined here) can be considerably more complex because of the 'curse of dimensionality'(Dhawale et al., 2017). For example, at the neural level, there is evidence that exploration during learning is constrained along certain low-dimensional manifolds (Sadtler et al., 2014). Given that the movement repertoire itself is affected by aging (Allen and Franz, 2018) and neurological conditions like stroke (Ranganathan, 2017), further understanding of these altered motor exploration strategies are needed to establish its causal role in learning. In addition, the results suggest that development of practice strategies that actively manipulate motor exploration may be critical to facilitating learning throughout the lifespan.

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