*Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 19, No. 2, pp. xx-xx.*

# Fractal Coordination in Adults' Attention to Hierarchical Visual Patterns

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***Abstract:*** *A display that contains hierarchically nested levels of order requires the perceiver to selectively attend to one of the levels. We investigate the degree to which such selective attention is sustained by a soft-assembled emergent coordinative process, one that does not require designated executive control. In the case of emergent soft-assembly, performance from one trial to the next should show characteristic interdependence, visible in the fractal structure of reaction time. To test this hypothesis, we asked participants across three experiments to decide whether two displays matched in a certain way (e.g., in a local element). In order to gauge this coordinative process, task constraints were experimentally manipulated (e.g., familiarity, predictability, and task instruction). Obtained reaction-time data were subjected to a spectral analysis to measure the degree of interdependence among trials. As predicted, results show correlated structure across trials, significantly different from what would be predicted by an independent-process view selective attention. Results also show that the obtained spectral scaling exponents track the degree of coupling in the task as a function of the degree of task constraints. Findings are discussed in terms of the relative organism-environment coupling to sustain an adaptive behavior.*

***Key Words:*** perceptual organization, Gestalt, fractal exponents, emergence, soft-assembly

## FRACTAL COORDINATION IN ADULTS' ATTENTION TO HIERARCHICAL VISUAL PATTERNS

A prevalent feature of our visual context is its nested structure: Details of individual elements are nested within overarching patterns, which themselves are part of a global Gestalt, and so on. Take a child's room, for example. One can zoom in, to differentiate among small units (say the dirty spot on Elmo's fur); and one could zoom out to detect large patterns of Gestalt (say the thematic arrangements among the toy soldiers and the stuffed animals). To derive meaning, one needs to attend to a particular level of order along the hierarchy of

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orders, while ignoring variation that falls outside of that chosen level. What are the underlying processes that make such attentional processes possible? To use the example mentioned above: how can one perceive a whole scene in a child's room without getting distracted by – and yet still perceiving – a patch of dirt on an individual toy?

Postulating an a-priori preference for a certain level of order would provide part of the answer. There is indeed evidence of a so-called 'global precedence', a tendency to take into account a global aspect of a display, even after being instructed to ignore it (e.g., Blanca, Luna, López-Montiel, Zalabardo & Rando, 2002; Dukette & Stiles, 1996; 2001; Enns & Girgus, 1985; Hughes, Layton, Baird, & Lester, 1984; Kimchi, 1998; 2009; Kimchi, Hadad, Behrmann, & Palmer, 2005; Navon, 1977; Sanders & Poeppel, 2007). However, global precedence cannot account for the full story. Take for example the finding that global precedence is weakened (or missing altogether) when the display consists of only a few large elements (e.g., Burack, Enns, Iarocci, & Randolph, 2000; Dukette & Stiles, 1996; 2001; Enns & Girgus, 1985; Kimchi, 1990; Kimchi et al., 2005; Martin, 1979; Scherf, Behrmann, Kimchi, & Luna, 2009). Furthermore, there are reports that local elements can be detected more easily when they are part of a global order than when the global order is omitted (Dukette & Stiles, 1996; 2001; Quinn, Burke, & Rush, 1993). Such interactions among levels of orders are not anticipated by a theory of specialized attentional processes (see also Deutsch, & Deutsch, 1963; Kahneman, 1973; Treisman, 1960).

The idea pursued here is that attention to hierarchical displays is controlled by a soft-assembled coupling between multiple processes, emergent in the actor-task system (e.g., Kelso, 1995; Smith, 2005; Riley & Turvey, 2002; Turvey, 1990, 2007). The factors that contribute to soft-assembly reside neither exclusively in the actor's competences or biases, nor in the task's statistical contingencies. Instead, they combine a multitude of neurophysiological, perceptual, and motor sub-systems that interface with the details of the task. Soft-assembly implies the coming together of cooperative and competing factors, yielding a super-ordinate whole that sustains an adaptive task-actor coupling across trials. The resulting coupling is both stable enough to ignore perturbations and, at the same time, flexible enough to take into account seemingly irrelevant information (for a discussion see Kello & Van Orden, 2009).

The characteristics of emergent soft-assembled behavior are in line with the context effects of the global precedence, including the effects of age, experience, gender, and task specifics documented before (e.g., Kimchi, Amishav, & Sulitzeanu-Kenan, 2009). More importantly, soft-assembly can explain the dual nature of attention: its selective focus on an isolated level of order (to the expense of other levels of order), and its integrative and distributed property across multiple levels of order.

The theory of emergent soft-assembly has been applied to motor performance, perception, cognition, and social reasoning (for reviews, see Goldfield, 1991; Smith, 2005; Smith & Breazeal, 2007; Turvey, 2007). However, it has not been explored in the area of attention (for a review of current attention theories, see Fisher & Kloos, in press). The goal of the current paper is to fill this gap, using fractal procedures to measure the strength of the task-actor coupling.

Fractals represent self-similar structures with functional and topographical features that are reproduced in miniature on finer and finer scales (Bassingthwaighte, Liebovitch, & West, 1994; Brown & Liebovitch, 2010; Mandelbrot, 1967). Based on these properties, fractal analyses provide a way of gauging the coordination among processes that operate on different time scales (Bak, 1996; Bak, Tang, & Wiesenfeld, 1987; Holden, 2005). At the center of these analyses is the assumption that the degree of task-actor coupling is captured in a single value, namely the fractal scaling exponent (e.g., Gilden, 2009; Riley & Turvey, 2002; Van Orden, Kloos, & Wallot, 2011).

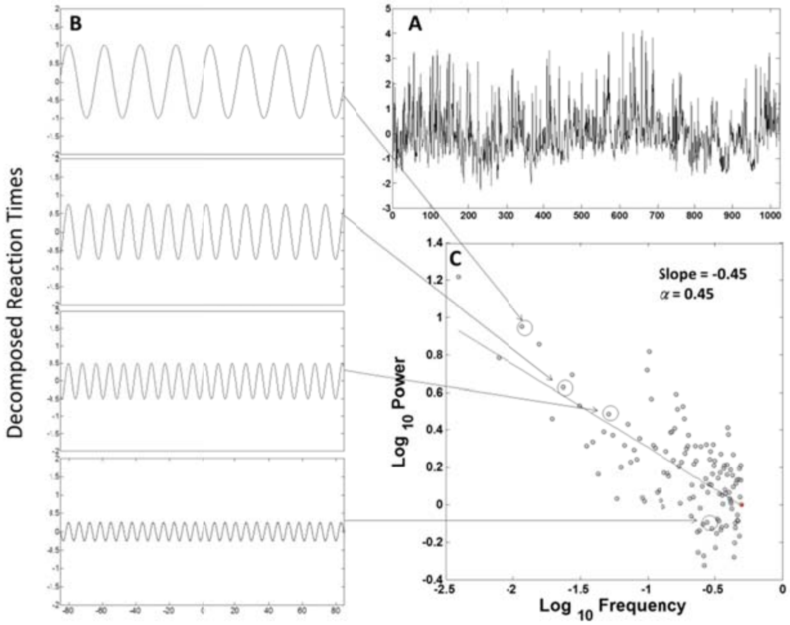

**Fig. 1.** Schematic explanation of a fractal analysis. A: reaction-time data of a participant completing 1100 trials of the current task. B: four example sign waves of a particular amplitude (power) and frequency. C: spectral plot of sign waves extracted from the reaction-time data, plotted as a function of their power and frequency, in log-log coordinates. The slope of the plot's regression line estimates the scaling exponent α. Here the scaling exponent is *α* = .45, an intermediate value between *α* = 0 (white noise) and *α* = 1.0 (idealized 1/*f* noise).

There are several mathematical approaches to return fractal scaling exponents, the most widely used being the spectral analysis (Castillo, Van Orden, & Kloos, 2011; Holden, 2005; Press, Teukolsky, Vetterling, & Flannery, 1992; Van Orden, Holden, & Turvey, 2003). Figure 1 provides a brief overview of it: The original trial series (Fig. 1A) is decomposed into a series of sinusoidal functions that vary in their oscillation frequency and power (Fig. 1B). Each sinusoidal function is thought to represent a process or aspect of behavior that varies on a unique time scale. To determine the degree of coordination among these time scales, each extracted sinusoidal function is then depicted on a double-logarithmic frequency-power scatter plot (Fig. 1C). The relative size of the slope of the resulting regression line (i.e., the scaling exponent of the fractal analysis) quantifies the relative strength of the coordination among time scales (see also Holden, 2005; Press et al., 1992).

A variety of motor and perceptual task have yielded above-zero scaling exponents, include walking (Kiefer, Riley, Shockley, Villard, & Van Orden, 2009), standing (Duarte & Zatsiorsky, 2000), tapping (Coey, Hassebrock, Kloos, & Richardson, 2013; Lemoine, Torre, & Delignières, 2006), tracing (Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009), generating pressure (Athreya, Van Orden, & Riley, 2012), and producing learned rhythms (Madison, 2004). Such patterns of variability were also found in cognitive tasks, including speeded classification (Clayton & Frey, 1997; Ward, 2002), the perception of reversible figures (Aks & Sprott, 2003), visual search (Aks, Zelinsky, & Sprott, 2002; McIlhagga, 2008), speech production (Holden & Rajaraman, 2012), time estimation (e.g., Gilden, 2001; Kuznetsov & Wallot, 2011), and mental rotation (Gilden, Thornton, & Mallon, 1995).

