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How to best characterize cognitive development? The claim put forward in this article is that development is the improvement of a kind of coordination among a variety of factors. To determine the development of coordination in a cognitive task, children between 4 and 12 years of age and adults participated in a time estimation task: They had to press a button every time they thought a short time interval had passed. The resulting data series of estimated time intervals was then subjected to a set of fractal analyses to quantify coordination in terms of its degree of "rigidity" (very highly integrated) vs. "looseness" (poorly integrated). Results show a developmental trajectory toward pink-noise patterns, suggesting that cognitive development progresses from a very loose, poorly integrated coordination of factors toward a pattern that expresses more integration, perhaps due to an optimization of constraints, that allows for a more stable coordination.

Keywords: motor and cognitive development, time estimation, fractals

Central to cognitive development is the question of how to best characterize the progression from a young mind to a more mature one. Does the trajectory include a progression from undifferentiated to differentiated thought, from implicit to explicit thought, from local to global thought, from isolated to interrelated thought, from concrete to abstract thought, or is it the other way around? Although existing proposals differ in a variety of ways, many have one limitation in common: They focus on changes in mental entities exclusively (i.e., a child's categories, concepts, schemas, beliefs, representations, etc.). As a result, they are not equipped to incorporate moment-to-moment mind–body interactions to explain how children can make quick, online adjustments to changes in the task context (cf. Adolph, Eppler, & Gibson, 1993a, 1993b; Berger & Adolph, 2003; Stoffregen, Adolph, Thelen, Gorday, & Sheng, 1997). Such adaptive adjustments to the amount of available information, to the material components of the task, or to the number of possible actions cannot be driven unidirectionally and top-down by mental entities alone. Thus, a developmental account that looks merely at changes in mental entities cannot be complete.

In the current article, we take motor coordination as a model to understand the development of cognitive performance. Our assumption is that task performance requires a form of coordination of mind, body, and environment that allows for adaptive adjustment to changes in the task environment. In particular, we assume that mind and body are connected in recurrent feedback loops, such that any changes in one component are reflected across the entire body. This allows the mind–body unit to perpetually update itself and, as a result, to reside in a state of preparedness to react to changes in the task environment (cf. Kloos & Van Orden, 2010; Van Orden, Kloos, & Wallot, 2011). The question addressed in this article, then, pertains to the development of such coordination.

Coordination and the Fractal Scaling Exponent

Before an action can take place, the mind–body system needs to assemble relevant components and coordinate them into a whole. Some of those components change on fast timescales (e.g., metabolic cell activity), others change on slower timescales (e.g., movement of limbs), and yet others change even more slowly (e.g., overt intention to act). For adaptive and flexible performance to be possible, it is unlikely that a single timescale can fully dominate the system. Instead, the system is likely to maintain a balance between competing and cooperating forces in a flexible coupling across the body (cf. Ulanowicz, 2009; West, 2010). Evidence for such coupling, or "concinnity" as it is sometimes termed, is seen as long-range coordination in a data series of performance, a structure of variability known as pink noise (cf. Diniz et al., 2011; Turvey, 2007; Van Orden et al., 2011; West & Griffin, 1999).

Pink noise is a fractal pattern of variability, where the power P of a signal grows with decreasing frequency f as $P = 1/f^{\alpha=1}$. This means that variability across multiple timescales is coordinated in a way to systematically contribute to the observed variations of measurements in time. A variety of methods have been developed to obtain this exponent, including detrended fluctuation analysis, or DFA (Peng, Havline, Stanely, & Goldberger, 1995), standardized dispersion analysis, or SDA (Bassingwaighte, Liebovitch, & West, 1994; Caccia, Percival, Cannon, Raymond, & Bassingthwaighte 1997; Holden, 2005), and spectral analysis, or SPA (Chen, Ding, & Kelso, 1997; Gilden, 2001.

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Pink noise has been demonstrated in the variability of reaction time for a wide array of motor and cognitive tasks (for summaries, see Riley & Holden, 2012; Riley, Shockley, & Van Orden, 2012; Riley & Turvey, 2002; Wallot & Van Orden, 2011). Example motor tasks with pink-noise signature include repeated aiming, walking, and tapping to the beat of a metronome (Ding, Chen, & Kelso, 2002; Hausdorff, Zemany, Peng, & Goldberger, 1999; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). Example cognitive tasks include temporal estimation, spatial estimation, word recognition, text reading, and visual search (Aks, Zelinsky, & Sprott, 2002; Chen, Ding, & Kelso, 1997, 2003; Ding et al., 2002; Gilden, 2001; Gilden, Thornton, & Mallon, 1995; Kello, Beltz, Holden, & Van Orden, 2007; Kuznetsov & Wallot, 2011; Van Orden, Holden, & Turvey, 2003, 2005).

