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Coordination of Attention to Local and Global Features: Fractal Patterns in a Speeded-Categorization Task

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Abstract

How does the mind coordinate local and global features of a display to allow for adaptive functioning? To answer this question, we presented adults with a speeded categorization task in which they had to decide whether two stimuli match in a local element, in their global pattern, or in neither the local nor the global feature. The trial series of reaction times were then subjected to fractal analyses to capture the coordination that gives rise to performance. The assumption is that long-range correlations reveal themselves in pink-noise exponents, ones that are higher than white-noises exponents. To investigate the stability of fractal exponent, we manipulated both the local elements (to be either familiar or novel), and the order of trials (to be either random or blocked). Results show a significant deviation from white-noise, but only in familiar-elements condition in which trials were presented randomly. Implications for local/global research are discussed.

Keywords: visual processing; categorization; spectral analysis, detrended fluctuation analysis; pink noise.

Introduction

How does the mind make senses of an ever changing array of light? This question has a long history, often addressed under the framework of local and global processing (e.g., Kimchi, 1990; Kimchi, Hadad, Behrmann, & Palmer, 2005; Köhler, 1969; Quinn, Burke & Rush, 1993). Indeed, a scene could be loosely divided into local elements and global patterns. And adaptive functioning needs both: the ability to integrate local elements into higher-order Gestalts, and the ability to segregate higher-order Gestalts into their component parts. In fact, processes of integration most likely must be coordinated fluidly with processes of segregation. The current paper is concerned with the question of this coordination. We first give a brief review of findings on local/global processing, and then we turn to describing a method of measuring this coordination.

Local & Global Processing

Traditionally, the emphasis has been on determining how attention to local aspects competes with the perception of global aspects, whether the stimuli pertain to faces, arbitrary items, or entire scenes. Navon's (1977) well-known task is a good illustration of this emphasis. Stimuli involved small letters arranged spatially in such a way that they form a larger letter. The element letters either matched the Gestalt letter or not. And the task was to name a letter (either the element letter or the Gestalt letter) as fast as possible. The general finding suggests an asymmetry in competition: Perception of Gestalt features appears to interfere more with the perception of elemental features than vice versa. Consistent with the laws of perception outlined by Gestalt psychology, the organization of whole entities apparently takes priority over the separation into isolated elements.

While subsequent research has supported the general finding of unidirectional competition between global and local processes (Dukette & Stiles, 1996; 2001), the issue might be more complex. Kimchi and her colleagues, for example, showed that the priority of global processes depends on the specific details of the stimuli used. When items consist of few elements (e.g., four triangles spatially arranged to form a square), the global preference disappears (e.g., Kimchi, 1990; Kimchi et al, 2005). It is only when items consist of many elements (e.g., twelve triangles spatially arranged to form a square) that global patterns take precedence. This pattern of findings was demonstrated in adults as well as children as young as 5 years of age; and it was replicated in speeded classification tasks, matching tasks, or visual searching task (Burack, Enns, Iarocci, & Randolph, 2000; Enns & Girgus, 1985). Together, these findings provide a first indication that local and global processing are coordinated with the specifics of the task context.

Further indication for a coordinated interaction between local and global processes comes from findings with young infants (Quinn et al, 1993). In a habituation task, infants were first familiarized with geometrical shapes that consisted of elements that formed higher-order Gestalts. While participants dishabituated to changes in the higher-order Gestalt, they were surprisingly sensitive to relatively minimal changes in local elements. In fact, perceiving elements was enhanced in the context of an organized whole (see Experiment 4 of Quinn et al, 1993). These findings suggest an intricate interdependence among attention to local and global features, one in which the perception of higher-order Gestalts highlights local elements that – in turn – make up the higher-order Gestalt.

Despite isolated findings on the interplay between local and global processing, the methods commonly employed in this domain do not lend themselves to explicitly measuring coordination. This is because the choice of stimuli is likely to bias the perceptual system to focus either on local elements (e.g., when the elements highly salient) or on global patterns (e.g., when small elements form highly salient patterns). Such methods are ideal to measure possible interferences of hierarchical scales, but they might miss the adaptive coordination that takes place when scales of hierarchical organizations interact. We therefore turn to a different method, one that can gauge a possible coordination among the many nested levels of order.