Yet, the interpretation of fractal patterns has seen some debate, contentious at times (cf., Gilden, 2001; 2009; Ihlen & Vereijken, 2010; Kelty-Stephen & Mirman, 2013; Stephen & Mirman, 2010). At one extreme, there is the claim that fractality in psychological tasks is nothing more than a statement in algebraic calculus, a methodological artifact of some sort with little to say about the underlying process (Bogartz & Staub, 2012; Wagenmakers, Farrell, & Ratcliff, 2004; 2005). At the other extreme, non-zero fractality is seen as evidence of a complex system being poised at a perfect balance of competing tendencies that combine randomness and order adaptively (Bak, 1996; Bak, Tang, & Wiesenfeld, 1987). Between these two extremes, there are various claims about the meaning of fractality (cf., Dale, 2008), ranging from relatively conservative views (e.g., fractality demonstrating interdependence of trials) to relatively radical reviews (e.g., fractality demonstrating self-organized criticality).

In our view, existing evidence supports at least an intermediate stance between the most conservative and most radical interpretation of above-zero fractal exponents, namely that fractal analyses provide a way of gauging the coordination among processes that operate on different time scales. This stance is motivated by findings that the relative size of fractal exponents varies with the degree to which adaptive coupling is achieved. For example, the scaling exponent was found to increase as participants gained more practice in a motor-aiming task (Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). And it increaseed when participants could anticipate the next trial in a speeded-decision task (Kello, Beltz, Holden, & Van Orden, 2007). In contrast, the scaling exponent decreased when memory requirements were ramped up in a classification task

(Clayton & Frey, 1997; Ward, 2002), or when binocular disparity was increased in a reversible-figure perceptual task (Aks & Sprott, 2003). A relative decrease was also found when trials were separated, either by feedback (Athreya, Van Orden, & Riley, 2012; Kuznetsov & Wallot, 2011) or by a variable amount of time (Holden, Choi, Amazeen, & Van Orden, 2011). In each of these cases, the modifications interrupted sustained actor-task coupling.

Finding that the relative size of the fractal exponent tracks the degree of coupling in the actor-task system is difficult to explain under a view that fractals are mathematical epiphenomena. Instead, fractal exponents appear to measure the interdependence of factors in a soft-assembled system (for discussions, see Holden et al., 2011; Riley & Turvey, 2002). Building on these insights, we devised a task that allowed us to determine the fractality of sustained attention. Specifically, we created hierarchical displays, each consisting of three unique elements that gave rise to a global contour. The task was to compare two of these displays, either in one or both levels of order. Trials differed in whether there was a match between the two displays or not. Reaction times of decisions across a large number of trials were subjected to a spectral analysis, the dependent measure being the size of a person's fractal scaling exponent.

We also manipulated a set of factors that might affect attention to a nested level of order. The first factor pertained to the instructed focus of attention. In Experiment 1, participants were instructed to attend to the global shape of the displays. Given the documented global precedence, we expected this task to yield a strong task-actor coupling, and thus to yield highest fractal exponents. In contrast, participants in Experiment 2 had to decide whether two displays shared an element. This task required participants to compare elements individually, likely to result in weaker task-actor coupling. Thus we expected lower fractal exponents in Experiment 2 than Experiment 1. In Experiment 3, we sought to further perturb the task-actor coupling, this time by asking participants to compare displays in both their global shape and their individual elements. This task was expected to result in lowest fractal exponents.

The second factor pertained to whether the elements readily gave rise to the global contour or not. Elements were either familiar letters printed on a salient background, ones that easily combined into the global contour. Or they were unfamiliar line drawings that needed to be integrated to support the perception of the global shape. When the task was to attend to the global shapes, we predicted higher fractal exponents with familiar elements (letters on salient background) than with unfamiliar elements (line drawings on white background). This difference was expected to disappear when no integration was required, namely when the task was to attend to individual elements.

Finally, the third factor pertained to the order in which different types of trials were presented to participants. Types of trials were presented either randomly or in a prescribed order that allowed participants to anticipate the next trial, at least to some degree. The random-order presentation mode most likely provides information about the baseline coupling that is necessary to perform in the task. In contrast, in the predetermined-order presentation mode, when some anticipatory learning is possible, the task-actor coupling was likely to be strengthened (see also Kello et al., 2007). We therefore predicted higher fractal exponent when trials appear in a predetermined order than when they appear randomly.

## EXPERIMENT 1

Participants were asked to compare displays in their global shape, derived from the contour of three individual elements in the display. A 2-by-2 between-group factorial design crossed element familiarity (familiar vs. unfamiliar elements) with trial order (random vs. predetermined order of trials).

## Method

### Participants

Participants in all three experiments were native English speakers who had no self-reported history of vision impairments. They received course credit in exchange for their participation. For this experiment, participants were 58 adults between 18 and 42 years of age (35 women, 23 men; *M* = 21.7 years, *SD* = 4.5 years), randomly assigned to one of the four experimental conditions. The number of participants in each condition ranged between 14 and 16, and age was about equally distributed across cells. Five additional participants were tested, but not included in the final sample, due to equipment problems (*n* = 2), or because they did not meet the 75% accuracy criterion (*n* = 3, see Procedure).

### Materials

Displays were created for which the contour of elements combined into global shapes. Elements were either lower-case letters printed on a background (see top row of Fig. 2), or unfamiliar line drawings printed without background (referred to as ‘characters’, see bottom row of Fig. 2). Four of the letters (*c*, *s*, *x*, *z*) had a square contour, another four other letters (*p*, *q*, *g*, *y*) had a low-rectangle contour (i.e., a rectangle that reaches below the bottom line of the square), and the remaining four letters (*b*, *h*, *f*, *l*) had a high-rectangle contour (i.e. a rectangle that reaches above the top line of the square). For characters, various types of lines combined into quadrilaterals. They gave rise to the same contour as the letters (i.e., square, low-hanging rectangle, or high-hanging rectangle), but without a background to highlight the contour.

Three elements (either letters or characters) were grouped into a display, with the restriction that no element was repeated within a display. Depending on the contour of an element, 27 unique global shapes were possible. We used 24 of these shapes, omitting the three shapes in which all three elements shared the same contour. Global shapes that contained two letters of the same contour were used in 48 unique displays, and global shapes that contained each of the three contours were used in 64 unique displays.

During a trial, two displays were presented next to each other. They could match in an element (i.e., ‘element-match’ trials, Fig. 2A-B), they could match in global shape (i.e., 'shape-match' trials, Fig. 2C-D), or they did not match in either element or shape ('no-match' trials, Fig. 2E-F). For the element-match trials, there was only one shared element, this element appearing in the same location in both displays. There were 440 unique shape-match trials, 440 unique element-match trials, and 220 unique no-match trials. Care was taken to ensure that a particular element (e.g., the letter *z*) appeared equally often throughout, and equally often within the left and right display of a trial.

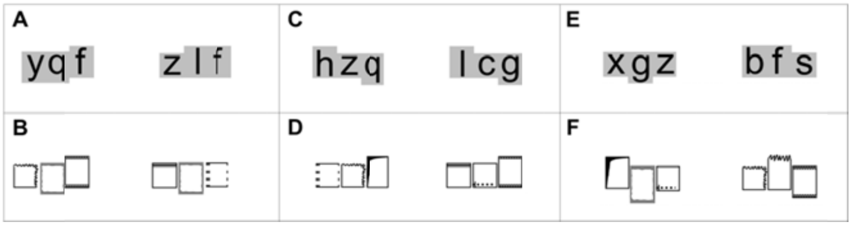

**Fig. 2.** Example pairs of displays, used in the three experiments. Top row: letters (i.e., familiar elements). Bottom row: characters (i.e., unfamiliar elements). A, B: element-match trials (i.e., displays share one element). C, D: shape-match trials (i.e., displays match in global shape). E, F: no-match trials.

A total of 1,100 trials were presented in five blocks of 220 trials each, with 88 shape-match trials, 88 element-match trials, and 44 no-match trials within a block. Trials within a block were presented either randomly or in a predetermined order. The predetermined order followed a sequence that consisted of three unique patterns, shown schematically in Table 1. Pattern 1 started with one no-match trial (N), followed by two shape-match trials (SS), and followed by two element-match trials (EE). This pattern was repeated six times in a row. Pattern 2 started with two no-match trial trials (NN), followed by four shape-match trials (SSSS), and followed by four element-match trials (EEEE). This pattern was repeated seven times in a row. Finally, Pattern 3 started with three no-match trials (NNN), followed by six shape-match trials (SSSSSS), and followed by six element-match trials (EEEEEE). This pattern was repeated eight times in a row. Together, the three patterns yielded a total of 220 trials. Reaction time and response accuracy were recorded for each trial.

**Table 1.** Patterns used in the Predetermined-Order Condition.

| *Pattern* | *Sequence* | *Number of repetitions* |
|---|---|---|
| 1 | N-S-S-E-E | 6 |
| 2 | N-N-S-S-S-S-E-E-E-E | 7 |
| 3 | N-N-N-S-S-S-S-S-S-E-E-E-E-E-E | 8 |

*Note*: N, S and E refer to the trial types No-match, Shape-match, and Element-match respectively. There were three patterns, referred to as Pattern 1, 2, and 3. A block started with Pattern 1, repeated six times, followed by Pattern 2, repeated seven times, and then followed by Pattern 3, repeated eight times.

### Procedure

Participants were tested individually in the laboratory, using Superlab Pro (Version 2.0) to administer the experiment on a PC laptop (Intel Core Duo processor of 2.40 GHz). Instructions and training were identical across conditions, the only difference pertaining to the stimuli and the order in which they were presented. During training, participants were shown an example of each type of trial, and a detailed explanation was given: For the shape-match trial, participants learned that the two displays did not share a letter/character, but that they had the same overall shape (the experimenter pointed to the shapes on the computer screen). Care was taken to clarify that mirror-image shapes were considered no-match. For the element-match trials, participants learned that the displays shared a letter/character, located in the same relative position of the display. Finally, for the no-match trial, participants learned that the two displays did not have the same shape, nor did they share a letter/character, and therefore did not match.