The ideal pink-noise coordination can be contrasted with less ideal kinds of coordination, ones in which competitive and cooperative forces are not fully balanced (Kello et al., 2007; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009; Ward & Richard, 2001). In particular, if there is less coordination among timescales, patterns of variability deviate from pink noise to resemble white noise, a pattern of variability that is characterized by $0.5 \leq \alpha < 1.0$.[1] In contrast, if slow-changing components dominate the coordination among timescales, patterns depart from pink noise in the direction of brown noise ($\alpha > 1.0$). In both cases, departures from pink noise can be seen as a loss of adaptive complexity (cf. Bassingwaighte et al., 1994; see West, 2006, for a review). In the former case, coordination is "too loose" or poorly integrated, and in the latter, coordination is "too rigid" or maladaptively overintegrated. The question of the current article deals with the changes in coordination across development.

An initial indication about the development of flexible adaptation comes from studies of adults training to better perform a speeded precision aiming task (e.g., Wijnants et al., 2009). During five blocks of practice, adults used a stylus to point back and forth with their nondominant hand between two targets. Results showed that trial-by-trial variations changed toward pink noise, as participants became more experienced. An investigation of children's walking comes to similar conclusions: Stride-to-stride intervals of children between 3 and 14 years of age progressed toward pink noise with increasing age (Hausdorff et al., 1999).

In the current article, we use those findings as a starting point to investigate the progression of coordination required to complete a cognitive task. Children between 4 and 12 years of age were asked to repeatedly estimate a short time interval after having been trained on the specific duration. Time interval estimation is a classical behavioral task (Wing & Kristofferson, 1973), generally thought to capture a participant's timing ability (Buhusi & Meck, 2005) as well as the participant's ability to coordinate motor activity and task demands (Kiefer et al., 2009; Kuznetsov & Wallot, 2011). The time interval was a short 0.4 s, chosen because it has been found to be a comfortable speed of repeated button pressing for children of a variety of age groups (McAuley, Jones, Holub, Johnston, & Miller, 2006). Adults were included as a control group in the current study to establish the end point of development. Given that the preferred speed of adults is slower than that of children (McAuley et al., 2006), adults participated in two separate estimation tasks that differed in the target interval (0.4 vs. 1.0 s).

Method

Participants

Children between 4 and 12 years of age were recruited through local schools and day-care centers, and adults were recruited through the Introduction to Psychology participant pool and participated in return for class credit. Of the participants included in the final sample ($N = 10$ per age group; 46 girls, 44 boys; eight women, two men), mean age in years was 4.6 ($SD = 0.2$), 5.7 ($SD = 0.2$), 6.6 ($SD = 0.3$), 7.4 ($SD = 0.3$), 8.5 ($SD = 0.2$), 9.2 ($SD = 0.3$), 10.4 ($SD = 0.3$), 11.4 ($SD = 0.3$), 12.5 ($SD = 0.2$), and 19.4 ($SD = 1.2$), respectively. An additional group of four children (5.7, 6.0, 7.2, and 8.3 years) and one adult were tested but omitted from the final sample because they did not complete the experimental session.[2]

Apparatus and Display

For time estimation, we used either a force sensor (91% of the data; 95% of which was sampled at 200 Hz, and the rest being sampled at 100 Hz; Biometrics Ltd., Ladysmith, VA) or a pressure switch (sampled at 125 Hz; BIOPAC Systems, Inc., Goleta, CA). Data were recorded on a PC computer using either DataLINK PC Software v. 3.00 (for the Biometrics force sensor) or Acquire PS Software v. 4.00 (for the BIOPAC pressure switch). Sampling rate did not appear to affect the overall patterns of results, underscoring the generality of our findings.

