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Factorization of Force and Timing in Sensorimotor Performance: Long-Range Correlation Properties of Two Different Task Goals

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Abstract

Long-range correlations are often manifested in the form of $1/f^{\beta}$ noise in a series of repeated measurements of the same neural or behavioral variable. Recent work has demonstrated that the magnitude and nature of these long-range correlations reliably capture individual differences and variation in task performance. In sensorimotor timing experiments, task characteristics such as tapping or circle drawing affect these long-range correlations during the production of isochronous time intervals. Such correlations are highly reproducible across multiple trials for the same task but do not correlate between tasks. In the present experiment, we investigate whether two behavioral variables that are simultaneously controlled by the same participant in a given experimental condition can show such differentially organized fluctuations. In order to answer this question, 13 participants were asked to produce repetitive movements with their right index finger at a specified time interval (500 ms) and a specified force (8N) in the absence of an auditory metronome and visual feedback of force levels following a synchronization-continuation paradigm. Although participants showed high levels of consistency in the long-range correlations for each task component separately over multiple trials/observations, the long-range fluctuations for force and timing were found to show no correlations with each other for each participant. Cross recurrence quantification analyses (CRQA) revealed that there was limited shared structure between the timing and force time series data. Taken together, these results suggest that complex systems can organize

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multiple processes in a relatively independent manner while maintaining a high degree of reliability within one task parameter.

Keywords: Long-range correlations; Coordination; 1/f processes; Force-timing; Individual differences

1. Introduction

1/f^{β} noise refers to a specific temporal structure: the persistence of long-range correlations in the fluctuations between the successive states of a given variable. Time series data containing 1/f^{β} noise are composed of high-frequency, low-amplitude fluctuations nested within low-frequency, high-amplitude fluctuations, with a roughly inverse-proportional relationship between the frequencies and amplitudes of fluctuations. From an empirical perspective, 1/f^{β} noise is very robust; it is considered a *universal* statistical property emerging from complex systems, such as those underlying cognitive and sensorimotor mechanisms (Kello, Beltz, Holden, & Van Orden, 2007; Van Orden, Holden, & Turvey, 2003). 1/f^{β} noise occurs in a number of specific systems and dynamical behaviors, including, for example, reaction times (Van Orden et al., 2003), word naming (Kello, Anderson, Holden, & van Orden, 2008), rhythmic movement timing (Gilden, Thornton, & Mallon, 1995), coordination (Torre, Delignières, & Lemoine, 2007a), repetitive force production (Sosnoff, Valantine, & Newell, 2009; Wing et al., 2004), healthy gait (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995), pathological gait (Hausdorff, 2009; Hove, Suzuki, Uchitomi, Orimo, & Miyake, 2012), heart rate (Peng, Havlin, Stanley, & Goldberger, 1995), and neural activity (Linkenkaer-Hansen, Nikouline, Palva, & Ilmoniemi, 2001).

A particular issue posed by the study of 1/f^{β} noise, or long-range correlations in experimental time series, is in choosing appropriately between broad and narrow focuses, between generic explanatory principles and specific accounts (Torre & Wagenmakers, 2009). It is not surprising then that even in the limited domain of human cognition and motor behavior, there are a wide variety of approaches to the 1/f^{β} phenomenon. Some are rather conceptual while others are more strongly model-based. Some researchers have taken the option to develop powerful nomothetic or law-based theoretical accounts, such as metastability (Kello et al., 2008) or self-organized criticality (Bak, 1996). Proponents of this approach propose to uncover the generic principles and forms of organization which are likely to account the ubiquitous finding of 1/f^{β} across diverse systems and behaviors. Some others have opted for a more object-specific (or mechanistic) approach, trying to make out which of the components, processes, and interactions particular to the behavior under study are responsible for the observed long-range correlations (e.g., Torre & Delignières, 2008; West & Scafetta, 2003).

Series of repeated performances under similar conditions are often used in research studies in the fields of psychology and behavioral neuroscience. These iterations of the same movements produced by single individuals are likely to fluctuate in a correlated fashion. In other words, in these experiments, each iteration of a repetitive behavior that originates from a single source is related to the iteration that precedes it. Such types of correlations, which persist over time, are also called long-range correlations.