The specific task was to decide if the two displays match in global shape. Participants were given a numeric keypad for with the keys 1 and 2 were marked with the letters Y and N (to correspond to “Yes” and “No” response options, respectively). Using their dominant hand, participants were instructed to press “Yes” when the displays matched in shape, and “No” otherwise. Feedback training consisted of nine trials, three of each type, administered in a random order. Incorrect responses were clarified. Participants were then given the following instruction: “The experiment will last about 60 minutes. Make sure to be as quick and precise as possible.” The experimenter then left the room, and the participants completed the task alone. Participants had to perform correctly on at least 75% of the trials to be included in the sample.

## Results & Discussion

To get at the main objective of the study, namely to explore the task-actor coupling sustained across trials, we describe the results of the spectral analyses of reaction-time data in detail. Performance in terms of reaction-time data and accuracy are provided in Fig. 3: Accuracy (Fig. 3A) was affected by (i) trial type [$F(2, 108) = 15.96$, $p < 0.001$; $\eta^2_p = 0.23$; better performance on no-match trials ($M = 0.972$) than either shape-match ($M = 0.947$) or element-match trials ($M = 0.934$), $p < 0.01$], and (ii) trial-type-order interaction [$F$ (2, 108) = 4.01, $p < 0.02$; $\eta^2_p = 0.07$; better performance on shape-match than element-match trials in the predetermined-order condition, but not in the random-order condition]. Reaction time (Fig. 3B) was affected by (i) familiarity [$F(1, 54) = 11.62$, $p < 0.001$, $\eta^2_p = 0.18$; shorter RT in the familiar-element ($M = 1.34$ s) than in unfamiliar-element ($M = 1.71$s) condition], and (ii) familiarity-order interaction [$F(1, 54) = 2.44$, $p < 0.10$, $\eta^2_p = 0.04$, the effect of familiarity was present only in the predetermined-order ($M_{Familiar} = 1.19$s; $M_{Unfamiliar} = 1.73$s), not the random-order ($M_{Familiar} = 1.49$s; $M_{Unfamiliar} = 1.69$s) condition]. No other interactions or main effects were significant.

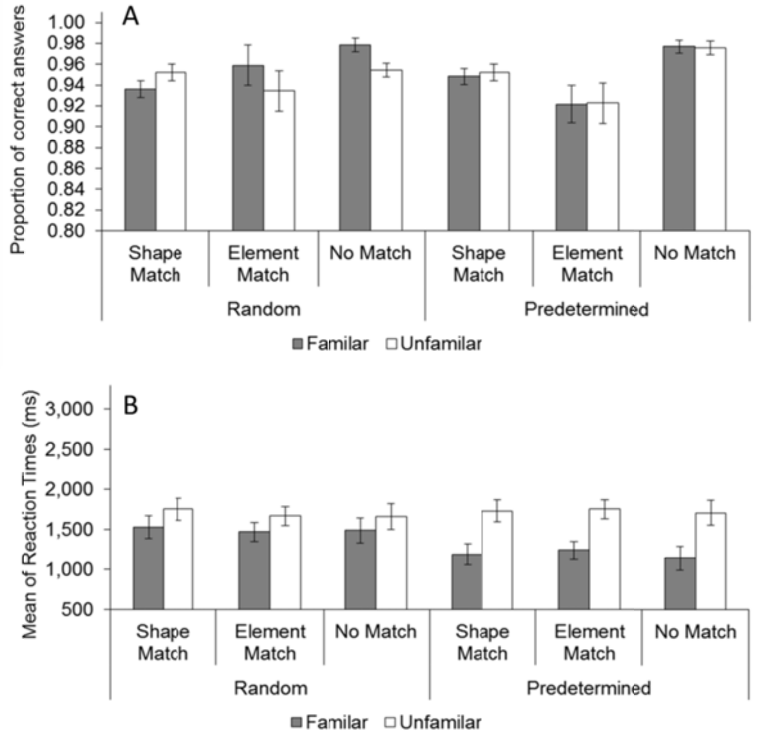

**Fig. 3.** Means and standard errors for proportion of correct answers (A), and reaction times (B) in Experiment 1, separated by trial type and experimental condition.

Following the spectral-analysis steps outlined by Holden (2005), reaction-time data of correct and incorrect trials were 'cleaned', to exclude trials that fell outside of the typical range. In particular, we first excluded trials that were longer than 10s or shorter than 300ms. Excluded trials were not replaced. The mean of the remaining trial series was then calculated (separately for each participant), and observations that fell beyond three standard deviations from the participant's own mean were removed from the series. Finally, each cleaned series was truncated to a length of 1024 trials (from a maximum length of 1100 trials).

In order to estimate the spectral exponent of a time series, a 127-frequency-window averaged power spectral density function was computed (see Press et al., 1992). For this and all subsequent experiments, Table 2 provides the average scaling exponents obtained, separated by condition. Results show that all experimental conditions yielded above-zero fractal exponents, single-sample *ts* $\geq 8.14$, *ps* $\leq 0.01$. Furthermore, all experimental conditions yielded average scaling exponents that were higher than the respective average scaling exponents obtained for the reshuffled trial series (when sequential dependence of trials was eliminated), paired-sample *ts* $\geq$ 3.78, *ps* $\leq$ 0.001. The average scaling exponents of the re-shuffled trial series were not different from zero, $p > 0.99$ (they ranged between 0.005 and 0.03).

To what extent did our experimental manipulation affect the size of the fractal exponent? For this and all subsequence experiments, we conducted a 2-by-2 between-subjects ANOVA, with presentation order and element familiarity as the between-group factors. Note that traditional statistical analyses are common to compare means of fractal exponents across different condition. To ensure that our data meet the necessary distribution requirements, we ran the Kolmogorov-Smirnov *Z* test for each condition (see Table 2). Finding non-significant results, *ps* > 0.58, implies that there is no deviation from normality in our data (see Guastello, 2011, for a full discussion in fractal distributions in the context of statistical analyses).

**Table 2.** Descriptive statistics of fractal exponents for Experiments 1, 2, and 3.

| | *Conditions* | | | |
|---|---|---|---|---|
| | *Familiar* | | *Unfamiliar* | |
| | *Random* | *Predetermined* | *Random* | *Predetermined* |
| Exp. 1: Decisions centered on shapes | | | | |
| *Mean* | 0.205 | 0.303 | 0.172 | 0.201 |
| *SE* | 0.023 | 0.022 | 0.023 | 0.023 |
| $Z_{K\text{-}S}$ | 0.405 | 0.429 | 0.387 | 0.533 |
| *p* | 0.99 | 0.99 | 0.99 | 0.94 |
| Exp. 2: Decisions centered on elements | | | | |
| *Mean* | 0.152 | 0.275 | 0.162 | 0.236 |
| *SE* | 0.023 | 0.024 | 0.023 | 0.023 |
| $Z_{K\text{-}S}$ | 0.605 | 0.727 | 0.503 | 0.588 |
| *p* | 0.86 | 0.67 | 0.96 | 0.88 |
| Exp. 3: Decisions centered on both shapes and elements | | | | |
| *Mean* | 0.115 | 0.223 | 0.119 | 0.161 |
| *SE* | 0.022 | 0.020 | 0.021 | 0.022 |
| $Z_{K\text{-}S}$ | 0.524 | 0.632 | 0.625 | 0.770 |
| *p* | 0.95 | 0.82 | 0.83 | 0.59 |

*Note*: A Kolmogorov-Smirnov *Z* test ($Z_{K\text{-}S}$) was implemented to assess the degree to which the distribution of the fractal scaling exponents falls within a normal distribution.

As predicted, results of this experiment revealed a significant effect of trial order, $F(1, 54) = 9.50, p < 0.01, \eta^2_p = 0.15$, with larger scaling exponents in the predetermined-order condition ($M = 0.26$, $SD = 0.10$) than in the random-order condition ($M = 0.19$, $SD = 0.06$). There was also an effect of element familiarity, $F(1, 54) = 10.75$, $p < 0.001$, $\eta^2_p = 0.17$, with a larger scaling exponents in the familiar-elements condition ($M = 0.26$, $SD = 0.09$) than in the unfamiliar-elements condition ($M = 0.19$, $SD = 0.08$). Interestingly, following up on a marginally reliable familiarity-predictability interaction, $F(1, 54) = 2.80$, $p = 0.10$, the effect of familiarity was apparent in the predetermined-order condition ($M_{Familiar} = 0.30$, $SD = 0.09$; $M_{Unfamiliar} = 0.20$, $SD = 0.09$), $F(1, 54) = 12.66$, $p < 0.001$, $\eta^2_p = 0.19$, but not in the random-order condition ($M_{Familiar} = 0.21$, $SD = 0.05$; $M_{Unfamiliar} = 0.17$, $SD = 0.07$), $p > 0.26$. This suggests that the coupling support provided by features of the elements is qualified by the predictability of trials.

As a way of checking the robustness of our spectral data, we generated cumulative spectral density plots (using the same 127-frequency window that was used for the spectral plots of individual participants). Figure 4 shows the plots, each amplitude representing the average amplitude of a specific frequency, across participants in a condition.

Consider first the white circles in Fig. 4: they represent the data series of the random-order condition, either in their original sequence (Fig. 4A, collapsed across element familiarity), or in a sequence resorted to match the predetermined order of trials (Fig. 4B, familiar-element condition; Fig. 4C, unfamiliar-element condition). Confirming the results with individual participants, the slope of the original trial series is visibly higher ($M = 0.22$) than the slopes of the resorted trials series ($M = 0.001$), $F(1, 54) = 508.87$, $p < 0.001$, $\eta^2_p = 0.90$.