A computer display was used to help participants sustain interest in the task. It showed a grid of 30 shapes, arranged in six columns and five rows (see Figure 1). At the beginning of the experimental session, the shapes were stars containing the words *Give Me Power*. As the participant completed the task, one star after the next turned into a circle with the word *Power* on it. In particular, the Give Me Power star at the top left of the screen changed first, followed by the star adjacent to it, and so on, left to right. Once the first row of stars had all changed to Power circles, a "Level 1"′ sign appeared, followed by a "Level Up!" sign. Once the second row of stars had all changed to Power circles, a "Level 2" sign appeared, again followed by "Level Up!", and so on through Level 4. After the fourth row was complete, a "Level 4" sign appeared, followed by "Expert Level." To provide the participant with a sense of progress from one change of shape to the next, a horizontal bar at the bottom of the screen filled in from left to right during two shape changes. The fill-in rate was fixed (e.g., 20 s for the 0.4 s task) to avoid perceived feedback. The fill-in pattern was continuous to avoid any extraneous timing information.

[1] Note that, even though biological systems are unlikely to show perfect white noise (i.e., a perfectly random variability with $\alpha = .5$), it is nevertheless common to talk about white-noise patterns, as long as there is a decrease in spectral exponent (cf. Hausdorff et al., 1997; Kiefer et al., 2009; Peng et al., 1995).

[2] Note that relatively few children failed to complete the task, despite its obvious tediousness. There was no apparent effect of age in participants who dropped out early, suggesting that task difficulty was manageable for even the youngest participants.

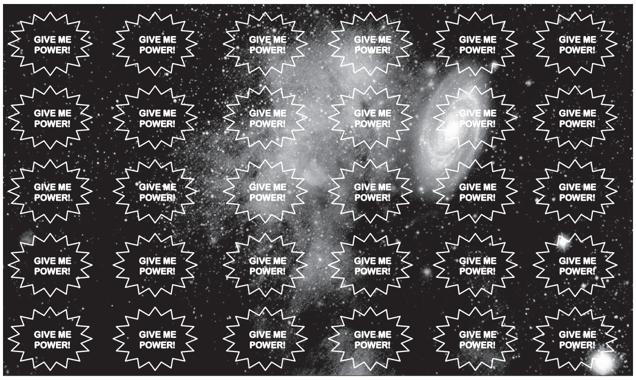

Figure 1. Display used during experimental trials.

Procedure

Participants were tested individually, either in a university lab or in a quiet room at their school. The cover story involved a robot that needed power to return to his planet. The robot was fed power through a special "power pod," as long as it was pressed at the exact rate of the robot's energy pulse. The power pod was the force sensor or pressure switch attached to a small round Macintosh computer mouse (chosen to fit easily into a child's hand). Participants were instructed that robot power would show up on the screen as they pressed the button, and the robot could return to his planet once the screen was filled with robot power.

A metronome was used to teach participants the target duration. Participants were told that the metronome (introduced as the energy pulse) would tell them when the robot needed power. One target duration was used for children (i.e., 0.4 s), and two target durations were used for adults (0.4 and 1.0 s), presented in counterbalanced order. The metronome remained on for 30 beats (i.e., 12 s for the 0.4 s task, and 30 s for the 1.0 s task), and participants were encouraged to press the button to the metronome beat. The metronome was then turned off, and participants were instructed to "remember in their head" when the robot needed power and to continue pressing the button in the same way as they did when the metronome was on—not too fast and not too slow. No performance feedback was given for the entirety of the session. Data collection started after the metronome was switched off, lasting about 10 min in the 0.4-s task and about 15 min in the 1.0-s task. At the end of the session, when the last row of stars had changed to Power circles, a smiling robot appeared and then was shown to fly off to his planet. Participants tended to enjoy the task, and very little encouragement to continue was needed.

Results

Accuracy of Time Interval Estimates

To determine the extent to which children could estimate the desired time interval, we calculated the mean duration between keypresses across the trials of a child. Table 1 reflects the averages of these mean durations (second column), separated by age group. Adults' performance was added for comparison purposes (both for the 0.4-s task and the 1.0-s task). We also included the mean of duration standard deviation, based on the standard deviation of duration obtained for each participant in an age group. As expected, older children were better at sustaining the target duration than younger children, with a negative correlation between mean interval duration and age, whether we considered only children, $r(88) = -.34$, $p < .01$, or included adults as well (0.4-s task), $r(98) = -.47$, $p < .001$. Similarly, older children showed less variable performance than younger children, as reflected in the negative correlation between mean interval duration and standard deviation, $r(88) = -.55$, $p < .001$.

However, despite improvements with age, the degree to which children consistently performed faster (or slower) than the target duration did not change with age. Only very few participants produced average durations that reliably differed from the target duration (see Table 1). This suggests that even 4-year-olds were able to estimate the target duration over time. Thus, despite the rather repetitive and potentially boring task, performance differences due to age do not appear to be qualitative in nature.

