

Walking Changes the Dynamics of Cognitive Estimates of Time Intervals

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Cognitive performance exhibits patterns of trial-to-trial variation that can be described as 1/f or pink noise, as do repeated measures of locomotor performance. Although cognitive and locomotor performances are known to interact when performed concurrently, it is not known whether concurrent performance affects the tasks' pink noise dynamical structure. In this study, participants performed a cognitive task (repeatedly producing a temporal interval) and a motor task (walking on a treadmill) in single- and dual-task conditions. In single-task conditions both tasks exhibited pink noise structure. For concurrent performance the dynamical structure of the cognitive task changed reliably in the direction of white (random) noise. The dynamical structure of locomotion remained pink noise. The change in cognitive dynamics occurred despite no reliable changes in mean or standard deviation measures for either task. The results suggest a functional reorganization of cognitive dynamics supporting successful task performance in dual-task conditions.

Keywords: gait dynamics, dual tasking, cognitive dynamics, temporal estimation, complexity

The time intervals between steps, when walking, vary from stride to stride as pink noise in healthy individuals (also termed 1/f noise; Hausdorff et al., 1996; Jordan, Challis, & Newell, 2006, 2007a, 2007b). A pink noise process is one in which the patterns of variation at one time scale are similar to those found at other scales, indicating the presence of long-range correlations. Long-range correlations imply that fluctuations or variations throughout the data series are positively correlated. The variability of stride intervals is thus not random but possesses a particular type of dynamical structure.

The structure of variability is informative about the processes of coordination that underlie human performance (Riley & Turvey, 2002; Slifkin & Newell, 1998, 1999). For example, the statistics of long-range correlated stride intervals can change when factors relating to the task or the actor are varied. Stride intervals become more random (less correlated) when healthy individuals walk to the beat of a metronome, for instance. Apparently, entrainment to the metronome constrains the timing of strides to suppress the normal timing of gait (Hausdorff et al., 1996). Stride intervals are also less correlated (more random) in participants with Huntington's disease (Hausdorff et al., 1997). Changes in both the actor (as in Huntington's disease) and the task (as in introducing a metro-

nome) change the constraints that influence the organization of the underlying motor synergy (Riley & Turvey, 2002).

Like locomotor performance, repeated measures of cognitive performance in word naming, memory, production, and decision tasks vary over time as pink noise in healthy individuals (Gilden, 2001; Kello, Beltz, Holden, & Van Orden, 2007; Van Orden, Holden, & Turvey, 2003, 2005). The clearest signals of pink noise are found in cognitive production tasks. For instance, clear pink noise profiles appear in the variation across repeated temporal estimates of 1 s or spatial estimates of 1 in (2.54 cm; Gilden, Thornton, & Mallon, 1995). Pink noise is also found in the performance variability of tasks that straddle the divide between cognitive and motor performance, such as simple reaction time and finger tapping (Chen, Ding, & Kelso, 1997, 2003; Ding, Chen, & Kelso, 2001).

Research on the pink noise structure of variability in cognition and motor coordination has been pursued independently. This is surprising considering the easily appreciated interactions between cognitive and motor performance: Consider anecdotal reports of two people slowing down or stopping altogether when engaged in an engrossing conversation while walking. Findings that mirror these anecdotal cases have been demonstrated in rigorous laboratory experiments, which have shown, for instance, that concurrent performance of locomotion and various cognitive tasks can result in reduced walking speed (Springer, Ghiladi, Simon, & Hausdorff, 2004) and impaired cognitive performance (Lajoie, Teasdale, Bard, & Fleury, 1996; see review by Woollacott & Shumway-Cook, 2002). Previous research has not, however, examined the structure of variability for concurrently performed locomotor and cognitive tasks.

The importance of investigating the structure of performance variability during concurrent task performance is twofold. First, it is possible that dual-task performance requires reorganization of

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the underlying control to support stable performance on both tasks (i.e., establishing new patterns of connectivity among the component degrees of freedom that make up a motor synergy or that make up a “cognitive synergy”; Pellecchia, Shockley, & Turvey, 2005; Shockley & Turvey, 2005). Contrasting the temporal structure in the variability of each task performed alone and concurrently is one way to determine if such reorganization occurs, because the temporal structure is determined by the organization of the underlying degrees of freedom (Riley, 2007).

Second, it is possible that changes in pink noise profiles may provide an index of task demands analogous to how such changes distinguish healthy versus impaired functioning (cf. Goldberger, 1996; Goldberger, Peng, & Lipsitz, 2002; Havlin et al., 1999; Lipsitz & Goldberger, 1992). Lipsitz and Goldberger (1992) have developed a perspective known as the *loss of complexity hypothesis*, which postulates that “healthy” performance variability has the complex, irregular pink noise profile, whereas “pathological” performance is less complex. Loss of complexity stemming from pathology can occur in two ways. Pathological dynamics can appear as more rigidly and predictably deterministic. However, pathology can also appear as a shift away from pink noise toward random white noise, so a more inclusive hypothesis would concern changes in direction away from healthy complexity, either more random or more regular (Van Orden, 2007; West, 2006). Departures from healthy complexity have been widely confirmed in cognitive, behavioral, and physiological deficits (e.g., Buxhoeveden, Fobbs, Roy, & Casanova, 2002; Gildea & Hancock, 2007; Hausdorff et al., 1997; Thurner, Mittermaier, & Ehrenberger, 2002; Vaillancourt & Newell, 2002).