Now consider the grey circles in Figure 4: they represent the data series of the pre-determined-order condition (Fig. 4B, familiar-element condition; Fig. 4C, unfamiliar-element condition). The spectral slopes of these plots are again higher than the slopes of resorted data. Importantly though, the cumulative plots in the predetermined-order conditions reveal several spikes in the high-frequency area. Similar spikes have been identified before, namely in tasks that used a rhythmic structure of stimuli (Voss & Clarke, 1975) or allow for predictability of the subsequent trial (Holden, 2010; Kello et al., 2007). In each case, the spikes appear to track the frequency of repeating patterns.

To investigate whether the same is the case here, we created the spectral plot of a dummy-coded trial series (dashed line in Fig. 4B-C). In the dummy-coded trial series, a shape-match trial was coded as '-1', an element-match trial was coded as '1', and a no-match trial was coded as '0'. As expected, the locations of spikes of the original data matched with the location of spikes of the dummy-coded trial series, appearing at frequencies of about -1.18 $\mathrm{Log}_{10}$Hz, -1.0 $\mathrm{Log}_{10}$Hz, -0.7 $\mathrm{Log}_{10}$Hz, and -0.54 $\mathrm{Log}_{10}$Hz. Using a reverse process of deriving the number of consecutive trials from the corresponding frequency [$x = (10^{f(x)})^{-1} = 1/10^{f(x)}$], we found that -1.18 $\mathrm{Log}_{10}$Hz frequency corresponds to a 15-trial wide sinusoidal function [$x = 1/(10^{-1.18}) = 1/0.667 = 15.13 \approx 15$], the -1.0 $\mathrm{Log}_{10}$Hz frequency corresponds to a 10-trial wide sinusoidal function, the -0.7 $\mathrm{Log}_{10}$Hz frequency corresponds to the 5-trial wide sinusoidal function, and the -0.54 $\mathrm{Log}_{10}$Hz frequency corresponds to the 3-trial pattern.

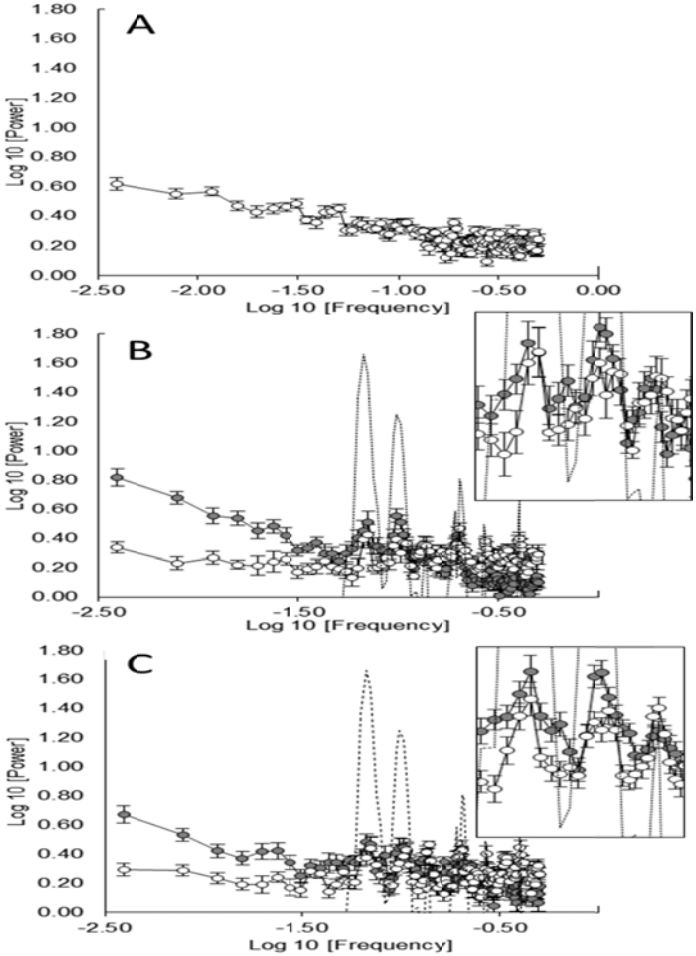

**Fig. 4.** Cumulative spectral plots of Experiment 1. A: Random-order condition (collapsed across familiar- vs. unfamiliar-element condition); B: Predetermined-order familiar-elements condition (grey circles); C: Predetermined-order unfamiliar-elements condition (grey circles). The white circles in Panels B and C represent the cumulative plot obtained from the data of the random-order condition, after the data was resorted to match the pre-determined order. The dashed line in these panels represents the cumulative plot of a dummy-coded time series.

Thus it appears that three of the spikes represent the periodicity of the stimulus sequence of the three patterns of trials used in the predetermined-order condition (15-trial, 10-trial, and 5-trial pattern; see Table 1). The spike visible in the fastest frequencies is likely to result from harmonics of the sub-patterns that exist within the longer patterns. Confirming this intuition, the spikes from the data the predetermined-order condition track those of the random-order condition, once these latter data were sorted to match the predetermined order of trials.

To better understand the nature of the spikes, we compared the amplitudes of the three main spikes (-1.18, -1.0, and -0.7 Log$_{10}$Hz) across different cumulative plots (top grey circles vs. top white circles in Fig. 4C-B). Table 3 shows the average amplitudes of spikes (and their standard deviations), separated by trial series (predetermined order, re-sorted random order). Given that there was no difference between familiar- and unfamiliar-element conditions, $ps > 0.42$, we collapsed amplitudes across element familiarity. A significant difference was found between the original and the resorted data for the -1.0 Log$_{10}$Hz spike, $t(36) = 2.99$, $p < 0.01$. Though this difference was not consistent across all spikes, it provides initial support that the spikes provide information that goes beyond a mere artifact of trial ordering. How do these findings hold up when the participant is instructed to focus on local elements?

**Table 3.** Average Maximum Amplitude of Spikes in the Predetermined-Order and the Re-sorted Random-Order Condition.

| | $f(x) \approx -1.18;\ x \approx 15$ | | $f(x) \approx -1.0;\ x \approx 10$ | | $f(x) \approx -0.7;\ x \approx 5$ | |
|---|---|---|---|---|---|---|
| | *Pre-determined* | *Re-sorted Random* | *Pre-determined* | *Re-sorted Random* | *Pre-determined* | *Re-sorted Random* |
| Exp. 1: Decisions centered on shapes | | | | | | |
| Familiar | 0.46 | 0.38 | 0.52 | 0.39 | 0.40 | 0.36 |
| | (0.21) | (0.20) | (0.18) | (0.16) | (0.18) | (0.13) |
| Unfamiliar | 0.44 | 0.38 | 0.47 | 0.34 | 0.32 | 0.39 |
| | (0.24) | (0.22) | (0.17) | (0.16) | (0.19) | (0.15) |
| Collapsed | $^{+}$0.45 | 0.38 | 0.50* | 0.37* | $^{+}$0.36 | 0.38 |
| | (0.16) | (0.19) | (0.20) | (0.16) | (0.16) | (0.12) |
| Exp. 2: Decisions centered on elements | | | | | | |
| | $^{+}$0.64 | 0.64 | 0.46 | 0.47 | $^{+}$0.46 | 0.45 |
| | (0.17) | (0.26) | (0.22) | (0.18) | (0.19) | (0.16) |
| Exp. 3: Decisions centered on both shapes and elements | | | | | | |
| | $^{+}$0.80* | 0.62* | 0.43 | 0.43 | $^{+}$0.58 | 0.61 |
| | (0.30) | (0.23) | (0.22) | (0.19) | (0.28) | (0.31) |

*Note*: Standard deviations are presented in parentheses. For the resorted random-order condition, trials were resorted to match the order of trials used in the predetermined-order condition. *refers to significant differences between predetermined vs. resorted random order. +refers to significant differences between experiments.

## EXPERIMENT 2

Experiment 2 differs from Experiment 1 in one crucial way: rather than asking participants to focus on the global shape of displays, we asked them to decide whether two displays match in a local element. The same two between-group factors were manipulated: element familiarity (familiar vs. unfamiliar element) and trial predictability (random vs. predetermined order of trials). We predicted a fractal-exponent effect of trial order, similar to the one found in Experiment 1. The degree to which element familiarity affects fractal exponents will speak to the degree to which sustained attention to an element is affected by the familiarity of that element.

### Method

#### Participants

Fifty-six adult participants between 18 and 56 years of age (38 women, 18 men; *M* = 21.5 years, *SD* = 6.26 years) were randomly assigned to one of the four experimental conditions. The number of participants in each condition ranged between 13 and 15, and age distribution was comparable across conditions. Six additional participants were tested but not included in the final sample due to equipment problems ($n = 2$), or because they failed to meet the 75% accuracy criterion ($n = 4$).

#### Materials and Procedure

Materials and procedure were identical to those from Experiment 1, the only difference pertaining to the different instruction: participants were asked to decide if displays matched in one of their elements. Thus the feedback training was modified such that the correct response pertained to detecting an element match, rejecting displays that matched in global shape, and rejecting displays that did not match at all.