Table 1
Descriptive Statistics of the Obtained Time Series, Separated by Age (With Standard Deviations)

Age group	Mean interval duration	Mean of *SD* of duration	Number of participants*		Mean number of trials
Children (0.4-s task)			[Slower]	[Faster]	
4-year-olds	564 (109)	374 (135)	2	0	1,072 (193)
5-year-olds	492 (101)	415 (255)	0	0	1,262 (236)
6-year-olds	468 (134)	292 (267)	2	0	1,373 (318)
7-year-olds	415 (49)	267 (168)	0	0	1,356 (222)
8-year-olds	457 (74)	186 (72)	1	0	1,309 (212)
9-year-olds	406 (59)	132 (73)	2	0	1,461 (193)
10-year-olds	412 (31)	154 (90)	1	0	1,367 (112)
11-year-olds	418 (117)	204 (190)	3	3	1,495 (375)
12-year-olds	383 (67)	141 (81)	0	3	1,571 (255)
Adults					
0.4-s task	417 (49)	53 (17)	4	1	1,420 (184)
1.0-s task	935 (199)	199 (46)	1	4	1,032 (238)

Note. The asterisk represents the number of participants (out of 10) with a mean estimated duration that was either significantly slower or significantly faster than the target duration ($p < .05$).

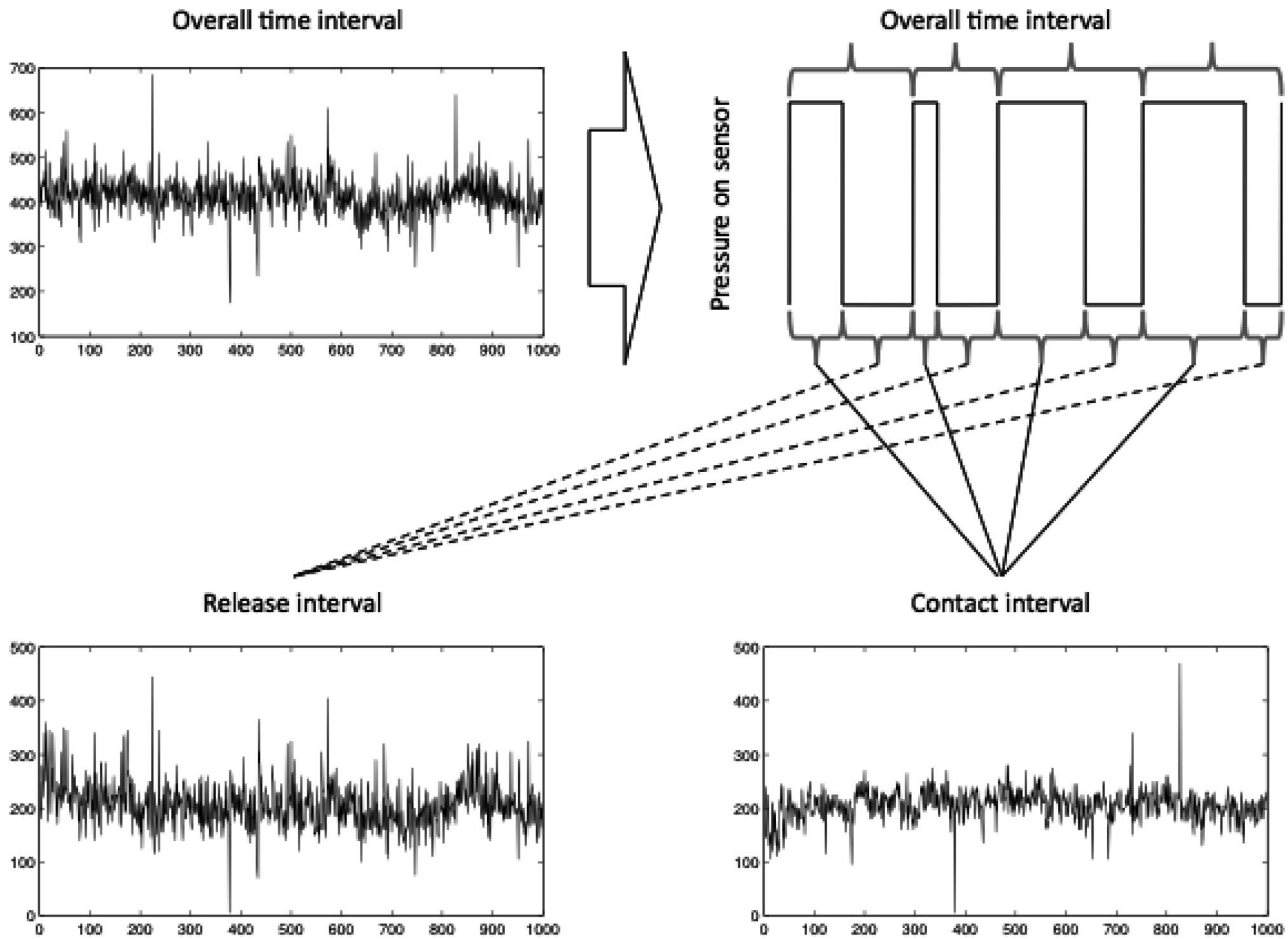

Figure 2. Data preparation of a 1,000-trial time series (shown in the upper-left corner). The full time series is decomposed into a time series of release intervals (i.e., where a data point is the duration the sensor is released, shown on the bottom left) and a time series of contact intervals (i.e., where a data point is the duration the sensor is pressed, shown on the bottom right).

Outcome of the Fractal Analyses

A participant's time series was broken down into two separate time series, one referred to as *release* intervals, and the other referred to as *contact* intervals (cf. Kello et al., 2007). Figure 2 shows how the two time series were obtained as well as an example of each. Release intervals pertain to the duration for which the participants' finger had no contact with the sensor. Contact intervals pertain to the duration for which the participants' finger had contact with the sensor. Each