If pathological loss of complexity is a general phenomenon, then even healthy participants may exhibit a loss of complexity under challenging conditions, such as the dual-task conditions of the present experiment. We investigated that hypothesis in an experiment that required participants to produce repeated temporal estimates alone or concurrent with a motor task (walking on a motorized treadmill) and compared the structure of performance variability in the cognitive (temporal estimation) and motor (walking) tasks when performed alone or concurrently.

We expected to see stronger effects of dual-task performance on the cognitive task compared with the motor task. Participants have less freedom to adjust walking patterns when walking on a motorized treadmill, because treadmill speed is fixed, whereas the temporal estimation task is relatively less constrained. In addition, there are stronger consequences for allowing locomotor performance to degrade excessively, such as falling, than there are for allowing performance of the cognitive task to degrade. The expectation was that participants would prioritize locomotor performance, in accordance with the *posture-first* principle (Woollacott & Shumway-Cook, 2002)—a greater departure from healthy complexity for cognitive performance dynamics in the dual-task condition compared with the single-task cognitive dynamics and with the locomotor dynamics. If concurrent locomotion has the effect of perturbing cognitive performance, then the specific expectation was that we would observe a whitening of the structure of cognitive performance variability, consistent with other research demonstrating that other types of perturbations whiten the profile of cognitive performance variability (e.g., Kello et al., 2007).

We quantified the structure of locomotor and cognitive performance variability in two ways, using *detrended fluctuation anal-*

ysis (DFA; Peng, Havlin, & Stanley, 1995) and *standardized dispersion analysis* (SDA; Bassingthwaighe, Liebovitch, & West, 1994; Caccia, Percival, Cannon, Raymond, & Bassingthwaighe, 1997; Eke, Herman, Kocsis, & Kozak, 2002; Holden, 2005). The computational steps of each method are described below. The methods differ with regard to those computational details; so if they produce converging results, then it is less likely that the results reflect an artifact.

We also determined whether locomotor and cognitive performance became synchronized at a stable phase relation. Although we did not give participants any explicit instruction to synchronize, it was possible that spontaneous coordination between these two rhythmic behaviors occurred or that participants explicitly adopted a strategy of timing the temporal estimation in relation to some salient event in the gait cycle. Although the phase coupling (PC) analysis we performed would not allow us to distinguish these two possibilities, it did allow us to determine whether cognitive responses and walking became synchronized and to quantify the strength of any such coordination.

Method

Participants

Participants were 10 healthy University of Cincinnati undergraduates (5 men, 5 women) who received credit to fulfill a course requirement. Participants ranged in age from 18 to 24 years, in height from 1.67 m to 1.85 m, and in weight from 54.43 kg to 84.82 kg. Participants had no history of lower extremity injury or neuromuscular disorders that would inhibit normal walking. This experiment was approved by the University of Cincinnati Institutional Review Board and adhered to guidelines for the ethical treatment of participants.

Apparatus

A Sole TT8 motorized treadmill (Sole Treadmills, Jonesboro, AR) was used for trials involving walking. The treadmill speed could be varied in 0.1-mph increments. The treadmill was located 1 m from a wall in front of participants, and an occlusion screen hung 30.5 cm in front of the treadmill. Walking performance was quantified by measuring participants' right knee flexion–extension angles during the gait cycle with a twin-axis SG-150 goniometer and DataLINK PC software Version 3.00 (Biometrics Ltd., Ladysmith, VA). The goniometer was secured to the leg with athletic tape (Cover-Roll Stretch Adhesive Gauze). A handheld, digital thumb button that was integrated with the goniometer hardware and software was used to record estimates of temporal duration. The data were sampled at a rate of 100 Hz and stored on a PC.

Procedure

Participants were tested individually in a laboratory setting. During a 10-min treadmill familiarization period, prior to the beginning of the experiment, participants were asked to select a comfortable speed that they would adopt if they were out for a stroll around campus. This walking speed was used for all subsequent trials. The treadmill speed was adjusted accordingly.

There were three conditions: temporal estimation performed alone (while seated), walking performed alone, and temporal

estimation and walking performed concurrently. In all trials participants were instructed to look straight ahead at a white screen, to avoid talking, and to limit other nonessential body movements (e.g., turning the head or performing unrelated arm movements). Condition order was randomized for each participant. One trial per condition was performed. Each trial lasted 16 min. Rest breaks were allowed between trials as needed.

The temporal estimation task required participants to repeatedly reproduce intervals of a fixed duration by pressing the handheld button after they estimated the target interval had elapsed. Each button press marked the beginning of a new interval. The target duration was presented to participants repeatedly for 30 s prior to the beginning of a trial. The target duration was presented with a metronome set to a rate of 1 Hz (i.e., the interval participants had to reproduce was 1 s long), but participants were not explicitly told the duration. After the 30-s period the metronome was turned off, and the participants were instructed to continue pressing a button for the duration of the 16-min trial with the goal of repeatedly reproducing the duration between the tones they had just heard.

The walking task simply required participants to walk for the entire trial (also 16 min) with the treadmill set at each participant's self-selected comfortable speed ($M = 1.77$ mph, $SD = 0.45$ mph). Treadmill speed was not changed once the trial was initiated. Data collection was not initiated until the treadmill reached the specified speed to eliminate the transient period during which the treadmill belt was accelerating.