### Results & Discussion

We again focus the discussion on the spectral analysis, as a means of understanding the processes that give rise to sustained attention – in this case, attention to local elements. Performance in terms of reaction-time data and accuracy are provided in Fig. 5: Accuracy (Fig. 5A) was affected by (i) trial type [$F$ (2, 104) = 173.35, $p < 0.01$; $\eta^2_p = 0.77$, better performance on shape-match (*M* = 0.988) and no-match trials (*M* = 0.984) than element-match trials (*M* = 0.859), *ps* < 0.01], and by (ii) a trial-type-order interaction [$F$ (2, 104) = 4.97, $p < 0.01$; $\eta^2_p = 0.09$, more pronounced effect of trial type in the random-order than the predetermined-order condition]. Reaction time (Fig. 5B) was affected by (i) trial type [$F$ (2, 104) = 74.36, $p < 0.01$; $\eta^2_p = 0.59$, shorter RT on shape-match (*M* = 2.42s) and no-match trials (*M* = 2,62s) than element-match trials (*M* = 1.92s), *ps* < 0.01], by (ii) familiarity [$F$ (1, 52) = 13.52, $p < 0.01$, $\eta^2_p = 0.21$; shorter RT in the familiar-element (*M* = 2.05s) than the unfamiliar-element (M = 2.59s) condition], and by (iii) a familiarity-order interaction [$F$ (2, 52) = 2.88, *p*

$< 0.10$, $\eta^2_p = 0.05$; the effect of familiarity was more extreme in the random-order ($M_{Familiar}$ = 1.88s; $M_{Unfamiliar}$ = 2.65s) than the predetermined-order condition ($M_{Familiar}$ = 2.23s; $M_{Unfamiliar}$ = 2.52s)]. No other interactions or main effects were significant.

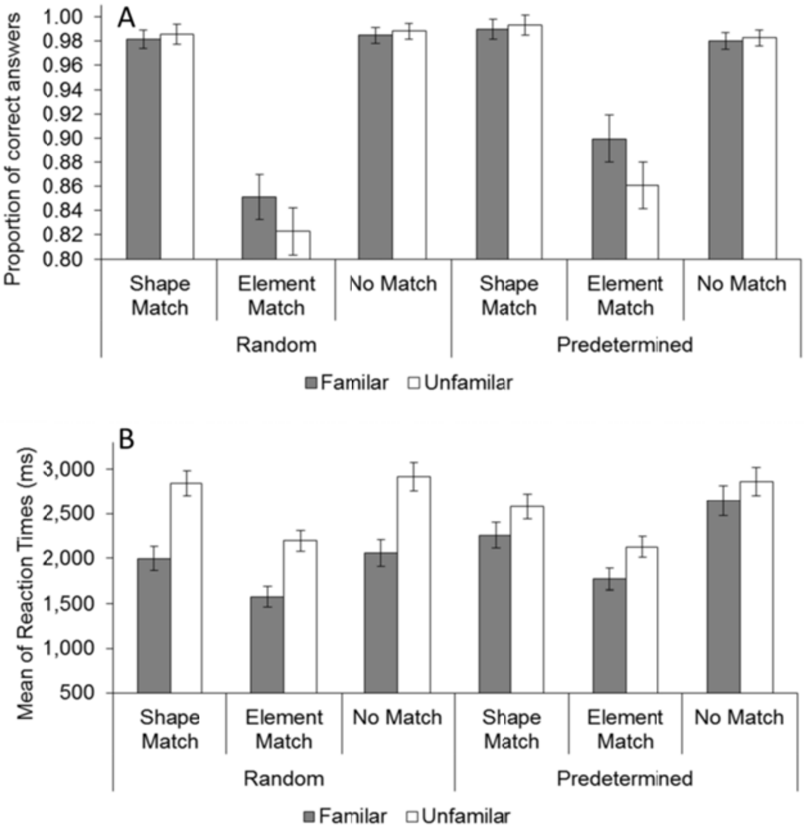

**Fig. 5.** Means and standard errors for proportion of correct answers (A), and reaction times (B) in Experiment 2, separated by trial type and experimental condition.

In line with what we found for Experiment 1, all experimental conditions yielded above-zero fractal exponents, single-sample *ts* $\geq 6.82$, *p*s $\leq 0.01$. Similarly, all experimental conditions yielded scaling exponents that were higher than their respective re-shuffled trial series, paired-sample *ts* $\geq 3.65$, *ps* $\leq 0.01$. The average scaling exponents of the re-shuffled trial series were not different from zero, $p > 0.99$ (they ranged between -0.04 and 0.01). In other words, we again found some degrees of interdependence among trials, indicative of a soft-assembled task-actor coupling.

Furthermore, and again as expected, a 2-by-2 between-subjects ANOVA revealed a reliable effect of trial order, $F(1, 52) = 14.83$, $p < 0.05$, $\eta^2_p = 0.22$, with the predetermined order yielding larger scaling exponents ($M = 0.25$, $SD = 0.11$) than the random order ($M = 0.16$, $SD = 0.08$). This finding parallels that of Experiment 1, showing again the relation between fractal exponent and predictability of trials. In contrast to Experiment 1, there was no effect of familiarity, nor a significant interaction with familiarity (*ps* > 0.34). This suggests that attention to elements was not affected by whether the elements were familiar or not. The element-familiarity effect found in Experiment 1, therefore, is likely due to the differences in integration ease afforded by the different types of elements.

Figure 6 depicts the cumulative spectral plots for the random-order (white circles) and the predetermined-order condition (grey circles), collapsed across element familiarity. The white circles in Fig. 6B show the re-sorted series from the random-order condition, and the dashed line indicates the spectral plot of the dummy-coded variable. The predetermined-order data (whether original or resorted) featured again the spikes at the three frequencies that correspond to the 15-trial pattern (~ -1.18 $\text{Log}_{10}$Hz), the 10-trial pattern (~ -1.0 $\text{Log}_{10}$Hz), and the 5-trial pattern (~ -0.7 $\text{Log}_{10}$Hz). However, unlike what was found in Experiment 1, there was no difference in amplitude in any of the spikes, $ts(30) \leq 0.33$, $ps > 0.74$ (see Table 3 for amplitude means).

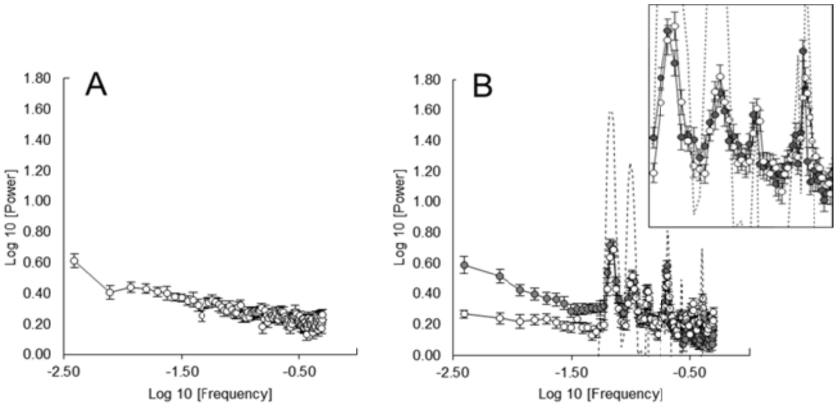

**Fig. 6.** Cumulative spectral plots of Experiment 2 collapsed across familiar-element and unfamiliar-element conditions. A: Random-order condition; B: predetermined-order condition (grey circles), resorted random-order condition (white circles), dummy-coded time series (dashed line).

Interestingly, the spike amplitude was higher in Experiment 2 than in Experiment 1 (mean differences ≥ 0.09): The difference was significant for -1.18 $\text{Log}_{10}$Hz, $t(53) = 5.08$, $p < 0.01$, and marginally significant for -1.0 $\text{Log}_{10}$Hz and -0.7 $\text{Log}_{10}$Hz, $ts > 1.85$, $ps < 0.07$. This suggests that the attentional focus on elements (Exp. 2) raised the amplitude of the spikes, both for the original data series (stemming from the predetermined-order condition) and for the resorted data series (stemming from the random-order condition). It is possible that the added difficultly of focusing on individual elements exaggerates the effect of the trial order. How do these findings change when participants have to focus on both the elements of the displays and their global shape?

## EXPERIMENT 3

So far, our method required participants to attend to one aspect of the hierarchical order: either the global shape (Exp. 1) or the local elements (Exp. 2). In this final experiment, participants had to pay attention to both at the same time. The same factors of element familiarity and trial predictability were manipulated.

### Method

#### Participants

Participants were 69 adults between 18 and 55 years of age (46 women, 23 men; $M$ = 22.0 years, $SD$ = 5.4 years), randomly assigned to one of the four experimental conditions. The number of participants in each condition ranged between 16 and 20, and age was about equally distributed across cells. Six additional participants were tested but not included in the final sample due to equipment failure ($n$ = 4), or failure to meet the accuracy criterion ($n$ = 2).

#### Materials

Stimuli were identical to those used in Experiment 1 and 2, with the exception that the key pad had three values marked for this experiment, rather than just two. In particular, the numbers 1, 2 and 3 were covered with the letters S, N and L (or C), to correspond to the answer categories ‘shape-match’, ‘no-match’, and ‘letter-match’ (or character-match), respectively.

#### Procedure

Procedure was the same, with the exception of the task instruction (and thus the feedback training). Participants were instructed to decide if two displays match in a letter (or character), in overall shape, or not at all. Thus, during feedback training, the correct response pertained to detecting a present element match and to detecting a present shape match.