of these obtained time series was subjected to three fractal analyses: DFA, SPA, and SDA. In the ideal case, all of these analyses will yield converging results. However, given somewhat heterogeneous performances of children, DFA is likely to be the most robust technique (cf. Gao et al., 2006). We therefore first report the results from DFA, after which we provide data on the degree of convergence of results.

Two Hurst scaling exponents H were calculated for each child, one for release time, and one for contact time. For adults, these two exponents were calculated both for the 0.4-s task and the 1.0-s task. Considering adults only, a 2×2 repeated measure analysis of variance, with time series (release vs. contact) and task (0.4 s vs. 1.0 s) as within-group factors, revealed no significant main effects and no significant interaction (Fs < 1.35, ps > 0.27).[3] Also, the mean exponents for adults (ranging from 0.74 to 0.81) fell within the range of what is typically considered pink noise. Finding that performance was preserved in the face of changing task constraints could imply that adults' coordination of relevant components fluctuates near a critical point (Fuchs, Kelso, & Haken, 1992; Hausdorff et al., 1997, 1996, 1999; Kiefer et al., 2009; Kloos & Van Orden, 2010; Vaillancourt & Newell, 2002; Van Orden, 2007; Van Orden et al., 2011; Werner, 2010).

Figure 3 shows the scatterplot of H exponents obtained for the 0.4-s task as a function of age. In terms of release intervals (see Figure 3a), there was a positive correlation between age and H among children, $r(88) = .36$, $p < .001$, which became more pronounced when adults were taken into account, $r(98) = .42$, $p < .001$. Similar results were found for the contact interval time

[3] The lack of difference between exponents across the four conditions was corroborated by the other two spectral analyses (the SDA, Fs < 1.00; the SPA, Fs < 1.00).