Although the existence of long-range correlations is a ubiquitous phenomenon that seems to be an intrinsic property of many complex system, that is, systems that have interdependent components that interact with each other at various time scales (Holden, Van Orden, & Turvey, 2009), some studies have shown that these long-range correlations might not be generic properties of complex time series but rather seem to be task and individual specific. For instance, in a timing experiment in which participants had to execute two unimanual rhythmic movement tasks that differed only by the type of motor output: rhythmic circle drawing, which involves continuous movements, and rhythmic tapping, which involves discontinued movement, Torre, Balasubramaniam, Rheaume, Lemoine, and Zelaznik (2011) have demonstrated that participants had distinct long-range correlations for tapping and circle drawing. They also showed that there was a high degree of consistency in the long-range correlation within each task.

In this context, the present work asks whether individuals have characteristic long-range correlations that affect sensorimotor performance very generally or in a task-specific manner. Our aim is to clarify whether the interaction between an individual and a specific task is likely to generate significant variance in the long-range correlation properties obtained from commonly designed cognitive or motor behavior experiments. In particular, we propose to assess the reproducibility of the long-range correlation properties, that is, the extent to which the serial correlation structure demonstrated by a subject in one trial represents (or predicts) the structure of the fluctuations from another task whose goals are realized simultaneously. Take, for example, a complex task like playing the piano. We can measure two outcome performance variables that could constitute successful performance, namely striking the key with the desired amount of force and at the appropriate time. Serial performance of force and timing have shown long-range correlation properties in previous experiments (Torre & Balasubramaniam, 2011; Torre et al., 2011; Wing et al., 2004). Although serial performance of force and timing have shown long-range correlation properties in previous experiments (Torre et al., 2011; Wing et al., 2003), the question of whether the long-range properties of force and timing collected from the same trial (and participant) are related remains open. Here we present the first systematic exploration toward coordination between two different task goals performed during the same trial.

Looking for relations between long-range correlation properties of simultaneous performance variables has been examined in two recent studies (Coey, Hassebrock, Kloos, & Richardson, 2015; Rigolli et al., 2014). In the former, dependencies between two different performance variables in the same task were explored: inter-tap intervals and key press durations in timing. In the latter, the relation between long-range properties of sensorimotor timing and autonomic nervous system activity was examined. However, the question of how two specific sub-goals are factorized for the achievement of successful performance in the same task (such as striking a piano key at the right time with the desired level of force) is yet to be examined.

To address this question, in the present experiment, we investigated whether two simultaneously controlled behavioral components (i.e., time interval production and force production) resulting from a single repeated motion (i.e., right index finger tapping) produced by the same participant in a given context could give rise to two different long-range correlations that are unrelated and dissociable. We hypothesized that participants will exhibit two distinct levels of serial correlation from the two simultaneously controlled behavioral variables resulting from a single repeated movement sequence. The relationship between long-term variation in force and timing will inform us about the neural and behavioral organization that is similar and different across the control process for each.

2. Methods

Thirteen participants (6 male; mean age 24.6 years) volunteered for the study. All participants were students from McMaster University and were right handed according to both self-report as well as the Edinburgh Handedness Inventory (average score was 73.3; Oldfield, 1971). Participants were free of any known neurological impairments or musculoskeletal impairment to the upper extremities and had normal or corrected normal vision at time of collection. In keeping with the Declaration of Helsinki, volunteers gave their informed consent prior to participation in accordance with McMaster Research Ethics Board regulations.

2.1. Apparatus

The apparatus used is similar to the one described in detail in Therrien and Balasubramaniam (2010). Force data were collected, using a 6 DOF load cell (ATI Nano 17) mounted on vertical stainless steel t-stands so that forces were applied on the horizontal (z axis). Both stands were fixed to the table surface with a computer monitor placed behind for displaying the participants' force-contingent visual feedback. The data were sampled at 1,000 Hz using custom software written with Labview (Labview 8.2, National Instruments, Austin, TX). The software provided visual feedback to the participants on a Viewsonic 19-inch flat panel display with a refresh rate of 60 Hz. The force transducers were calibrated using a factory generated 6 × 6 matrix that describes the relation of voltage gain to resolved force and allowed for correction of crosstalk between each measured force and moment arm. Voltage signals were amplified with an AMTI amplifier and digitized with the National Instruments PCI-6220 DAQ, at a resolution of 1/320 N in the z axis. There was no hysteresis in the zero level of the resolved forces, indicating no significant drift or offset in the force data associated with continued use of the device.