Coordination across Scales

Changes in the mind-body system happen at different rates or scales. The metabolic activity in a motor cell, for example, is a process changing on very fast timescales; and the overt movement of eyes is an example of a process changing on a slower time scale. For adaptive and flexible performance to be possible, no single timescale can dominate coordination. Instead the system has to maintain a balance between competing and cooperating changes in a flexible coupling across the body. Similarly, the focus of attention is likely to change on multiple time scales: For example, paying attention to local elements of a display necessarily needs to change on a fast timescale (to track small changes in shape, texture, or color), while paying attention to more global patterns of a display needs to change on slower timescales. Are these different timescales coordinated?

Coordination of smaller and larger timescales can be studied by looking at long-term correlational patterns across many trials, a mathematical constructs named fractals (e.g., Van Orden, Holden & Turvey, 2003; for a different view Hausdorff & Peng, 1996; Peng, Havlin, Stanley, & Goldberger, 1995). Fractals represent self-similar structures with functional and topographical features that are reproduced in miniature on finer and finer scales (e.g., Brown & Liebovitch, 2010; Gilden, 2001; Kello, & Van Orden, 2009; Kloos & Van Orden, 2010). They provide a potentially useful way of gauging the coordination among different time scales. The necessary ingredient is a task that produces a sufficiently long trial series. Figure 1 shows such a trial series, one that has over 8000 data points (top right). To determine the fractal exponent, the trial series is then decomposed into sinusoidal components of different wavelength. Slow changes in the data series are captured by low-frequency high-amplitude sine waves (top left of Fig. 1), and fast changes are captured by high-frequency low-amplitude waves (bottom left of Fig. 1). A power spectrum is then constructed, with relative amplitude on the vertical axis, and frequency of change on the horizontal axis (on log-log scales). The amplitude represents the relative size of change, also referred to as power. The slope of the regression line in the spectral plot defines the scaling relation between amplitude and frequency. The estimated exponent (α) reflects the degree of long-range correlations across the different time scales.

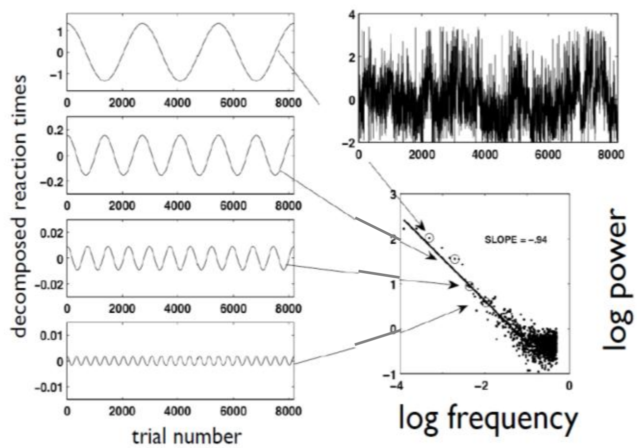

Figure 1: Illustration of the creation of a spectral plot (bottom right) for a time series (top right) that shows pink-noise type long-range correlations.

A multitude of tasks have been subjected to fractal analyses (e.g., Gilden, 2001; Kello & Van Orden, 2009; McIlhagga, 2008; Van Orden, Holden & Turvey, 2005), including motor tasks (e.g., walking, standing, tapping, tracing, or sensori-motor synchronization), perceptual tasks (e.g., Necker-cube task; visual search), or cognitive tasks (e.g., word recognition, speeded categorization, speech production time estimation; mental rotation). However, there has been little research on the coordination of attention to local and global aspects of stimuli.

At the same time, fractal exponents are susceptible to task manipulations. For example, by introducing changes in the inter-stimulus-interval in simple reaction tasks, the slope decreased in magnitude, reflective of added randomness in the mind-body system (Holden, Choi, Amazeen, & Van Orden, 2010). In other words, fractal exponents – while illustrative of the system's coordination might need to be interpreted in the context of a specific task. We therefore introduced a set of task manipulations to explore changes in the fractal scaling exponent.