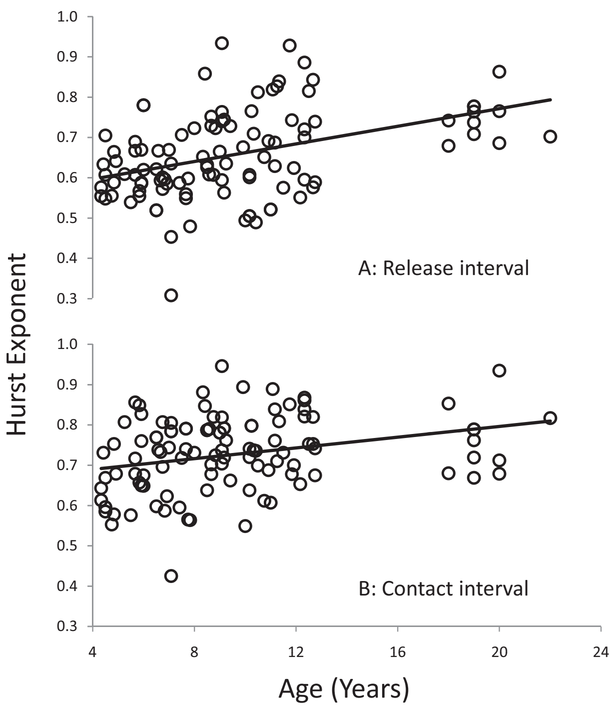

Figure 3. Scatterplots of the participants' scaling exponent *H* (against age) estimated for the release-interval time series (A) and for the contact-interval time series (B). A least-square regression line was fitted to the data to illustrate the increase of scaling exponents with age.

series: There was a positive correlation between age and the scaling exponent *H*, whether the analysis included only children, $r(88) = .33$, $p < .01$, or also adults $r(98) = .29$, $p < .01$. These correlations are in line with our prediction that development is accompanied by changes in the fractal exponent. There was no difference between correlations (*z*s < 1.00).

We also correlated the *H* exponent with performance measures, again separately for release interval and contact interval. Interestingly, there was no significant correlation between the *H* exponents and mean duration of the estimated time interval (absolute *r*s < .11 for children, and *r*s < .13 when adults are included). That is to say, the average length of the time intervals for which participants pressed down the key (or released it) was unrelated to the fractal scaling exponent of the produced time series. This is particularly important given that younger children produced somewhat longer mean durations than older children. The finding that mean durations were uncorrelated with the size of the scaling exponents suggests that the developmental trend in scaling exponents is not a function of task success.

Next, we correlated the *H* exponent with the standard deviation of time estimates. Negative correlations were found, both for release intervals, $r(88) = -.32$, with children alone, and $r(98) = -.36$, with all participants, and for contact intervals, $r(88) = -.24$, with children alone, and $r(98) = -.26$, with all participants ($p < .01$ in all four cases). Figure 4 shows the correlation between scaling exponent and standard deviation as a function of age group (and separated for contact interval and release intervals, respectively). Although none of these individual correlations reached significance (all $p > .05$), an interesting developmental trend was observed. The relation between *H* and the standard deviation of release intervals appears to be fairly unstable in children younger than 8 years of age, and then begins to stabilize in a positive direction until adulthood. Developmentally, they hint at an optimized coordination between the component processes in that performance variability is correlated with timing dynamics.

Finally, we correlated the size of the *H* exponents with each other and with the exponents obtained by other fractal analyses. The top left and bottom part of Table 2 (parts of the table shown to the left and below the shaded part) provide the correlations between different scaling exponents (for release time and contact time, respectively). As can be seen in the table, there was a high correlation between scaling exponents obtained for different analyses. In particular, when considering the values obtained for release intervals only, the average correlation was $r = .78$ ($p < .001$). When considering contact intervals, the average correlation was $r = .81$ (all *p*s < .001). There was no difference between any two correlations, suggesting that the exponents capture similar structures of variability.

The top-right part of Table 2 (boldface values) shows how exponents of the release-interval time series compared with the exponents of the contact-interval time series. To avoid an age confound, the correlations represent partial correlations, after age was factored out. Findings show that the *H* exponents (DFA) obtained for the release-interval time series significantly correlated with the same exponent obtained for the contact-interval time series (*p*s < .01). Note, however, that these correlations between the two time series are lower than the correlations of the same time series across the different analyses. This suggests that, although the exponents returned for the two different time series (release interval vs. contact interval) are correlated to each other, this correspondence is smaller than the exponents returned by different analyses of the same time series (DFA, SPA, SDA).

Discussion

The main goal of our study was to assess the developmental trend in fractal organization of children's time estimation performance. The task was to press a button repeatedly, for about 10 min, to estimate a short time interval over and over again—a task that even the youngest children could complete. The resulting time series of over 1,000 estimates each were then subjected to fractal analyses, revealing an organization that changed toward more and more pink-noise variation across development. Fractal exponents in younger children indicate relatively uncorrelated fluctuations of time estimates, a pattern that contains less systematic variability in the slower timescales than pink-noise variability. It suggests that young children's performance might lack sufficient voluntary control to bind together processes of faster timescales into a sustained performance pattern (cf. Gilden & Hancock, 2007; Kloos & Van Orden, 2010; but see Hausdorff et al., 1999). A change of this pattern with development indicates that development consists of establishing a superior coordination of relevant components.

