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Cue predictability changes scaling in eye-movement fluctuations

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Abstract Recent research has provided evidence for scaling-relations in eye-movement fluctuations, but not much is known about what these scaling relations imply about cognition or eye-movement control. Generally, scaling relations in behavioral and neurophysiological data have been interpreted as an indicator for the coordination of neurophysiological and cognitive processes. In this study, we investigated the effect of predictability in timing and gaze-direction on eye-movement fluctuations. Participants performed a simple eye-movement task, in which a visual cue prompted their gaze to different locations on a spatial layout, and the predictability about temporal and directional aspects of the cue were manipulated. The results showed that scaling exponents in eye-movements decreased with predictability and were related to the participants' perceived effort during the task. In relation to past research, these findings suggest that scaling exponents reflect a relative demand for voluntary control during task performance.

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Introduction

For humans, controlling eye movements is a critical part of sustaining effective and adaptive behavior within the environment. This adaptability is highlighted by two complementary components of eye movement behavior that serve to maintain a stable point of gaze to gather important visual information (fixations) and to quickly shift gaze between important sources of visual information (saccades). There is a long intellectual history of regarding these two types of eye movement behaviors as fundamentally separate processes (Erdmann & Dodge, 1898; Rayner, 1998). However, this picture of eye movements has been complemented by research investigating the dynamic patterns in fluctuations in eye movements. Recent studies have shown fluctuations across fixations and saccades are intimately connected, suggesting that eye movements of all sizes are governed by fundamentally interdependent processes (e.g., Stephen & Mirman, 2010; Wallot, Coey, & Richardson, 2015; Wallot & Kelty-Stephen, 2014). More specifically, like many other kinds of behavioral and physiological measures (see Van Orden, Kloos, & Wallot, 2011 for a review), eye movements display complex patterns of fluctuations that conform to power-law scaling relations (e.g., Aks, Zelinsky, & Sprott, 2002; Coey, Wallot, Richardson, & Van Orden, 2012; Mirman, Irwin, Stephen, 2012; Stephen & Anastas, 2011).

In time-series data (such as a time-series of saccades – e.g., Shelhamer & Joiner, 2003), power-law scaling – also commonly called $1/f$ noise – is characterized by a scaling relation between the size (or power, P) of changes in the measured variable and the frequency (f) with which changes of that size occur, expressed as $P(f) = 1/f^{\alpha}$. As shown in Fig. 1, the dynamic pattern evident in a time series can be captured by the scaling exponent (α). Here, the time series are first broken down into a set of sine waves with variable power (i.e.,
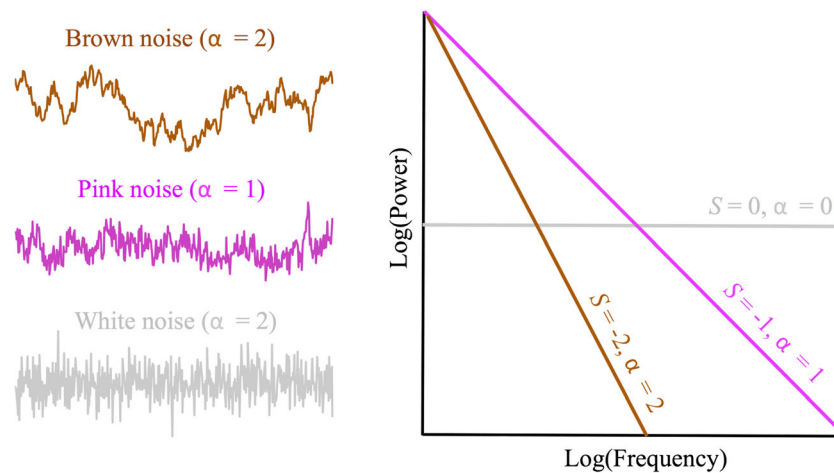
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Fig. 1 **Left panel:** Idealized brown noise (top), pink noise (middle), and white noise (bottom). **Right panel:** The associated scaling relations for these noises, shown as their spectral power density profiles on a log-log plot

oscillatory amplitude squared) and frequency. The power is plotted against the frequency on a double-logarithmic "spectral plot." The inverse of the slope of the regression line fitting this plot is taken as an estimate of the scaling exponent. True "white" noise, wherein the fluctuations in the series are completely random and uncorrelated in time, is indicated by a scaling exponent of $\alpha = 0$. In contrast, "pink" (or $1/f$) noise, which is indicated by a scaling exponent of $\alpha = 1$, entails a "persistent" dynamic, wherein increases tend to be followed by further increases, and decreases by further decreases. Alternatively, "brown" noise (or fractional Brownian motion; see Holden, 2005), entails yet a far more regular, extremely persistent pattern in the time-series, and is indicated by $\alpha = 2$.