Overview of Current Study

Using insights from fractal analyses, the goal of the current study was to measure the long-range correlation in a task that pits local and global features against each other. Stimuli were created that varied in both local elements and global structure. However, unlike traditional local/global stimuli, we used few-elements displays, analogous to a subset of stimuli used in Kimchi et al (2005). This was done to avoid large salience discrepancies between local elements and global patters, and thus to mimic the ecological task of navigating complex natural scenes that vary on multiple hierarchical scales.

The task was to decide as quickly as possible whether two stimuli matched in a local element, in the global pattern or in none of the two. Trials differed in whether there was a local match, a global match, or neither. Furthermore, we varied the nature of elements to be either familiar or novel to gauge possible changes in the fractal exponent. Familiar elements were letters, and novel elements were tetragons with various details in their lines. The global pattern was the same in both cases and pertained to the overall shape formed by the elements. We predicted a higher fractal organization in the case of familiar elements, based on findings that expertise increased the likelihood of long-range correlations (e.g., Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). Finally, we varied the order of trials to be either random or blocked to investigate changes in fractal parameters as a function of an external interference. Previous research had shown that fractal values had been very close pink noise if items were self-paced without any interference or noise (Holden, Choi, Amazeen, & Van Orden, 2010). The resulting four conditions (Random Letter, Random Tetragon; Blocked Letter; and Blocked Tetragon) were varied between participants.

Method

Participants

Seventy undergraduate students served as participants to fulfill a course requirement. They ranged in age from 18 to 47 years (M = 21.4, SD = 6.1), and participated in one of the four conditions (Ns = 26, 25, 8, and 11 in Random-Letter, Blocked-Letter, Random-Tetragon, and Blocked-Tetragon condition respectively[1]). An additional group of 14 participants was tested and dropped from the final sample because of technical errors (3), or because their overall accuracy was below 75%, suggesting that they did not perform according to task instructions (11).

[1] Due to the unequal N between letter conditions and tetragon conditions, comparisons on this factor are interpreted with caution.

Materials

Stimuli were strings of three elements. Elements were either letters or tetragons, arranged horizontally. Figure 2 shows some examples of those strings. Letters were 12 lower-case consonants printed on a red background. Four letters (c, s, x, z) had the contour of a square, another four letters (p, q, g, y) had the contour of a low-reaching rectangle, and another four letters (b, h, f, l) had the contour of a high-reaching rectangle. Similarly, four of the tetragons were squares, another four tetragons were low-reaching rectangles, and another four tetragons were high-reaching rectangles. Each of the resulting 12 tetragons was unique on the basis of their sides (thickness, patterns, etc.).

Strings were combined into pairs, such that the two strings matched in an element (element-match trial) or in their overall shape across the three elements of a string (shape-match trial). Filler items were pairs of strings that matched neither in an element nor in the overall shape (no-match trials).

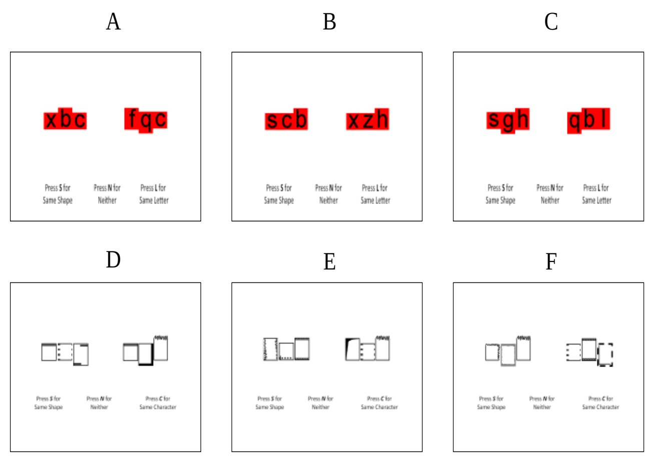

Figure 2: Examples of trials depicting pairs of strings. Elements in a string were letters (Panels A-C) or tetragons (Panels D-F). And strings matched in a single element (Panels A and D), in their global shape (Panels B and E), or be a filler item with no-match (Panels C and F).

Implementing an iterative process, we created 400 unique shape-match trials, 400 unique element-match trials, and 200 no-match trials. Care was taken to ensure that an element appeared equally often in the left and right string of a pair.