The developmental trend in coordination of performance was observed in two different time series: the time it took for the finger to press the button (release interval) and the time it took for the finger to lift off from the button (contact interval). These two time series do not necessarily capture the same kind of coordination:

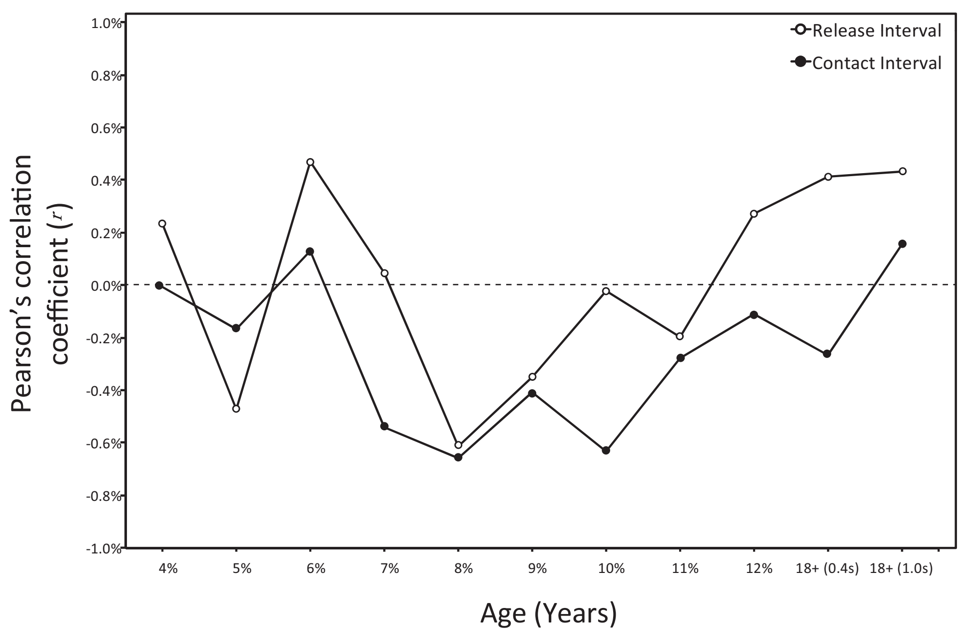

Figure 4. Pearson's correlation coefficient (r) of the relation between each age group's scaling exponent H and standard deviation for both the release- and contact-interval time series data.

Contact interval can be thought of mainly capturing a simple finger movement that is initiated to signify the end of a trial and the beginning of a new one, and release interval can be thought of mainly capturing the actual estimation of the target duration. Indeed, previous research has documented independent patters of fluctuation in these two time series (Kello et al., 2007). Yet, in our study, we observe a developmental change in coordination in both kinds of time series, indicating that development of coordination spans across the whole range of the motor and cognitive system (Hausdorff, 2007; West & Brown, 2005; Wijnants et al., 2009; Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012).

The overall pattern of our developmental findings in fractal exponents is in line with the trend reported by Wijnants et al.'s (2009) training study, in which improved performance in adults went along with higher fractal exponents, progressing toward a more pronounced pink-noise pattern. Our results are also in line with those presented by Hausdorff et al.'s (1999) motor study, in which development of gait in children showed a decrease of variability with age. However, the comparison of the current results with those of the Hausdorff et al. (1999) study also indicates an important difference: Although the developmental starting point of human gait was marked by scaling exponents that were higher than pink-noise exponents, the developmental starting point for our task was marked by scaling exponents that were lower than pink-noise exponents. In other words, although development showed a trend toward pink-noise patterns in both gait and time estimation, the starting point of the developmental trajectory was different. In what follows, we explore these differences in trajectory.

Woollacott and Sveistrup (1992) first suggested that the developmental phases of walking reflect the alternation of freezing and release of *degrees of freedom* (i.e., different muscles, joints, and body segments, and groups of these). Borrowing from Bernstein's (1967, 1996) theory of motor coordination, Woollacott and Sveistrup identified three phases of learning: (a) an inability to manage excessive degrees of freedom (e.g., infants just learning to modulate their postural control system to sit upright and, eventually, to walk), (b) a reduction (or freezing) of degrees of freedom in an attempt to compensate for a lack of control that serves to temporarily stabilize motor control (e.g., the developmental course from toddler to adolescent walking behavior), and (c) a systematic and controlled release of degrees of freedom that eventually leads to adultlike patterns of locomotion (see also Kamm, Thelen, & Jensen, 1990; Newell & Vaillancourt, 2001; Thelen, 1995).