2.2. Task

Participants sat in a comfortable non-rotating chair with no armrests and had both forearms resting on a table. They were positioned so that they could comfortably reach both force transducers without strain to the upper extremities and successfully perform the pinch grip motion. During the experiment, participants were presented with a visually specified target force and were asked to match it by pinching the force transducer between the thumb and index fingers of the right hand. The target force was presented as a column of a bar plot on the computer monitor, which was placed at a comfortable distance in front of the participant. Axis labels of the graph were present, providing participants with additional information about the absolute magnitude of force to be produced. A second column, adjacent to the first, displayed the participant's current force output. The height of the second column varied contingent upon the amount of force applied to the transducer. The system gain was set so that 5 N of force produced by the participant corresponded to a 1 cm increase in the amplitude of that second column.

Participants wore headphones, through which an auditory metronome could be heard. Participants were instructed to repeatedly match the amplitude of the second column to the target bar by pinching the force transducer with the correct amount of force: 8N as specified by the height of the target column on the visual display, each time the metronome sounded. The height of the target column remained fixed at the prescribed target force magnitude throughout each trial. The metronome was set to a frequency of 2 Hz, corresponding to 500 ms intervals between pinches on the force transducer. The metronome was present for the first 10 s of each trial, allowing participants to synchronize their movements to the 2 Hz movement frequency and the 8N force level. After 10 s, both the auditory metronome and the visual feedback were extinguished and participants were instructed to continue squeezing the force transducer at the prescribed rate for the remainder of the trial. All participants performed a total of 512 iterations of performance in the continuation phase of the trials, thus simultaneously producing a series of force and timing responses, which were both subject to short- and long-range correlation analyses. Each participant performed a total of 10 continuation trials, yielding a total of over 5,000 data points for each variable per participant.

3. Results

3.1. Tests of short–term correlations

In order to rule out the presence of short-term correlations (in the form of negative successive forces/intervals), we performed a lag-one autocorrelation across all trials of all participants for both the timing and the Force data. Lag-one autocorrelations were positive for both Force (0.28 ± 0.08) and timing (0.39 ± 0.11), suggesting the lack of any short-term anti-persistence in the data. Our data are consistent with previous findings; although short-term anti-persistence is commonly seen in the control of timing (Wing & Kristofferson, 1973), it is not seen in even relatively short force-continuation trials (Therrien & Balasubramaniam, 2010a).

3.2. Long-term correlational structure

To assess the long-range correlation properties, we used a method called detrended fluctuation analysis (DFA) in a standard way (for details on the method, see Peng et al., 1993; Weron, 2002). The DFA uses diffusion properties of a time series, assessing the relationship between the mean amplitude of fluctuations and the size of the window within which the fluctuations are observed. Basically, the series is first integrated and divided into non-overlapping intervals of equal lengths. After applying a linear detrending function within each interval, the mean standard deviation $F(n)$ is determined. This process is repeated and averaged for all possible interval lengths n ranging between 10 and 256 points. For fractal series, a power relationship between $F(n)$ and n, characterized by a scaling exponent $\alpha \in [0, 2]$, is expected. The results of the analysis are represented in a so-called diffusion plot [$\log(F(n))$ as a function of $\log(n)$]. A linear diffusion plot is thus expected, and α is given by the slope of the regression line. For $\alpha \in [0, 1]$, the series can be considered fractional Gaussian noises (i.e., stationary series), and for $\alpha \in [1, 2]$, the series are fractional Brownian motions (i.e., nonstationary series). According to the current definition of $1/f^{\beta}$ noise in the literature, and given the linear relationship that exists between the spectral indexes β and the exponents provided by DFA, series can be considered to contain $1/f^{\beta}$ noise, or persistent long-range correlations for α ranging from 0.75 to 1.25. All calculations were made using a toolkit adapted from the algorithm of Weron (2002) in MATLAB® using the steps outlined in Torre et al. (2011).