Procedure

Participants were tested individually, using Superlab® software (Version 2.0) on a Dell Computer (Intel Core Duo processor of 2.40 GHz; 1.58 GHz; 2.96 GB RAM memory). The instruction was to decide as quickly and as accurately as possible whether two strings matched in overall shape, in a single element (either letter or tetragon, depending on condition), or in neither. The experiment started immediately after instruction phase and a training phase. For each slide, reaction time and response was recorded.

In the two random-order conditions (one for letters and one for tetragons), the three types of trials (element-match shape-match, or no-match) were presented randomly, with the following constraints: The first 400 trials had 160 element-match trials, 160 shape-match trials and 80 no-match trials. The next set of 400 trials had the same distribution of trial types. And the last 200 trials had 80 element-match trials, 80 shape-match trials, and 40 no-match trials. Participants were allowed to take a break after the first 400 trials, and then again after the next 400 trials.

For the two blocked-order conditions, the order of trials was pre-determined according to a sequential pattern, while keeping the same frequency distribution of trials before and after the two breaks. In particular, there were three sequences of trials that were repeated in a set way. The first sequence consisted of one no-match trial, two shape-match trials, and two element-match trials. In short, this sequence can be abbreviated as N-S-S-E-E. The second sequence had the form N-N-S-S-S-S-E-E-E-E, and the third sequence had the form N-N-N-S-S-S-S-S-S-E-E-E-E-E-E. Each sequence was repeated five or six times (depending on block), after with the next sequence started. After the third sequence, the first one started again, and so on.

Data Preparation and Analyses

For each participant, we eliminated reaction times greater than 10 seconds and smaller than 300 milliseconds. We then submitted the time series to a process of eliminating linear trends (Holden, 2005; Holden, Choi, Amazeen, & Van Orden, 2010). Between 2% and 9% of the trials were eliminated with this procedure per participant. In all cases the prepared data were analyzed by Detrended Fluctuation Analysis and Spectral Analysis.

Detrended Fluctuation Analysis (DFA) provides an index of self-similarity of time series with itself over time and information equivalent to the correlation dimension. This index is called Hurst's exponent [H], and it is estimated by dividing the logarithm of the range of amplitudes normalized by the logarithm of the intervals. $H = 0.50$ indicates randomness of the signal of white noise; whereas $H > 0.50$ are indicative of long-range correlations of pink noise (Eke, Hermán, Kocsis & Kozak, 2002; Peng et al., 1995).

Spectral Analysis (SA) provides a description of the correlational structure of fluctuations in a time series of response. The result is a set of coefficients that characterize the relative amplitudes of all the wave forms, ordered from lowest to highest frequency, named the power spectrum of the signal. Using this power spectrum it is possible to determine the value of the slope of the regression line. Response time series yield negatively accelerated slopes indicative of pink noise, or slopes that are statistically equivalent to zero, which suggests white noise (Holden, 2005). Following custom procedures, the spectral-analysis exponent was estimated for the data across 25% of the spectrum. Once estimated the slope for each participant, the obtained value is multiplied by [-1], in order to transform it into a positive alpha exponent.

Results

Accuracy and Reaction Times Analyses

Table 1 shows mean accuracy and mean reaction time for each trial type, separated by order of trials (random vs. blocked) and element type (familiar letter vs. novel tetragon). Two mixed-design 2 x 2 x 3 ANOVAs were conducted, one for accuracy and one for reaction time, with order and element type as between-group factors, and trial type as within-group factor. Even thought there was very high overall accuracy, there was a significant triple-interaction effect, F (1, 66) = 6.62, p = .01, $\eta_p^2 = .09$. Post-hoc analyses show that mean accuracy was lowest for element-match trials, compared to shape-match and no-match trials (ps < .001). Order of trials affected accuracy only in the tetragon conditions, where accuracy was significantly lower in the random vs. the blocked order (p < .01).

Table 1: Mean proportion of correct answers (in %) and reaction time (in ms) for each experimental condition, with standard errors in parenthesis.