Table 2
Absolute Magnitude of Partial Correlations Between the Scaling Exponents Returned by DFA, SPA, and SDA, Respectively, Both for Release Intervals and Contact Intervals

	Release intervals			Contact intervals		
Variable	DFA	SPA	SDA	DFA	SPA	SDA
Release intervals						
DFA	—	0.79	0.78	**0.47**	0.38	0.30
SPA		—	0.76	0.31	**0.37**	0.25
SDA			—	0.40	0.32	**0.41**
Contact intervals						
DFA				—	0.87	0.76
SPA					—	0.79
SDA						—

Note. DFA = detrended fluctuation analysis; SPA = spectral analysis; SDA = standardized dispersion analysis. Boldface values show how exponents of the release-interval time series compared with the exponents of the contact-interval time series.

When this theoretical approach is taken within the context of fractal dynamics, the first phase of locomotor development leads to a noisy, uncoordinated pattern of control. This is similar to the locomotor dynamics exhibited by patients with Huntington's disease (Hausdorff et al., 1997)—a disorder that can lead to, among other things, random muscle spasms that give rise to uncontrolled movements. The second phase typically results in a very rigid, deterministic pattern of gait, similar to what one might observe in the motor dynamics of an adult with Parkinson's disease (Maurer, Mergner, & Peterka, 2004; Schmit et al., 2006; van Emmerik & Wagenaar, 1996; van Emmerik, Wagenaar, & Wolters, 1999; van Wegen, van Emmerik, Wagenaar, & Ellis, 2001). With development, the child might be able to slowly increase flexibility to certain coordinative structures, thereby freeing up these different muscle and joint groups and demonstrating better modulation of the various constraints. The end result is a more fluid coordination that exhibits a stochastic pattern of gait dynamics (i.e., normal, healthy gait dynamics with less random variability).

Coordination of performance in a cognitive task, in contrast, is likely to involve a different control problem altogether. Whereas locomotion is achieved by releasing degrees of freedom that were initially overcontrolled, cognitive performance may involve the establishing of integration or coherence among independently functioning components. Children might still be able to complete a novel cognitive task, even when relevant components are only loosely coupled, without voluntary control forcing an overly regular coordination and locking in place degrees of freedom. Such suboptimal coupling among components might restrict successful performance to only a narrow set of task conditions (e.g., a child failing to adapt to changes that fall outside of this narrow range). Indeed, when we changed the target duration to 1.0 s during pilot work, all of the children failed to complete the full 10-min trial. With development, this coupling is achieved, yielding pinker variability and widening the range of tasks to which the participant can adapt.

Taken together, our results support the idea that a flexible reorganization of coordinative structures develops, an idea borrowed from the motor control literature in which soft assembly allows for the temporary assemblage of muscle synergies to sustain motor behavior (Bingham, 1988; Kugler & Turvey, 1987; Turvey & Carello, 1995; Withagen, 2004). The application of this strategy to understand cognitive performance has been suggested previously (Kiefer et al., 2009; Kloos & Van Orden, 2010; Riley et al., 2012), and it lends itself well to understanding the plasticity and adaptability in cognitive development.

In the current experiment, the dynamics found in younger children were representative of their attempt to organize themselves into a "0.4 s responding device" and their struggle with the various ways in which they can coordinate themselves cognitively. This would be similar to how a child might struggle when first learning to throw or kick a ball. In such a situation, a child would not only be less fluid in his or herr performance of the task at hand but also exhibit a less fluid transition between the dynamic contexts that they might face. Conversely, the dynamics of older children and adults allows for an enhanced range of flexibility and smooth transitions between changes in context as they assemble and constrain cognitive synergies to perform a given task.

The current research adds to the already existing effort to reframe cognitive development questions as questions of managing constraints, thus making both the behavioral variability and the behavioral dynamics equally important measures in identifying strategies used during task performance (cf. Kugler, Kelso, & Turvey, 1980, 1982; Newell, 1986; Smith, Thelen, Titzer, & McLin, 1999; Spencer, Thomas, & McClelland, 2009; Spencer, Vereijken, Diedrich, & Thelen, 2000; Thelen & Smith, 1994). A next step is to further our understanding as to how children organize and manage cognitive synergies, particularly during their improvement of task performance while they navigate the challenges of changing environmental and task constraints.

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