During the dual-task condition, participants were instructed to perform the temporal estimation task while walking on the treadmill for the 16-min trial.

Data Reduction and Analysis

To create stride interval time series, customized MATLAB (Mathworks, Inc., Natick, MA) routines that implemented a peak-picking algorithm were used to identify the time of occurrence of peak knee flexion on each stride. The times for adjacent strides were subtracted from one another to obtain the time interval between successive strides. MATLAB routines were also used to determine intervals between button presses for the temporal estimation task by identifying the time of onset of button pressing for each response and subtracting the time between adjacent responses. The mean and standard deviation of the resulting stride interval and temporal estimation interval time series were computed to characterize walking and temporal estimation performance (see Figure 1).

The interval time series were submitted to DFA (Goldberger et al., 2000; Peng et al., 1995) and SDA to characterize the structure of performance variability for each task. DFA quantifies the structure of variability by computing scaling exponents that relate a measure of variability, the detrended fluctuation function (see Equation 1), to the time scale over which the function was computed. The first step in DFA is dividing the time series into segments (boxes) of equal length. A trend line is fit to the data in each box and the time series is detrended by subtracting the local trend in each box. The variability of the detrended time series within each box is quantified by the detrended fluctuation function $F(n)$, according to

$$F(n) = \sqrt{\frac{1}{N} [y(k) - y_n(k)]^2}. \quad (1)$$

The detrended fluctuation function is then averaged across boxes of the same size to obtain one average measure of variability for that box size (i.e., time scale). The process is repeated for the next largest box size and then for all possible box sizes (the smallest box size is limited by the sampling rate, and the largest by trial duration).

As commonly practiced, we dropped the smallest and largest box sizes because they approach the small and large absolute size limits of the data set, which may distort the outcome of the analysis (see, e.g., Duarte & Zatsiorsky, 2001; Roerdink et al., 2006). The result of these analysis steps is a characterization of the relation between the magnitude of the detrended fluctuation function and the size of the box (i.e., the time scale) over which the function was computed. This relation is plotted in log-log coordinates (see Figures 2A and 2B). A positive linear relation between the amount of fluctuation and time scale suggests the presence of fractal ($1/f^\alpha$) scaling, with the slope α of a linear fit to the plot (the scaling exponent) providing a quantitative index of the structure of performance variability. A slope of $\alpha = .5$ indicates white noise (random fluctuations), $\alpha = 1.0$ indicates "perfect" pink noise, and $.5 < \alpha < 1.0$ indicates a stochastic process with a tendency toward pink noise (the fluctuations are not random white noise, but the correlations are weaker than perfect pink noise; see Riley & Turvey, 2002, for a discussion of how scaling exponents index degree of randomness).

Similar to DFA, SDA is used to characterize the relative coherence of the patterns of fluctuations in the data by computing a fractal dimension statistic. The fractal dimension is computed by repeatedly resampling the same data with different box sizes and calculating a dispersion statistic (standard deviation of the sample mean) for each box size. The resulting pairs of dispersion statistics and box sizes are graphed in log-log coordinates to depict the function relating the measure of variability (standardized dispersion) to the time scale over which it was measured (box size), similar to plotting the detrended fluctuation function versus box size in DFA. The slope of a linear fit to that function is subtracted from 1, yielding the fractal dimension (FD; see Figures 2C and 2D). An FD = 1.5 indicates white noise, FD = 1.2 indicates pink noise, and $1.2 < FD < 1.5$ indicates a stochastic process with a tendency toward pink noise. We used SDA in addition to DFA to provide converging evidence for any changes in fractal scaling of cognitive or locomotor performance variability.

PC Analysis

We also determined whether spontaneous coupling occurred between locomotion and temporal estimates, and determined the strength of coupling when it occurred, using a PC analysis (McDermott, Van Emmerik, & Hamill, 2003). We selected this method rather than other measures of relative phase (RP; such as continuous RP; see, e.g., Schmidt, Shaw, & Turvey, 1993) because visual inspection of the data suggested the possibility of multifrequency coordination and because of the discrete nature of the temporal estimation data. Using the original raw data time series, we calculated discrete RP by indexing the time of occurrence of each left knee flexion in relation to the time of occurrence of the subsequent button press, using the following equation:

$$RP = \frac{t + nT}{T} \cdot 360, \quad (2)$$

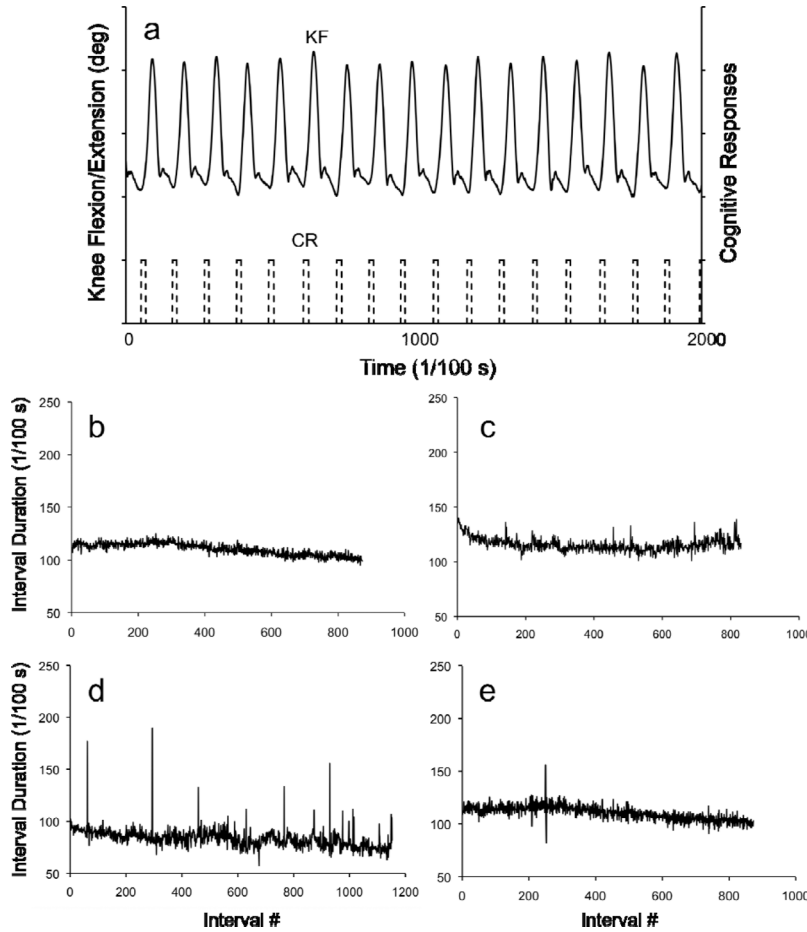


Figure 1. Representative data from Participant 3: (a) raw time series for both tasks during concurrent task performance, (B) locomotion interval data (indexed by time interval from peak knee flexion to subsequent peak knee flexion) during single-task performance, (C) locomotion interval data during concurrent task performance, (D) cognitive response interval data (indexed by time interval from cognitive response to subsequent cognitive response) during single-task performance, and (E) cognitive response interval data during concurrent task performance.

where n is the number of button presses between two successive flexions of one knee, T is the time duration of the stride (the time between successive flexions of the same knee) in which the time estimation response occurred, and t is the time lag from the beginning of the stride to the subsequent time estimation response.

The choice of peak knee flexion was somewhat arbitrary; we did not assume that peak knee flexion was necessarily a salient event in the gait cycle that would tend to become synchronized with time estimates. Another event, such as heel strike, might be more salient than peak knee flexion, but with our equipment we could not measure heel strike. Nevertheless, peak knee flexion also permits reliable calculations of RP between the gait cycle and cognitive responding, and peak knee flexion was easy to determine reliably with a peak-picking algorithm. Moreover, we analyzed knee angles from the left leg, but if coordination between locomotion and cognitive responding occurred, it could have been between time estimate responses and some event in the gait cycle of the right leg. Thus, although the value of RP indicates the phase relation between one event in the gait

cycle and cognitive responding, the value should be interpreted circumspectly. The value of the PC statistic, in contrast, provides a more easily interpretable quantification of coordination between the gait cycle and cognitive responding; PC indexes the strength of the coupling (i.e., coordination stability) between, in this case, the knee flexion and temporal estimation signals.

The PC statistic was quantified by first plotting $RP(i)$ as a function of time-delayed $RP(i + \delta i)$, where the delay δi corresponds to the lag used in the return map to yield data that cluster along the line of identity (McDermott et al., 2003) (see Figure 3). The Euclidean distance (dn) was then taken for each point from the line of identity and the distances were weighted (wd ; $dn \leq 40$ was weighted as 0 and $dn > 40$ was weighted to actual distance) and summed:

$$wd_n = 1 - \frac{|d_n|}{40 \cos(45^\circ)}, \quad (3)$$

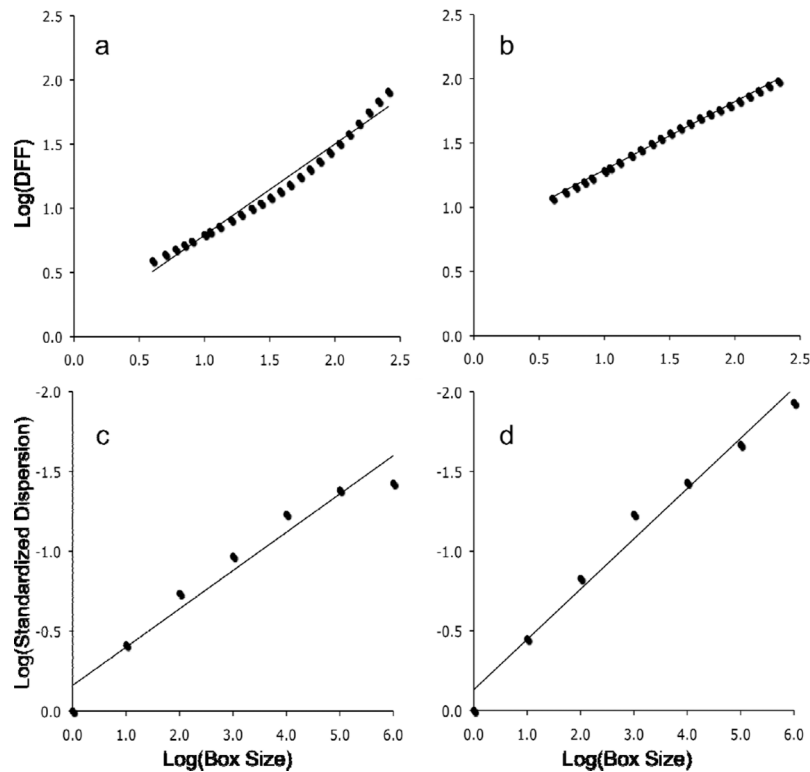


Figure 2. Representative data of cognitive responding from Participant 3: (A) detrended fluctuation analysis (DFA) during single-task performance, (B) DFA during concurrent task performance, (C) standardized dispersion analysis (SDA) during single-task performance, and (D) SDA during concurrent task performance. DFF = detrended fluctuation function.

$$PC = \frac{\sum_{n=1}^m wd_n}{m} \times 100, \quad (4)$$

with m equal to the number of points within the lowest range of the return maps (via the weighted values) with their sum expressed as a percentage of the highest possible sum.

A value of $PC = 0$ indicates no PC, and $PC = 1$ indicates absolute PC between the two signals. PC is independent of the phase relation (i.e., the value of RP) or frequency ratio (e.g., 1:1, 2:1) between the two signals. We computed both RP and PC a second time using peak extension of the left knee as the relevant gait event as a way of determining and enhancing the reliability of these measures. Like peak knee flexion, peak knee extension is also a somewhat arbitrary event during the gait cycle, although it does occur fairly close in time to toe-off. Results with both knee flexion and knee extension time series are presented.

Results

Indices of Performance

See Table 1 for a summary of each participant's data. The mean and standard deviation of stride and temporal estimation intervals were submitted to paired-samples t tests to compare performance in single- and dual-task conditions. For the stride intervals there

were no significant differences across single- and dual-task conditions, $t(9) = 0.22$, $p = .83$, and $t(9) = 0.76$, $p = .47$, for mean and standard deviation, respectively; nor were there any significant differences for cognitive response intervals, $t(9) = -1.54$, $p = .16$, and $t(9) = 1.08$, $p = .31$, for mean and standard deviation, respectively. Although on average there were no differences in these parameters, inspection of Table 1 suggests that some participants exhibited substantial increases in temporal estimates across single- and dual-task conditions, whereas others exhibited substantial decreases, and a few participants (most notably Participant 5, whose estimates were quite accurate) differed very little across conditions.

Indices of the Dynamical Structure of Performance Variability

DFA. Performed in isolation, both gait and temporal estimation performance variability exhibited a tendency toward pink (correlated) noise structure with respective mean $\alpha = .788$ and $.752$. Temporal estimation performance variability was significantly less pink and more random ($\alpha = .581$) when performed while walking compared with the single-task condition, $t(9) = 3.32$, $p = .009$. This result indicates a qualitative change in the structure of cognitive performance variability—performance variability exhibited a structure less like pink noise and more akin to white noise as intervals became less correlated with one another—

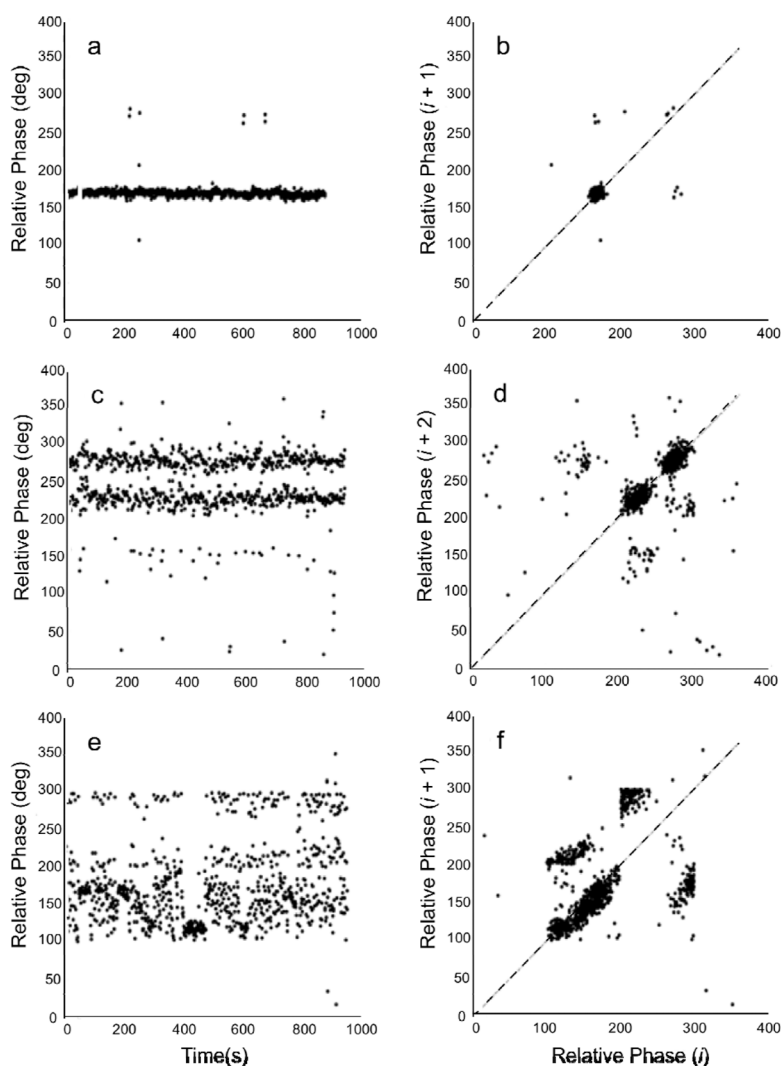


Figure 3. Relative-phase time series during concurrent task performance for Participants 3, 7, and 5 (A, C, and E, respectively) and return maps for Participants 3, 7, and 5 (B, D, and F, respectively). Dotted line represents the line of identity—the temporal alignment of the abscissa and ordinate.