	Order of Trials	
	Random	Blocked
Familiar Element (Letter)		
Trial Type		
Element Match	92% (0.9) 2318 ms (87)	91% (1.4) 1850 ms (72)
Shape Match	96% (0.7) 2473 ms(195)	96% 1316 ms (104)
No Match	96% (0.5) 3886 ms (185)	95% (0.6) 2932 ms (124)
Novel Element (Tetragon)		
Element Match	84% (5.2) 2646 ms (100)	90% (1.2) 2210 ms (165)
Shape Match	95% (0.7) 2615 ms (185)	95% (1.3) 1809 ms (236)
No Match	96% (1.3) 3906 ms (214)	96% (2.5) 3603 ms (226)

For reaction time, we found a significant order x trial type interaction, F (1, 66) = 11.62, p = .001, $\eta_p^2 = .15$. Post-hoc analyses indicated the participants were faster in the blocked order than the random order (p < .001). And they took longer on no-match trials than on shape-match or element-match trials (ps < .001). Reaction times were similar between shape-match and element-match trials, but more so when the trials were administered randomly. When they were administered in blocked form, performance on shape-match trials was faster than on element-match trials ($p < .01$).

Fractal Analyses

Figure 3 shows the mean Hurst's coefficients estimated by DFA, separated by trial order and type of elements.

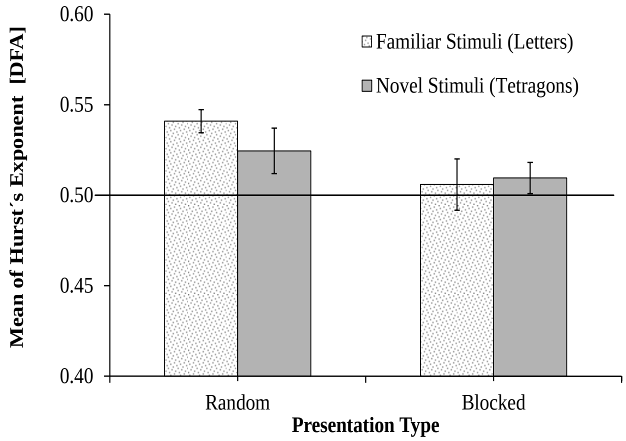

Figure 3: Mean Hurst's Coefficient for each condition, obtained through a Detrended Fluctuation Analysis. Error bars display standard errors, and the vertical line illustrates the exponent for ideal white noise.

A 2 by 2 between-subject ANOVA revealed a marginally significant main effect of order, which a higher average exponent in the random order than the blocked order, F (1, 66) = 3.41, p = 0.069. Using a series of t-tests, we compared the H values of each experimental condition with the reference value of H = .50 (white noise). The only condition that had an exponent significantly different from white noise was the random-letter condition, t (25) = 6.41; $p < .001$; whereas the others conditions were not different from white noise, $ts < 2$; $ps > .09$.

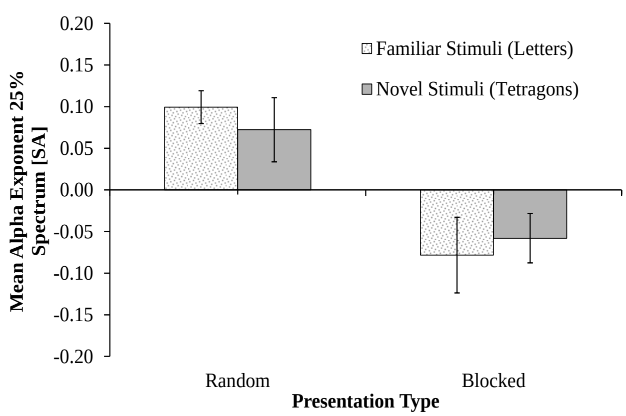

Figure 4: Mean scaling exponent alpha, estimated with a spectral analysis (SA) at 25% of the spectrum, separated by experimental condition. Error bars display standard errors.

Figure 4 shows alpha values from a spectral analysis that was estimated with a 25% spectrum. A 2 by 2 ANOVA revealed a main effect of order, F (1, 66) = 12.69, p = .001, η_p^2 = .16, with random-presentation conditions yielding a higher alpha coefficients than the blocked-presentation conditions. There was no effect of trial type, nor a significant interaction, $p > .58$. As was done with DFA, we compared the mean exponent of each condition against the reference value of white noise [α = 0]. Only the random-letter condition had an exponent that was significantly higher than white noise, t (25) = 5.03; $p < .001$; whereas the others conditions were not different, $ts < 1.953$; $ps > .10$[2]. In concordance with previous analysis, the random-letter condition is the only one that had an alpha exponent different from a random pattern.