### Results & Discussion

Figure 7 provides information about participants’ mean reaction time and accuracy, as a function of condition and trial type: Accuracy (Fig.7A) was affected by (i) trial type [$F$ (2, 130) = 27.00, $p < 0.001$, $\eta^2_p = 0.29$, better performance on shape-match ($M$ = 0.954) and no-match trials ($M$ = 0.957), than on element-match trials ($M$ = 0.897), $ps < 0.001$], and by (ii) a trial-type-familiarity interaction [$F$ (2, 130) = 3.24, $p < 0.04$, $\eta^2_p = 0.05$, familiarity affected accuracy in element-match trials, $F$ (1, 65) = 5.99, $p = 0.017$, $\eta^2_p$ = 0.08, but not in the other types of trials]. Reaction time (Fig. 7B) was affected by (i) trial type [*F* (2, 130) = 214.35, $p < 0.001$, $\eta^2_p$ = 0.0.77, shortest RT on shape-match trials (*M* = 2.27 s), followed by element-match trials (*M* = 2.64 s), and followed by no-match trials (*M* = 4.20 s)], by (ii) familiarity [*F* (1, 65) = 22.37, $p < 0.001$, $\eta^2_p = 0.26$, shorter RT in the familiar-element (*M* = 2.60 s) than the unfamiliar-element (*M* = 3.48 s) condition], by (iii) trial order [*F* (1, 65) = 8.12, $p = 0.006$, $\eta^2_p = 0.11$, shorter RT in the predetermined (*M* = 2.77 s) than the random-order (*M* = 3.31 s) condition], and by (iiii) a trial-type-order interaction [*F* (2, 130) = 4.56, $p < 0.02$, $\eta^2_p = 0.07$, trial-type effect was more pronounced in the predetermined order than the random-order condition]. No other interactions or main effects were significant.

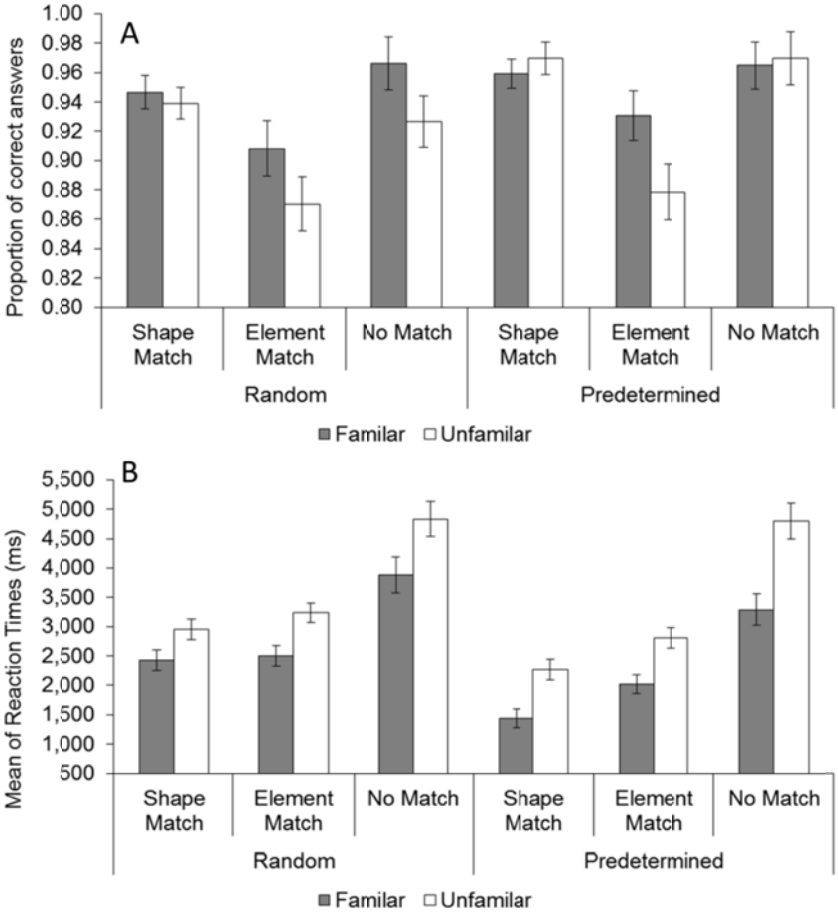

**Fig. 7.** Means and standard errors for proportion of correct answers (A), and reaction times (B) in Experiment 3, separated by trial type and experimental condition.

As was found in Experiments 1 and 2, fractal exponents of each condition were significantly higher than zero, one-sample $ts \geq 4.28$, $ps \leq 0.01$, and they were higher than the respective randomized shuffled trial series, $ts \geq 3.70$, $ps \leq 0.01$. By comparison, the average scaling exponents of the re-shuffled trial series were not different from zero, $ps > 0.90$ (they ranged between -0.008 and 0.020). Thus, despite the heightened difficulty of the task (requiring participants to pay attention to two separate levels of order), there was some degree of interdependence among trials, indicative of a soft-assembled task-actor coupling.

The 2-by-2 between-subjects ANOVA revealed a reliable effect of trial order, consistent with what we found in Experiments 1 and 2, $F\ (1, 65) = 12.11$, $p < 0.05$, $\eta^2_p = 0.16$: The predetermined-order condition yielded a larger scaling exponent ($M = 0.20$, $SD = 0.09$) than the random-order condition ($M = 0.12$, $SD = 0.09$). In terms of element familiarity, we did not detect a significant main effect, nor a significant interaction, $ps > 0.12$. To shed light on differences across experiments, we carried out two separate 2x2x2 ANOVAs, one comparing Experiments 1 and 3 (to get at the impact of the added element focus), and one comparing Experiments 2 and 3 (to get at the impact of added shape focus). Because Experiment 3 was carried out at a different time than Experiments 1 and 2, we used the more stringent alpha value of 0.01. The effect of experiment was significant in both analyses, whether the comparison pertained to Exp. 1-versus-3, $F\ (1, 119) = 19.15$, $p < 0.001$, $\eta^2_p = 0.14$, or to Exp. 2-versus-3, $F\ (1, 117) = 9.75$, $p < 0.01$, $\eta^2_p = 0.08$. In both cases, higher fractal exponents were obtained when participants attended to a single level of order ($M_{Exp.\ 1} = 0.22$, $M_{Exp.\ 2} = 0.21$) than when they attended to both ($M_{Exp.\ 3} = 0.16$).

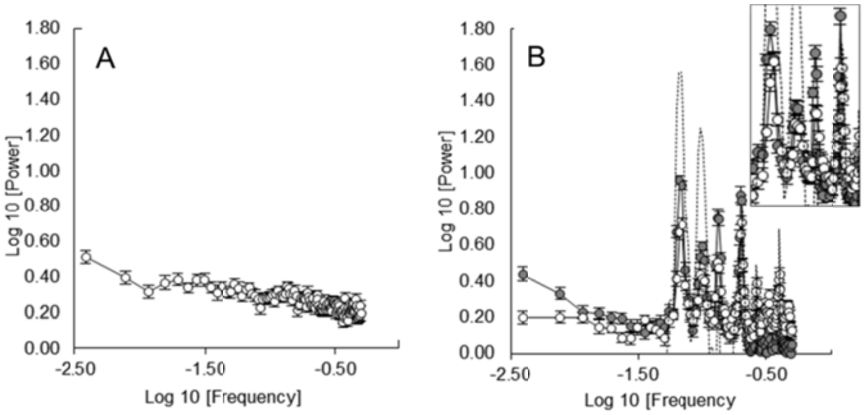

**Fig. 8.** Cumulative spectral plots of Experiment 3, collapsed across familiar-element and unfamiliar-element conditions. A: Random-order condition; B: predetermined-order condition (grey circles), resorted random-order condition (white circles), dummy-coded time series (dashed line).

Turning now to cumulative plots of Experiment 3, Figure 8 shows the spectral plots obtained for the random-order condition (white circles in Fig. 8A), the predetermined-order condition (grey circles in Fig. 8B), the re-sorted random-order trials (white circles in Fig. 8B) and the dummy-coded trial series (dashed lines in Fig. 8B). The findings mimicked those of the previous experiments: Spikes were again visible in the predetermined-order data, as well as the re-sorted random-order data and the dummy-coded series. And they mapped onto the same three frequencies that correspond to the 15-trial, the 10-trial, and the 5-trial pattern (-1.18 $\text{Log}_{10}$Hz, -1.0 $\text{Log}_{10}$Hz, and -0.70 $\text{Log}_{10}$Hz, respectively).

Table 3 shows the means of the maximum amplitude of each of the three main spikes, separated by type of trials series (predetermined order; resorted random order). In our first set of analyses, we compared spike height between the predetermined-order condition and the resorted random-order condition (grey vs. white circles in Fig. 8B). Findings are comparable to those of Experiment 1, in that there was a higher amplitude in the predetermined-order condition ($M = 0.80$) than in the resorted random-order condition ($M = 0.62$) at one of the frequencies (-1.18 $\text{Log}_{10}$Hz), $t(67) = 2.68$, $p < 0.01$. It appears that an attentional focus on global shape (Exp. 1 and 3), but not a focus on individual elements (Exp. 2), yields a spike pattern that is affected by participants' learning of the embedded structure of trials.

In our second set of analyses, we compared spike heights between experiments. For both the Exp. 1-versus-3 comparison and the Exp. 2-versus-3 comparison, we obtained significant differences (namely at -1.18 Log10Hz and at -0.7 $\text{Log}_{10}$Hz), $ts \geq 2.11$, $ps < 0.04$, with highest spike height in Experiment 3. In fact, it appears that spikes were relatively low in Experiment 1 (overall $M = 0.44$), higher in Experiment 2 (overall $M = 0.52$), and even higher in Experiment 3 (overall $M = 0.60$). The same increase can be observed for the resorted random-order condition ($M_{Exp.\ 1} = 0.38$, $M_{Exp.\ 2} = 0.52$, $M_{Exp.\ 3} = 0.55$). While this relation is not visible for the spikes at each frequency (see Table 3), the findings are an initial indication that spikes are not merely an artifact of trial order.