As mentioned above, previous research has shown that many different kinds of human performances reveal power-law scaling (Van Orden, et al. 2011). The theoretical significance of power-law scaling in human data is still debated (cf. Van Orden, et al. 2003, 2005, vs. Farrell, Wagenmakers, & Ratcliff, 2006; Wagenmakers, Farrell, & Ratcliff, 2005, vs. Ihlen & Verejiken, 2010), but there seems to be a general agreement that this reflects the ongoing coordination of physiological, neural, and cognitive processes (Kayser & Ermentrout, 2010, Kello et al., 2010). The scaling relation entails a *scale invariant* relationship between the size of fluctuations in measurement (i.e., power) and how often they occur (i.e., frequency). In other words, the same relationship between the size and frequency of fluctuations in the time-series holds across many timescales. Several researchers have taken this scale invariance to mean that the different physiological and behavioral processes underlying the performance of a task are highly interdependent (Stephen & Mirman, 2010; Van Orden et al., 2011).

Finding that power-law scaling relations are a defining feature of eye movements in different kinds of visual search tasks (Stephen & Mirman, 2010), in scene perception (Rhodes,

Kello, & Kerster, 2011), in text reading (Wallot, O'Brien, Coey, & Kelty-Stephen, 2015), and in fluctuations in gaze during fixation (Coey, et al., 2012) suggests that eye movements are similarly organized by interdependent processes (Kelty-Stephan & Mirman, 2013; Wallot, Coey et al., 2015). Moreover, the previous research has also demonstrated that the scaling relations in eye movements are predictive of task performance. For instance, Stephen and Anastas (2011) found that individual differences in scaling predicted speed differences of participants in two visual search tasks. Similarly, Mirman and colleagues (2012) showed that children with autism spectrum disorder differed from typically developing children in the scaling of eye movements during a visual speech perception task.

Hence, scaling relations in eye movements seem to be predictive of mental conditions and cognitive performance, but the question remains what aspects of psychological processes they might reflect in particular. One proposal holds that scaling relations are indicative of the difficulty of a cognitive task (Grigolini, Aquino, Bologna, Lukovic, & West, 2009). However, the relation between task difficulty and scaling in eye movements is not straightforward. For example, although Stephen and Anastas (2011) showed that faster completion of a visual search task corresponded to increases in scaling exponents, results by Wallot, O'Brien, Coey, and Kelty-Stephan (2015) showed that increases in text difficulty in a reading task also led to an increase of scaling exponents in eye movement fluctuations. While the former finding seems to indicate that a *reduction* in task difficulty during visual search goes together with higher scaling exponents, the latter finding seems to indicate that an *increase* in task difficulty during reading goes together with higher scaling exponents. Hence, the scaling exponents do not seem to be directly related to cognitive task difficulty per se.

However, both of the studies referenced above are also ambiguous with regard to the notion of task difficulty. Perhaps participants that showed faster completion of the visual search task had simply put more effort into a task that was equally difficult for all participants. Also, the easy and difficult text stimuli in the reading task are not strictly comparable. More difficult texts more highly constrain reading performance, in that they require the reader to visually follow the word sequence of the text more strictly, which is evident in lower word-skipping rates for difficult texts (Rayner, Slattery, Drieghe, & Liversedge, 2011), and hence might lead to shallower scaling exponents in difficult texts due to a different visual sampling stragegy, not differences in cognitive processing.

A theoretical proposal that might be able to bridge this gap is the interpretation of scaling exponents as ultimately reflecting a mixture of the voluntary cognitive task demands and the involuntary task constraints that together control cognitive performance (Kloos & Van Orden, 2010). That is, scaling exponents may not be directly reflective of task difficulty, but rather reflect the demand of voluntary control *relative to* the (environmental) task constraints that also govern behavior. For example, two experimental conditions that differ in the level of difficulty of an information-processing problem, which would increase the demand for voluntary control, might also differ in the level of involuntary constraints that affect cognitive performance (as might have been the case for reading of difficult and easy texts). In this proposal (Kloos & Van Orden, 2010), increases in the demand for voluntary control are associated with increases in scaling exponents, and increases in the degree of involuntary constraints are associated with decreases in scaling exponents. If, however, a cognitive task leads to similar increases in involuntary constraints *and* the demand for voluntary control, then no change in scaling exponents is observed. Also, if a task leads to increases in the demand for voluntary control, but at the same time to disproportionally greater increases in involuntary constraint, then a decrease in scaling exponents is observed despite an absolute increase in the demand for voluntary control.