3.3. Mean performance and individual differences

The mean interval of the series for 480 ms (*SD* = 30) and the mean force was 8.59 N (*SD* = 1.47) for the force component of the task. The mean standard deviations were 30 ms (*SD* = 8) and 1.53 N (*SD* = 0.63), respectively. Representative samples of the series of force and timing intervals can be found in Fig. 1. In previous experiments on repetitive force production after visual feedback withdrawal, a short-term escalation effect is observed (Therrien & Balasubramaniam, 2010). Although we did not perform any specific analyses to look for short–range force escalations, the positive lag-one correlation suggests that successive intervals were more likely to be positively correlated than not. Secondly, there was no long-term escalation effect, as seen in the bottom panel of Fig. 1.

Inspection of Fig. 1 reveals that participants exhibit similar correlation structures across different trials of the same task sub-goal (force vs. timing), but they exhibit qualitative differences between each. However, there were no differences in the exponents for each task.

DFA yielded a mean α value of 0.82 (*SD* = 0.10) for the time intervals and 0.87 (*SD* = 0.13) for the force intervals, which places them both in the pink noise range. In order to use a similar metric as used by Torre et al. (2011), we tested for linear correlation between the mean individual α exponents in tapping and force production. As shown in Fig. 2, there was no significant correlation, $r\ (11) = .17$, $p = .28$, between the long-range correlation properties demonstrated by the participants in force and timing components of the task. It is important to keep in mind that these correlations were performed on the mean values of a participant obtained from averaging over all the trials, instead of creating one long composite trial. We also normalized the obtained DFA exponents for force and timing on each trial across the 13 subjects (thus yielding 130 data

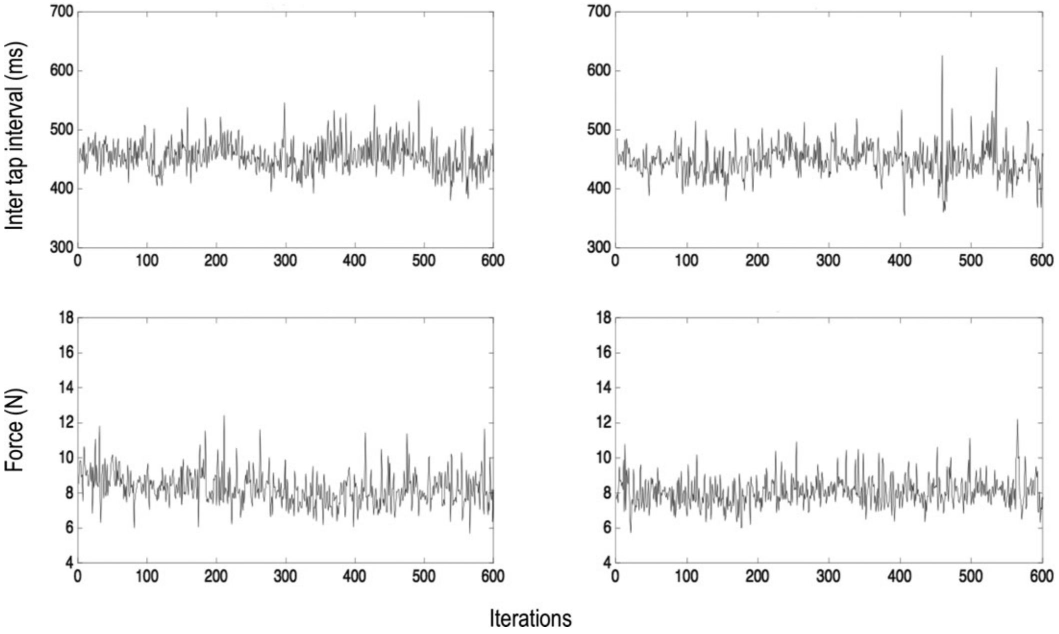

Fig. 1. Representative time interval and force series produced by one participant in different trials. The figure illustrates the within-individual consistency of the serial correlations produced. Within the same task, two timing and force time series produced by the same participant exhibit very similar correlation structures (characterized by similar α exponents). But different patterns of exponents can be seen for the force and interval data for the same participants on the same trials.