when the temporal continuation task was performed while walking. One participant (Participant 5) who exhibited very accurate temporal estimates exhibited an increase, rather than a decrease, in α . During dual-task performance, the structure of gait variability ($\alpha = .813$) was not significantly affected by concurrently performing the cognitive task, $t(9) = -0.836$, $p = .425$.

SDA. According to SDA, too, performance variability of both the gait and temporal continuation tasks performed independently exhibited a tendency toward pink noise with mean FD = 1.174 and 1.179, respectively (FD = 1.2 for ideal pink noise). Similar to the DFA findings, SDA revealed that when the two tasks were performed concurrently, cognitive performance exhibited a less pink and more random profile, $t(9) = -3.064$, $p = .013$ (mean FD = 1.358; FD = 1.5 for white noise), whereas gait dynamics did not change reliably, $t(9) = 0.380$, $p = .713$ (mean FD = 1.160). The SDA results confirm the DFA results of a qualitative change in the

structure of cognitive performance variability when the temporal estimation task was performed while walking.

Coupling Between Locomotion and Cognitive Responding

There was much disparity among participants regarding the frequency ratios (stride frequency:temporal estimation response frequency) and phase relations exhibited (see Figure 3). The majority of participants exhibited a 1:1 knee flexion:temporal estimate or knee extension:temporal estimate frequency ratio (see Figure 3A), but some participants alternated repeatedly between particular 1:1 phase relations. Only one participant (Participant 7) exhibited a 1:2 frequency ratio (see Figure 3C), performing with less stability than the participants coordinating at 1:1 ratios (see Table 2). Some participants' temporal estimates were roughly in-phase with left knee flexion, whereas others were roughly

Table 1
Mean and Standard Deviation Intervals, Scaling Exponents, and Fractal Dimensions for All Participants

Participant	Locomotor task							
	Single-task condition				Dual-task condition			
	<i>M</i>	<i>SD</i>	α	FD	<i>M</i>	<i>SD</i>	α	FD
1	1.42	0.03	.79	1.29	1.40	0.02	.65	1.33
2	1.53	0.03	.66	1.28	1.58	0.04	.80	1.09
3	1.16	0.06	.78	1.08	1.10	0.06	.83	1.12
4	1.36	0.04	.84	1.06	1.36	0.03	.89	1.06
5	1.18	0.04	.86	1.14	1.15	0.04	.87	1.13
6	1.31	0.02	.72	1.21	1.21	0.02	.72	1.24
7	1.82	0.14	.87	1.04	1.95	0.09	.77	1.26
8	1.48	0.03	.87	1.17	1.42	0.04	.92	1.05
9	1.11	0.02	.70	1.27	1.09	0.02	.74	1.24
10	1.59	0.07	.78	1.20	1.64	0.08	.93	1.07
<i>M</i>	1.40	0.05	.79	1.17	1.39	0.04	.81	1.16
	Cognitive task							
1	0.84	0.12	.75	1.20	1.39	0.14	.50	1.52
2	0.86	0.10	.72	1.15	0.80	0.07	.46	1.46
3	0.83	0.09	.71	1.24	1.10	0.09	.60	1.32
4	1.81	0.65	.98	1.02	1.36	0.10	.60	1.25
5	1.01	0.12	.70	1.40	1.00	0.18	.87	1.31
6	0.80	0.09	.65	1.11	1.21	0.07	.37	1.39
7	1.12	0.17	.84	1.19	1.01	0.23	.53	1.51
8	1.05	0.07	.80	1.14	1.40	0.11	.56	1.11
9	0.83	0.16	.61	1.15	1.10	0.16	.54	1.58
10	1.40	0.34	.77	1.18	1.64	0.14	.76	1.14
<i>M</i>	1.06	0.19	.75	1.18	1.20	0.13	.58	1.36

Note. α = scaling exponent (obtained through detrended fluctuation analysis); FD = fractal dimension (obtained through standardized dispersion analysis).

antiphase (in-phase with the right leg). One participant (Participant 5) did not exhibit any discernibly stable phase relation or stable frequency ratio at any point during the dual-task trial (see Figure 3E), although the apparent phase wandering exhibited by this participant was largely constrained between 100° and 300°. As described in more detail in the Discussion, the frequency ratio and phase relation (or absence thereof) observed did not relate systematically to the changes observed in alpha or FD of cognitive performance in the dual-task trial.

PC was somewhat variable among participants (see Table 2 and Figures 3B, 3D, and 3F). The average PC value when performed using peak knee flexion was .627 (*SD* = .185), ranging from .293 to .804 across participants (recall that PC = 0 indicates no PC and PC = 1 indicates a perfect, stable phase relation). When PC was performed using peak knee extension, the PC values were slightly lower and more variable (*M* = .504, *SD* = .225), ranging from .128 to .767.