Discussion

Our research was aimed at obtaining a measure of coordination between what were traditionally considered two separate processes: the process of segregating information into local details, and the process of integrating information into larger patterns of Gestalt. Our general assumption was that attention fluctuates on various scales, the fastest scale being attention to the most local elements, and a slower scale being attention to larger patterns. These scales need to be coordinated for adaptive functioning to take place, such that the perceiver can quickly adjust to miniscule changes as needed (cf., Kloos & Van Orden, 2010). Using methods of fractal analysis, we tested this hypothesis in a task in which participants has to determine whether two stimuli matched in local element, global Gestalt, or neither of the two.

Findings confirm our hypothesis in the case in which when elements were sufficiently familiar to the perceivers and trials were presented with as little outside interference as possible. More specifically, we applied two time-series analyses, the detrended fluctuation analysis and the spectral analysis, to a time series of reaction times that resulted from the speeded-categorization task. Results of the two analyses converge in that the fractal exponent significantly departed from random white noise when the task involved familiar elements (letters) and trials were presented in random order. In this case, the fractal exponent pointed in the direction of pink noise, which reflects a kind of coordination that is neither too regular nor too random. It is the exponent that indicates long-range correlations across the various scales of change and as such it demonstrates an ideal coordination (Van Orden, Holden & Turvey, 2005).

When local elements of our experimental display were novel to the perceiver (i.e., unfamiliar shapes that differed in the details of their lines), level of coordination dropped. The

[2] When the spectral analysis was conducted across 100% of the spectrum, the blocked-order condition had far higher exponents than the random-order condition. However, upon inspecting the power spectrum more closely, its distribution was not typical of a pink-noise distribution. The 25% spectrum therefore yields a more reliable measure of long-range correlations.

novelty of the elements most likely decreased their salience, and therefore increasing the salience of the higher-order Gestalts. This discrepancy in salience might have interfered with an attempt to coordinate the local and global processes. Similarly, when the trials were presented in a blocked order – thus providing some outside support for task performance, levels of coordination dropped. In each case, the obtained fractal exponent approached that of random white noise. These findings suggest that the local-global coordination is intertwined with the details of the task, showing ideal long-range correlation only when local and global patterns have similar salience, which outside interference is kept minimal.

Taken together, we were able to provide evidence of long-range correlations in a speeded categorization task in which local and global processes were pitted against each other. To our knowledge, this is the first of such attempts, with an important implication. Rather than treating local and global processes as separable and interfering forces, our results show an inherent coordination among these levels of attention – a coordination that is affected by task constraints. When experimental stimuli are such that one scale is much more salient than the others, this adaptive coordination would remain hidden from the eye of the researcher.

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References

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.

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.

Eke, A., Hermán, P., Kocsis, L., & Kozak, L. R. (2002). Fractal Itemization of complexity in temporal physiological signals. *Physiological Measurement, 23*, R1-R38.

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

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

Hausdorff, J. M. & Peng, C. -K. (1996). Multiscale randomness: A possible source of 1/f noise in biology. *Physical Review E, 54*(2), 2154-2157.

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., Choi, I., Amazeen, P. G., & Van Orden, G. (2010, December 6). Fractal $1/f$ Dynamics Suggest Entanglement of Measurement and Human Performance. *Journal of Experimental Psychology: Human Perception and Performance*. Advance online publication.doi: 10.1037/a0020991

Kello, C. T. & Van Orden, G. (2009). Soft-assembly of sensorimotor function. *Nonlinear dynamics, psychology, and life sciences, 13*(1), 57-78.

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

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. (2010). Voluntary behavior in cognitive and motor tasks. *Mind and Matter, 8*(1), 19-43.

Köhler, W. (1969). *The Task of Gestalt Psychology*. Princeton, NJ: Princeton University Press.

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

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

Peng, C. K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos, 5*, 82-87.

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.

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., Holden, J. G., & Turvey, M. (2005). Human cognition and $1/f$ scaling. *Journal of Experimental Psychology: General, 134*, 117-123.

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.