## GENERAL DISCUSSION

The goal of the current paper was to shed light on the process that allows the mind to focus on an isolated pattern of order within a hierarchy of orders. What makes it possible to selectively focus on an overall Gestalt, while, at the same time, attend to local elements in a distributed way? Our proposal was that the necessary attentional process is soft-assembled, emergent in the coupling of a multitude of processes in the task-actor system, captured by the fractal scaling exponent of reaction-time data.

Results were in line with this proposal, documenting, for the first time, some degree of fractality in attention to hierarchically nested order: we found non-zero fractal exponents across all conditions, but not when trials were re-shuffled randomly. The variation in fractal exponents we documented here (their value being in the neighborhood of 0.20) is in line with previous demonstrations of non-random noise in visual-search and simple-decision tasks (e.g., Aks & Sprott, 2003; Aks, Zelinsky, & Sprott, 2002, Clayton & Frey, 1997; Gilden, 2001; McIlhagga, 2008; Stephen & Mirman, 2010; Ward, 2002). While these values are generally lower than what is typically observed in self-guided motor tasks (e.g., Gilden, Thornton, & Mallon, 1995), they speak to the question of whether the perception of hierarchical order is sub-served by a self-organized soft-assembled task-actor system.

As mentioned in the introduction, the significance of above-zero fractal exponents in reasoning tasks has been debated in the literature, the concern being that fractality can stem from a variety of systems, not necessarily a system that is based on a soft-assembled coupling of a multitude of processes (for a discussion, see Gilden, 2009). Here we found further evidence against this concern. First, consider our effect of trial predictability on the size of the fractal exponent. Trial predictability was far from transparent in the current set of experiments: there were three different patterns, each repeated six to eight times. Participants most likely did not fully learn the embedded sequences, as evidenced in their accuracy. Yet, their performance reflected the soft-assembly of an anticipatory system that transcended the time scale of an individual trial and includes the propensity to act on a future trial (cf., Brandone, Horwitz, Aslin, & Wellman, 2014; Munakata, Snyder, & Chatham, 2012; Stepp & Turvey, 2010).

Consider next our results related to the instructed focus of attention: Highest fractal exponents were obtained when participants focused on one level of order (Exp. 1 and 2) than when they focused simultaneously the overall Gestalt and the local elements (Exp. 3). Divided attention is likely to disrupt a trial-transcending emergent system – lending support to the idea that the size of the fractal exponents signifies the ease of coupling that the task affords. Element familiarity, lastly, is too in line with the overall claim of above-zero fractal exponents: In the case in which element familiarity yielded an effect, fractal exponents were higher for the familiar-element than the unfamiliar-element condition.

Considering all the factors together – trial predictability, element familiarity, and task instruction, we devised an ad-hoc strategy to dummy code each factor with 0 or 1 (or 2 in the case of task instruction), depending on whether the approach of emergent soft-assembly predicts a higher (vs. lower) task-actor coupling. We then added up these codes to obtain a value for each condition. Following this strategy, the predetermined-order condition with familiar elements in Experiment 1 yielded the lowest sum ($0 + 0 + 0 = 0$), while the random-order condition with unfamiliar elements in Experiment 3 yielded the highest sum ($1 + 1 + 2 = 4$). The Spearman correlation coefficient between mean fractal exponents and sum dummy score was highly significant, at -0.80, $p < 0.001$, implying a meaningful relation between fractal exponent and relative strength of task-actor coupling.

Spike height found in cumulative plots of the current study provides corroborative information about the degree of task-actor coupling. Specifically, spikes were attenuated in the easiest task, namely when attention was focused only on overall shape (Exp. 1), compared to the more difficult task, when attention was focused on individual elements (Exp. 2). Spikes were even higher when participants had to focus on both elements and overall shape (Exp. 3). As such, spike height is in line with the degree to which the underlying coupling transcends the unique contribution of trial order. A similar argument can be made for the difference in spike height between the original data of the predetermined-order condition and the resorted data of the random-order condition.

Taken together, our findings suggest that attention to hierarchical patterns has the signature of self-organization and soft-assembly of a multitude of processes. This implies that no single process is responsible for the ability to focus on an isolated level of order, just as there is no single process responsible for the ability to distribute attention across many elements. Instead it is the coming together of all pertinent processes, ranging from those that take into account the most detailed of elements, to those that take into account the largest of Gestalts (cf., Stephen & Anastas, 2011). As such, the current results offer a sharp departure from theories of attention that attribute the fluctuation of attention in local and global aspects to independent processes or separate components.

The next step then is to define the control parameter that drives attention to a local versus a global level of order. Generally speaking, control parameters are ratios that lead the system through the variety of potential states, without any kind of code or algorithm for a specific pattern of performance (cf., Kelso, 1995). More specifically, control parameters are ratios of constraints, where constraints that support a particular pattern of behavior are pitted against constraints that support a different pattern of behavior (Kloos & Van Orden, 2010). In the case of visual hierarchical stimuli, we can envision a control parameter that captures the relative salience of local versus global order. Consider, for example, the stimuli in Kimchi et al. (2005): Displays differed in the number of local elements within the overall Gestalt (which did not change in size). Thus displays differed in the size of the local elements, while the size of the global patterns stayed the same. Such change in relative size and sparcity is likely to affect changes in salience of local versus global patterns. Thus, these features are likely to change the control parameter for attention to global order. Indeed, as had been previously demonstrated by Martin (1979), Kimchi et al. (2005) corroborated that the degree of global precedence increased as the size of local elements decreased. It remains to be seen how such a control parameter would be modified by factors of trial predictability and instructed focus of attention.

## ACKNOWLEDGMENT

We thank Shana Vanderburgh, Dustin Faller, Keith Needham and Hanna Davis for their help in the construction of the stimuli and with data collection. We also thank Guy Van Orden and Sebastian Wallot for their advice on data analysis, as well as feedback on earlier versions of this manuscript. Part of the data reported here was published as a proceedings paper at the 33rd Annual Conference of the Cognitive Science Society. The completion of this manuscript was supported in part by grants from the National Science Foundation (DHB #0728743, PI: Kloos; BCS-0843133, PI: Holden).

# REFERENCES

Aks, D. J., & Sprott, J. C. (2003). Resolving perceptual ambiguity in the Necker cube: A dynamical systems approach. *Nonlinear Dynamics in Psychology & Life Sciences, 7,* 159-178.

Aks, D. J., Zelinsky G. J., & Sprott, J. C. (2002). Memory across eye-movements: 1/*f* dynamic in visual search. *Nonlinear Dynamics, Psychology, and Life Sciences, 6,* 1-25.

Athreya, D. N., Van Orden, G., & Riley, M. A. (2012). Feedback about isometric force production yields more random variations. *Neuroscience Letters, 513*(1), 37-41.

Bassingthwaighte, J. B., Liebovitch, L. S., & West, B. J. (1994). *Fractal physiology*. New York: Oxford University Press.

Bak, P. (1996). *How nature works: The science of self-organized criticality*. New York: Springer-Verlag.

Bak, P. Tang, C., & Wiesenfeld, K. (1987). Self-organized criticality: An explanation of the 1/f noise. *Physical Review Letters, 59*(4), 381–384.

Blanca, M.J., Luna, R., López-Montiel, D., Zalabardo, C., & Rando, B. (2002). Effect of similarity between target and global and local levels in hierarchical stimuli processing. *Psychological Research, 66*, 124-132.

Bogartz, R. S., & Staub, A. (2012). Gaze step distributions reflect fixations and saccades: A comments on Stephen and Mirman (2010). *Cognition, 123*(2), 325–334. http://dx.doi.org/10.1016/j.cognition.2011.12.014.

Brandone, A. C., Horwitz, S. R., Aslin, R. N., & Wellman, H. M. (2014). Infants' goal anticipation during failed and successful reaching actions. *Developmental Science, 17,* 23-34. doi: 10.1111/desc.12095

Brown, C., & Liebovitch, L. (2010). *Fractal analysis*. London: Sage.

Burack, J. A., Enns, J. T., Iarocci, G., & Randolph, B. (2000). Age differences in visual search for compound patterns: Long- versus short-range grouping. *Developmental Psychology, 36*, 731–740.

Castillo, R. D., Van Orden, G., & Kloos, H. (2011). The Embodiment of Time Estimation. In A. Vatakis, A. Esposito, M. Giagkou, F. Cummins, and G. Papadelis (Eds.), *Time and Time Perception 2010, LNAI/LNCS 6789*, (pp. 196–206). Berlin Heidelberg: Springer-Verlag.

Clayton, K. F., & Frey, B. B. (1997). Studies of mental "noise". *Nonlinear Dynamics, Psychology, and the Life Science, 1,* 173-180.

Coey, C. A., Hassebrock, J., Kloos, H., & Richardson, M. J. (2013). Fractal structure of the nested actions in keeping the beat. *Proceedings of the 35rd Annual Conference of the Cognitive Science Society* (pp. 2076-2081). Berlin, Germany: Cognitive Science Society.

Dale, R. (2008). The possibility of a pluralist cognitive science. *Journal of Experimental & Theoretical Artificial Intelligence, 20*(3), 155–179.

Deutsch, J. A., & Deutsch, D. (1963). Attention: Some Theoretical Considerations. *Psychological Review, 70*, 80–90. doi:10.1037/h0039515

Duarte, M., & Zatsiorsky, V. M. (2000). On the fractal properties of natural human standing. *Neuroscience Letters, 283*, 173-176.

Dukette D., & Stiles J. (1996). Children's analysis of hierarchical patterns: Evidence from a similarity judgment task. *Journal of Experimental Child Psychology, 63,*103–140.