Correlations Among the Measures

Two-tailed Pearson product-moment correlations between mean stride and temporal estimation intervals, standard deviation of stride and temporal estimation intervals, DFA scaling exponents, and PC values were computed. Five reliable correlations stand out in this analysis. First, the mean intervals of the cognitive responses during single-task performance and the standard deviation of the

cognitive responses during single-task performance were reliably correlated, $r(8) = .93$, $p < .01$. As response interval durations increased, they also became more widely dispersed (e.g., Holden, Van Orden, & Turvey, 2008; Luce, 1986; Wagenmakers & Brown, 2007). This is not surprising, as larger magnitudes of perceptual estimates generally coincide with wider dispersion in human performance (e.g., Ekman's Law; Ekman, 1959).

Second, the mean intervals of the cognitive responses during single-task performance were significantly correlated with the scaling exponent of the cognitive response intervals during single-task performance, $r(8) = .86$, $p < .01$, indicating a relation between the mean temporal estimates and the pink noise structure of the temporal estimation performance variability. As the mean temporal estimate duration increased, the structure of temporal estimation variability exhibited a more pink (more correlated) structure of variability.

Third, the standard deviation of the cognitive response intervals during single-task performance was significantly correlated with the scaling exponents of the cognitive response intervals during single-task performance, $r(8) = .75$, $p < .05$. This finding is related to the first correlation discussed and indicates that clearer signals of pink noise in temporal estimates are associated with a greater amount of variability. This falls out of the relation between the scaling exponent and the definition of a scaling relation in variability. The 1/*f* scaling relation implies that variability will

Table 2
Phase Coupling, Frequency Ratios, and Phase Modes for Each Participant

Participant	PC-KF	PC-KE	Frequency ratios	Representative phase mode ^a (°)
1	0.695	0.707	1:1	120, 170
2	0.540	0.265	1:2	(240, 280)
3	0.776	0.551	1:1	170
4	0.718	0.643	1:1	180, 120
5	0.308	0.207	None ^b	None ^b
6	0.804	0.695	1:1	170, 120
7	0.293	0.128	1:2	220, 270
8	0.700	0.767	1:1	110, 200
9	0.711	0.528	1:1	180, 120
10	0.725	0.548	1:1	170

Note. PC-KF = phase coupling indexed by consecutive peak knee flexions; PC-KE = phase coupling indexed by consecutive peak knee extensions.

^a Relative phase values were visually determined on the basis of relative phase plots (see Figures 3A, 3C, and 3E) because mean relative phase is not representative for bimodal distributions. When two values are listed, adjacent values refer to the copresent phase modes defining the 1:2 frequency ratio and values in parentheses refer to the phase modes between which the participant alternated in a 1:1 frequency ratio, with the top value corresponding to the dominant mode. ^b Denotes no discernible phase relation for that particular participant.

grow in a data set as more data are collected (e.g., see Van Orden et al., 2005). The scaling exponent estimates how fast variability grows in a data set (all other things equal), and a scaling exponent close to that of pink noise predicts more rapid growth in variability, and thus more variability, compared with exponents closer to white noise (for data sets of the same size).

Fourth, the mean cognitive response intervals during dual-task performance were correlated with PC during dual-task performance—as temporal estimate durations became longer, PC became stronger, $r(8) = .70$, $p < .05$. However, this appears to have been driven by data from Participants 2 and 7, who showed lower PC values as well as 1:2 ratios.

The final noteworthy finding is that the scaling exponents obtained from DFA and SDA were reliably correlated, $r(18) = -.64$, $p < .01$, providing evidence that the two measures deliver similar indexes for quantifying the change in performance variability for the temporal estimation task.

Discussion

The present study examined the reciprocal influences of two behavioral performances that exhibit pink noise when performed in isolation. The primary result was that temporal estimates changed from clearer signals of long-range-correlated pink noise in the single-task condition to less clear, whiter signals in the dual-task condition in which participants performed the temporal estimation task while walking on the treadmill. The structure of variation in gait performance did not change from single- to dual-task conditions. Both DFA and SDA revealed this pattern of results, providing convergent evidence for the dramatic change in the dynamical structure of cognitive performance while walking.

By contrast, means and standard deviations of both stride intervals and temporal estimation intervals remained statistically un-

changed, irrespective of whether the tasks were performed concurrently or in isolation. The latter two measures are typical performance metrics, but they failed to capture changes in the intrinsic dynamics of performance, changes that were revealed by the fractal time series analyses (DFA and SDA).

The fact that this experiment involved treadmill walking requires comment. Treadmill walking seems to affect the local dynamic stability of gait compared with overground walking (Dingwell, Cusumano, Cavanagh, & Sternad, 2001). During treadmill walking long-range correlations are still present, as demonstrated in the present study and previous studies (Jordan et al., 2007a, 2007b), though the strength of the correlations may be reduced. Comparisons between treadmill and overground walking are not a simple matter, however, because of a host of potential confounds, so those differences might be due to other factors. Nevertheless, the present results may not straightforwardly generalize to overground walking.