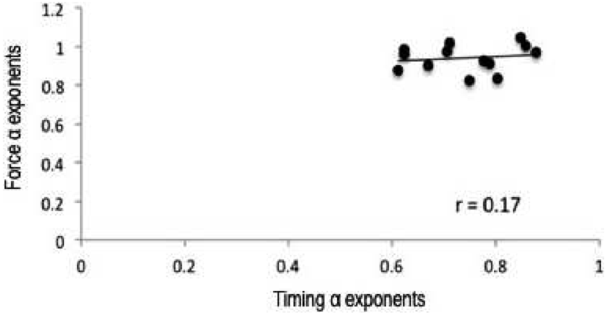

Fig. 2. Correlations between the individual average α exponents demonstrated in force and timing components, showing the absence of a significant correlation (p = .28) for the 13 participants.

points). Correlating across these data points also did not yield any significant relationship (*r (128)* = .12, *p* = .46).

We estimated the reproducibility of the exponents across the repetitions performed by the participants for each component of the task. The Cronbach's alpha was 0.93 for timing and 0.91 for force (*M* = 0.92). Thus, the timing and force sequences are extremely reliable within subjects. Said differently, participants produced very similar profiles of *1/f* noise across trials for each task, but they had different profiles for force and timing.

3.4. CRQA analysis and surrogate data

In order to test the data for dependencies across multiple timescales of activity between force and timing, we ran a cross-recurrence quantification analysis or CRQA (see Cluff, Boulet, & Balasubramaniam, 2011, for details of the method used) between the two time-series for the experimental data and for phase-randomized surrogate data (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992). Cross-recurrence quantification (CRQ) was introduced by Zbilut et al. (1998) as an extension to RQA (Balasubramaniam, Riley, & Turvey, 2000; Riley, Balasubramaniam, & Turvey, 1999). This extension involves effectively embedding two synchronous time series in a reconstructed phase space. Rather than tallying the recurring locations of a single embedded time series (auto-recurrence), the number of instances for which locations are shared by the two time-series is tallied in CRQ. Percent recurrence (%REC) in CRQA corresponds to the ratio of the number of shared location relative to the number of possible shared locations in phase space. This method, also referred to as aggregative CRQA (Coco & Dale, 2014), was preferred over cross-correlational methods since it requires no assumptions about the nature of the data in question, and it offers an objective method for studying coupling between time series.

The following CRQA parameters were used: Embedding delay $\tau = 50$ ms; Embedding dimension = 3, radius = 10 and minimum line length = 5. CRQA parameters (%REC) were computed for the time series data generated in each trial and then averaged across all trials for each participant. Results revealed a higher %REC value $M = 1.29 \pm 0.3$ for the actual time series compared to $M = 0.81 \pm 0.5$ for the surrogate time series. This difference was, however, not statistically significant, suggesting independence of the two timing and force time series.

4. Discussion

The results may be summarized as follows. While both force and timing variables show pink noise indexed by DFA values in the 0.8–0.9 range, there was no evidence of either value being significantly different from each other. Both exponents were extremely reliable across trials for each participant, but they were different across participants themselves. And most important, the value of the DFA exponent for force was not correlated with that of timing for the same participant, thus supporting the idea that they may be independently organized and controlled. The CRQA analyses revealed that any shared structure in the the timing and force time series was not qualitatively different from that seen in phase-randomized surrogate data.

It has been argued that pink noise (DFA exponents in the range observed here for force and timing) is indicative of interaction-dominant dynamics and reflects the nonlinear interaction of many interdependent processes (Holden et al., 2009; Ihlen & Vereijken, 2010; Stephen & Mirman, 2010; Van Orden et al., 2003). Pink noise is an emergent property of the coordination of many (neural and behavioral) processes operating across timescales, rather than being the product of a single system component or mechanism (Bak, 1996). The behavior of complex systems is primarily defined by the interactions of their components, and this functional organization is reflected in the dynamics of behavior (Van Orden, Kloos & Wallot, 2011). The question we asked is if two variables that are the product of different (but perhaps related) interaction dominant dynamics can be organized and controlled independently of one another. Evidence from Coey et al. (2015) suggests that it is indeed possible. However, in their study they looked at systematic long-range variation in two different dependent measures that can be extracted from a time series that could explain performance, namely key-press durations and response intervals. In our present study, we asked whether two sub-goals that are part of the same behavioral performance (force and timing) can be organized reliably within and across participants, yet independent of one another.