Dukette, D., & Stiles, J. (2001). The effects of stimulus density on children's analysis of hierarchical patterns. *Developmental Science, 4,* 233–251.

Enns, J. T., & Girgus, J. S. (1985). Developmental changes in selective and integrative visual attention. *Journal of Experimental Child Psychology, 40*, 319–337.

Fisher, A. V., & Kloos, H. (in press). Development of selective sustained attention: The Role of Executive Functions. In L. Freund, P. McCardle, and J. Griffin (Eds.), *Executive Function in Preschool Age Children: Integrating Measurement, Neurodevelopment and Translational Research*. APA Press.

Gilden, D. L. (2001). Cognitive emissions of 1/*f* noise. *Psychological Review, 108*, 33-56.

Gilden, D. L. (2009). Global model analysis of cognitive variability. *Cognitive Science, 33*, 1441-1467.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/*f* noise in human cognition. *Science, 267,* 1837-1839.

Goldfield, E. C. (1991). Soft assembly of an infant locomotor action system. Advances in Psychology, 81, 213–229. http://dx.doi.org/10.1016/S0166-4115(08)60767-0

Guastello, S. J. (2011). Frequency distributions and error functions. In Guastello, S. J., & Gregson, R. A. M. (Eds.), *Nonlinear dynamical systems analysis for the behavioral sciences using real data* (pp. 33-72). Boca Raton, FL: C R C Press/Taylor & Francis.

Holden, J. G. (2005). Gauging the fractal dimension of response times from cognitive tasks. In M. A. Riley & G. C. Van Orden (Eds.), *Contemporary nonlinear methods for behavioral scientists: A webbook tutorial* (pp. 267–318). Retrieved October 13, 2010, from http://www.nsf.gov/sbe/bcs/pac/nmbs/nmbs.jsp

Holden, J. G. (2010, August). *Multifractal "waves" in cognitive performance*. The 5th Annual Workshop on Nonlinear Dynamics and Cognitive Processes, Storrs, CT.

Holden, J. G., Choi, I., Amazeen, P. G., & Van Orden, G. (2011). Fractal 1/*f* dynamics suggest entanglement of measurement and human performance. *Journal of Experimental Psychology: Human Perception and Performance, 37*(3), 935-948. doi: 10.1037/a0020991

Holden, J. G., & Rajaraman, S. (2012). The self-organization of a spoken word. *Frontiers in Psychology, 3*, 209. doi: 10.3389/fpsyg.2012.00209.

Hughes, H. C., Layton, W. M., Baird, J. C., & Lester, L. S. (1984). Global precedence in visual pattern recognition. *Perception & Psychophysics, 35*, 361-371.

Ihlen, E. A. F., & Vereijken, B. (2010). Interaction-dominant dynamics in human cognition: Beyond 1/fα fluctuation. *Journal of Experimental Psychology: General, 139*, 436–463.

Kahneman, D. (1973). *Attention and effort*. Englewood Cliffs, NJ: Prentice Hall.

Kiefer, A. W., Riley, M. A., Shockley, K., Villard, S., & Van Orden, G. C. (2009). Walking changes the dynamics of cognitive estimates of time intervals. *Journal of Experimental Psychology: Human Perception and Performance, 35*, 1532-1541.

Kello, C. T., Beltz, B. C., Holden, J. G., & Van Orden, G. (2007). The emergent coordination of cognitive function. *Journal of Experimental Psychology: General, 136*, 551-568.

Kello, C. T., & Van Orden, G. (2009). Soft-assembly of sensorimotor function. *Nonlinear Dynamics, Psychology, and Life Sciences, 13*(1), 57-78.

Kelty-Stephen, D. G., & Mirman, D. (2013). Gaze fluctuations are not additively decomposable: Reply to Bogartz and Staub (2012). *Cognition, 126*(1), 128-134.

doi: 10.1016/j.cognition.2012.09.002.

Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. Cambridge, MA: MIT Press.

Kimchi, R. (1990). Children's perceptual organization of hierarchical visual patterns. *European Journal of Cognitive Psychology, 2*, 133–149.

Kimchi, R. (1998). Uniform connectedness and grouping in the perceptual organization of hierarchical patterns. *Journal of Experimental Psychology: Human Perception and Performance, 24*, 1105–1118.

Kimchi, R. (2009). Perceptual organization and visual attention. *Progress in Brain Research, 176*, 15-33.

Kimchi, R., Amishav, R., & Sulitzeanu-Kenan, A . (2009). Gender differences in global-local perception? Evidence from orientation and shape judgments. *Acta Psychologica, 130*(1), 64-71. doi: 10.1016/j.actpsy.2008.10.002.

Kimchi, R., Hadad, B., Behrmann, M., & Palmer, S. E. (2005). Microgenesis and ontogenesis of perceptual organization: Evidence from global and local processing of hierarchical patterns. *Psychological Science, 16*, 282-290.

Kloos, H., & Van Orden, G. C. (2009). Soft-assembled mechanisms for the unified theory. In J. P. Spencer, M. Thomas, and J. McClelland (Eds.), *Toward a new grand theory of development? Connectionism and dynamics systems theory reconsidered* (pp. 253-267). Oxford: Oxford University Press.

Kloos, H., & Van Orden, G. C. (2010). Voluntary behavior in cognitive and motor tasks. *Mind and Matter, 8*(1), 19-43.

Kuznetsov, N. A., & Wallot, S. (2011). Effects of accuracy feedback on fractal characteristics of time estimation. *Frontiers in Integrative Neuroscience, 5,* 62. doi:10.3389/fnint.2011.00062.

Lemoine, L., Torre, K. & Delignières, D. (2006). Testing for the presence of 1/f noise in continuation tapping data. *Canadian Journal of Experimental Psychology, 60* (4), 247-257.

Madison, G. (2004). Fractal modeling of human isochronousserial interval production. *Biological Cybernetics, 90*, 105-112.

Mandelbrot, B. (1967). How Long Is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension. *Science, 156*(3775), 636-638.

Martin, M. (1979). Local and global processing: The role of sparsity. *Memory & Cognition 7*(6), 476-484.

McIlhagga, W. (2008). Serial correlations and 1/f power spectra in visual search reaction times. *Journal of Vision, 8*(9), 1-14.

Munakata, Y., Snyder, H. R., & Chatham, C. H. (2012). Developing cognitive control: Three key transitions. *Current Directions in Psychological Science, 21*, 71-77.

Navon. D. (1977). Forest before trees: The precedence of global features in visual perception. *Cognitive Psychology, 9*, 353-383.

Press, W. H., Teukolsky, S. A., Vetterling, W. T., & Flannery, B. P. (1992). *Numerical recipes in C: The art of scientific computing*. Cambridge, UK: Cambridge University Press.

Quinn, P.C., Burke, S., & Rush, A. (1993). Part-whole perception in early infancy: Evidence for perceptual grouping produced by lightness similarity. *Infant Behavior and Development, 16*, 19–42.

Riley, M. A., & Turvey, M. T. (2002). Variability and determinism in motor behavior. *Journal of Motor Behavior, 34*, 99-125.

Sanders, L. D., & Poeppel, D. (2007). Local and global auditory processing: Behavioral and ERP evidence. *Neuropsychologia, 45*, 1172-1186.

Scherf, K. S., Behrmann, M,, Kimchi, R,, & Luna, B. (2009). Emergence of global shape processing continues through adolescence. *Child Development, 80*(1), 162-177. doi: 10.1111/j.1467-8624.2008.01252.x.

Smith, L. B. (2005). Cognition as a dynamic system: Principles from embodiment. *Developmental Review, 25*(3-4), 278-298.

Smith, L. B., & Breazeal, C. (2007). The dynamic lift of developmental process. *Developmental Science, 10*(1), 61-68.

Stephen, D. G., & Anastas, J. (2011). Fractal fluctuations in gaze speed visual search. *Attention, Perception, & Psychophysics, 73*, 666-677.

Stephen, D. G., & Mirman, D. (2010). Interactions dominate the dynamics of visual cognition. *Cognition, 115*, 154-165.

Stepp, N., & Turvey, M. T. (2010). On Strong Anticipation. *Cognitive Systems Research, 11*, 148-164.

Treisman, A. M. (1960). Contextual cues in selective listening. *Quarterly Journal of Experimental Psychology, 12*(4), 242–248. doi:10.1080/17470216008416732

Turvey, M. T. (1990). Coordination. *American Psychologist, 45*, 938-953.

Turvey, M. T. (2007). Action and perception at the level of synergies. *Human Movement Science, 26*, 657-697.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General, 132*, 331-350.

Van Orden, G. C., Kloos, H., and Wallot, S. (2011). Living in the pink: Intentionality, wellbeing, and complexity. In C. A. Hooker (Ed.), *Philosophy of complex systems: Handbook of the philosophy of science* (pp. 639-682). Amsterdam: Elsevier.

Voss, R.F., & Clarke, J. (1975). 1/*f* noise in music and speech. *Nature, 258*, 317-318. doi: 10.1038/258317a0.

Wagenmakers, E-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of 1/fα noise in human cognition. *Psychonomic Bulletin & Review, 11*, 579–615.

Wagenmakers, E-J., Farrell, S., & Ratcliff, R. (2005). Human cognition and a pile of sand: A discussion on serial correlations and self-organized criticality. *Journal of Experimental Psychology: General, 134*, 108-116.

Ward, L. M. (2002). *Dynamical cognitive science*. Cambridge, MA: MIT Press.

Wijnants, M. L., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., & Van Orden, G. C. (2009). 1/*f* scaling in movement time changes with practice in precision aiming. *Nonlinear Dynamics, Psychology, and the Life Sciences, 13*, 79-98.