The increased randomness of cognitive dynamics in the dual task might be interpreted as supporting an account based on limited attentional resource pools (Wickens, 2002). An argument could be made that more random performance stems from an impairment caused by competition for limited resources. However, the absence of an overall performance decrement for standard measures of either task is not consistent with this interpretation. Limited attentional resources would more readily predict a performance decrement than a change in performance dynamics.

Presently, to our knowledge, no existing model of dual-task performance—whether cast in terms of limited attentional resource pools or some other mechanism—has been articulated in such a way as to predict changes in the dynamics of cognition under dual-task conditions. The development of such a model will be important to gain a better understanding of cognition. A model developed in the context of concurrent walking and cognitive performance should be informed by the posture-first principle (Woollacott & Shumway-Cook, 2002), according to which participants place greater priority on locomotor or balance performance compared with cognitive performance because the danger of falling, for example, exists while walking on a motorized treadmill.

Another candidate cause of the change in cognitive dynamics was entrainment of cognitive responses to the locomotor rhythm, whether the result of an explicit strategy by participants or the reflection of spontaneous coupling between two rhythms. It has been demonstrated that fluctuations in finger tapping (Chen et al., 1997) and locomotion (Hausdorff et al., 1996) become less pink and more random or white when explicitly paced by a metronome. Presumably, entrainment to the metronome supplements or substitutes for purposeful coordination and overrides the intrinsic (pink noise) dynamics of purposeful coordination. Consequently, fluctuations in the data series come to reflect errors in synchronizing to the pacing signal, exclusively (Van Orden et al., 2003).

If the locomotor rhythm had acted like a metronome in the present experiment, however, we should have seen consistent relations between the fractal scaling indices and measures of coupling, which we did not. Among the 9 participants who showed a decrease in the scaling exponent for temporal estimation in the dual-task condition, there was no common trend in terms of frequency ratio, RP relation, or PC. Moreover, Participants 5 and 7 were similar in exhibiting relatively low PC, but they exhibited opposite changes in scaling exponent for the cognitive task (an

increase in α and FD from single-task to concurrent task performance for Participant 5 vs. a decrease for Participant 7). This failure occurred despite the perhaps optimal choice of “rhythm” for the temporal estimation task (1 Hz), near the very center of the range of what most participants adopted as a comfortable stride frequency (Danion, Varraine, Bonnard, & Pailhous, 2003). In short, the presence or absence of coupling between the cognitive and locomotor tasks, or the strength of the coupling when it occurred, did not explain changes in cognitive dynamics.

Given the status of the previous explanations, we favor an alternative in which whitened variation in temporal estimations indicates a reorganization of the underlying cognitive synergy when temporal estimation was performed while walking. The change in the dynamics results from a change in the underlying organization of control, because it is the coordination of the available degrees of freedom—the way components of the hypothetical cognitive synergy are organized to work together—that determines the patterns of variation exhibited by the coordinated system (cf. Newell, 1998; Newell & Vaillancourt, 2001; Riley & Turvey, 2002; Shockley & Turvey, 2005).

Increased randomness signals, in this case, a change in the complexity of cognitive dynamics, a symptom of reduced flexibility or adaptability of cognitive performance (Van Orden, 2007). Roughly speaking, cognitive dynamics are closer to inherent limits on flexible adaptive performance when the temporal estimation task is performed while walking but not past those limits. Performance is sustained, but the component processes entailed by production of temporal estimates are less integrated in their coordinated activity; they acquire degrees of freedom and begin to vary with greater independence (which we see as a whiter signal). Such a hypothesis gains plausibility by the priority of dynamics in system identification. That is, one must first identify the inherent dynamics of a system before one can know reliably the nature of system components or how to go about their discovery (Holden et al., 2008; Kelso, 2003).

We speculate that past the limits of flexible adaptive performance, coordinated activity can no longer be sustained, as when a taxing or dangerous change in rough terrain stops a conversation between hikers. If we are correct, then the dynamics of performance yield more subtle prognostic information about dual-task performances, prior to performance breakdowns, or amplification of perturbations that shows up in more errors and reliably slower response times. Given also that pink noise is usually more pronounced in simple tasks compared with more difficult ones (Gilden, 2001; Kello et al., 2007), measures of performance dynamics might have practical value in human factors research, serving as indicators of pending performance breakdowns (Tollner, 2006).

The inherent sensitivity of control processes to task demands suggests a modeling strategy that assumes that synergies among cognitive processes, however conceived, are temporarily assembled or *soft assembled* to suit task demands (Hollis, Kloos, & Van Orden, in press; Kloos & Van Orden, in press; Riley, 2007). This strategy borrows from the motor control literature in which soft assembly equals the temporary assembly of muscle synergies to sustain motor coordination in real-time motor behavior, for example (Bingham, 1988; Kugler & Turvey, 1987; Turvey & Carello, 1995; Withagen, 2004). Soft assembly could explain the subtle changes in cognitive dynamics observed in the current experiment.

It provides an enhanced range of flexibility in how individuals assemble cognition to suit a task and thus accommodates the subtleties of context that dual tasks entail. Soft assembly also allows that dual tasks may be better seen as larger integrated tasks; the larger task differs in complexity from the sum of two tasks alone (Pellecchia et al., 2005; Shockley & Turvey, 2005). The participant does not perform two tasks, per se, but assembles dynamic synergies across the brain and body to become a temporal-estimating-while-locomoting device.

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