We raised the question of whether the control processes for force and timing are independent of one another as suggested by neuropsychological and behavioral evidence. In previous studies participants have shown differential accuracy and variability in producing sequential forces, while having little difficulty in maintaining time intervals in the absence of a metronome (Pope, Wing, Praamstra, & Miall, 2005). Further, Pope et al. (2005) demonstrated that Parkinson's patients showed marked impairments in a rhythmic force production task, but their ability to produce time intervals was spared. However, several studies have shown an interaction between force and timing control when they have to be constrained simultaneously (Billon et al., 1996; Sternad et al., 2000). However, our results seem to confirm the findings of Therrien and Balasubramaniam (2010), Therrien, Lyons, and Balasubramaniam (2010), Therrien, Richardson, and Balasubramaniam (2011), and Therrien, Lyons, and Balasubramaniam (2012), suggesting that the force and timing might be independently organized. It would be very interesting for the field to determine the neural and behavioral organization that support the long-range correlations discovered in repeated performance for both force and timing. Although both variables are the product of interaction dominant dynamics (Van Orden et al., 2003), their behavioral output seems to be largely uncorrelated. It is tempting to now argue that force and timing could be organized anatomically independently and that their behavior can be traced back to independent neural circuitry (Ivry, 1986).

Neuroimaging studies have confirmed enhanced activation of the basal ganglia in force production (Pope et al., 2005). Additionally, patients with focal basal ganglia lesions suffer from force production impairments (Aparicio, Diedrichsen, & Ivry, 2005), and the converse is true for individuals with cerebellar damage (Schlerf, Spencer, Zelaznik, & Ivry, 2007; Spencer, Zelaznik, Diedrichsen, & Ivry, 2003). Neuroimaging methods that have argued for force and time independence have well-known logical shortcomings that make it difficult to justify isolation or localization of function, regardless of whether the data are brain imaging or behavior (Anderson, 2014; Uttal, 2001). It is important to realize that emergent properties as specified by complex behaviors like force or time-interval production often use overlapping brain structures and networks. It is unlikely that such networks can ever be ruled as independent of each other.

Previous studies in the area such as Coey et al. (2015) and Rigoli, Holman, Spivey, and Kello (2014) have looked at the nested structure of multiple components from the same behavior. The novelty of this study comes from the fact that two sub-goals of the same behavioral task have not been studied in the context of the independence in their long-term performance. Human cognitive science experiments are replete with settings where two or more behavioral goals can be simultaneously achieved, for example, pitch and volume in singing or speech (Therrien et al., 2012). It is important to underscore that this differs from traditional accounts of dual tasking where two or more performance variables are controlled, for example, singing while riding a bike. This study reveals that individuals have reliable long-range correlations in each task goal, yet show independent control of each.

This study also complements the finding of Torre et al. (2011), who found that the long-range correlation properties of circle drawing and tapping show remarkable consistency. Yet performance on one does not predict the performance of another. We show that a very similar behavioral organization is possible when performing a task that has two different sub-goals. As indexed by long-range correlations in the form of pink noise, the performance of each sub-goal is internally consistent and reliable across participants, but the performance across tasks is not correlated.

As is evident from the present work, determining independence and causal dependence requires careful and concerted efforts borrowing from multiple methodologies available in modern cognitive science for studying cognition as coordination. Future studies should employ more sensitive tools to look at coordination across these multiple time series (Coco & Dale, 2014; Moscoso del Prado Martín, 2011). One should be careful not to look for mere temporal correlations (or coherence) in data sets where units of measurement are different (force and time). A good candidate model for studying such systems comes in the form of complexity matching, a term borrowed from statistical mechanics (West, Geneston, & Grigolini, 2008). Complexity matching is a form of convergence used to denote matching statistical distributions, when such distributions have power law characteristics. It would be very interesting to explore issues of dependence and independence of complex behavioral and neural signals using techniques developed for studying complexity matching (Abney, Paxton, Dale, & Kello, 2014; Rigoli et al., 2014). Using this technique could help us get closer toward understanding individual differences in studying cognition as coordination.

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