Two hypotheses can be formulated based on this proposal. First, experimental manipulations that aim to increase voluntary control through task difficulty, but hold involuntary sources of constraint relatively constant, will lead to increases in scaling exponents, and a positive relationship between the scaling exponents and task difficulty will be observed. Second, scaling exponents will be positively related to other measures of voluntary control, such as subjective reports of effort. We designed the current experiment to test these two hypotheses. Specifically, the current experiment tested whether the scaling in eye-movement fluctuations can be increased by experimental manipulations that try to keep sources of involuntary constraint relatively constant, but primarily change the demand for voluntary control. To do so, we employed a simple eye-movement task and manipulated the spatial and temporal predictability of cues that informed participants about how to execute their eye movements from one position on to another. In order to keep involuntary sources of constraint relatively constant, the basic properties of the cues (same layout of cues, same number of cues per condition) and the visual layout (same layout, same distances that participants eye movements had to bridge) were the same in each condition. Hence, cue predictability should primarily affect the demand for visual attention in the task, as participants need to monitor occurrence of cues more thoroughly as cues become increasingly unpredictable (Lamy, 2005).

Method

Participants

Nine graduate students from the University of Cincinnati volunteered to participate in the experiment. Participants' ages ranged from 21 to 29 years, and all participants had normal or corrected-to-normal vision.

Apparatus and stimuli

Eye movements were recorded using an ASL D6 remote eye-tracker with a sampling rate of 60 Hz and a maximal spatial resolution of 0.5° visual angle. Directly above the eye-tracker was a computer screen (1280 × 1024 pixel) used for displaying the target stimulus. The eye-tracker was placed on a desk 79 cm from the floor and participants were seated on a chair with a seat 46 cm from the floor. Participants were presented with a nine-dot display and were instructed to fixate on each of these nine dots, in turn, in an order prescribed by a cue (arrow) that varied in spatial or temporal predictability (see Fig. 2).

Procedure and stimuli

On each trial, participants were instructed to begin by fixating on the center dot until an arrow appeared on that dot. When the arrow appeared, participants were instructed to move their eyes as quickly as possible to the new dot that was indicated by the direction of the arrow and to fixate on that dot until a new arrow appeared (see Fig. 2). Each participant underwent several trials that differed in the predictability of the intervals in which arrows would appear (temporal predictability) and in the predictability of the direction to which arrows would point (spatial predictability). Each trial lasted for approximately 50 s, and participants encountered 62 arrow-cues during each trial.

In conditions of spatial predictability, the arrows always indicated a clockwise, center-peripheral-center pattern. That is, the participant began fixated on the central dot, then fixated on a peripheral dot, then moved back to
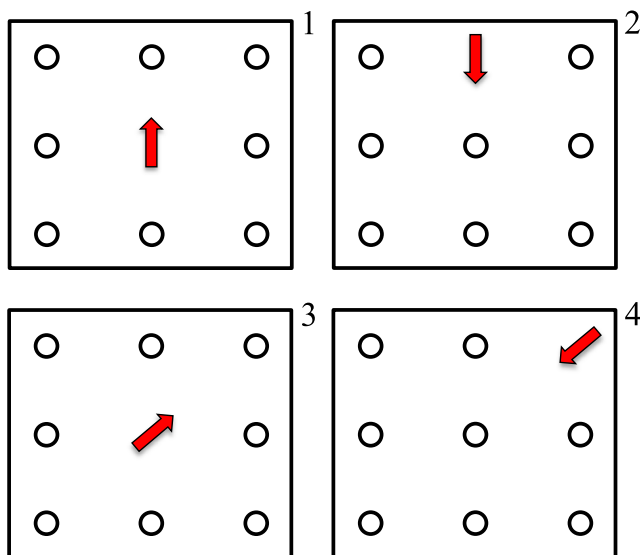
Fig. 2 Stimulus display for the eye-movement task. The slides illustrate an example of the first four steps (1–4) in a movement sequence that participants might perform. On each step an arrow indicated a new fixation location where the participant should look next. The sequence of fixation locations and the intervals between shifts from one location to the next were either predictable or unpredictable, depending on experimental condition

the central dot, and then on the next peripheral dot in a clockwise fashion (see Fig. 2). In conditions of spatial randomness, the arrows indicated the center-peripheral-center pattern, but not in a clockwise direction. Instead, which peripheral dot was next in the sequence was entirely random. That is, participants started at the central dot, but the arrow would cue a random peripheral dot on which participants had to next fixate. Then, cued again by an arrow, participants fixated back to the central dot, where again a random peripheral dot was cued. This center-peripheral-center pattern was implemented to keep the distances and overall nature of the task constraints in the dot-layout similar across conditions. In conditions of temporal predictability, the interval between arrow presentations was constant (800 ms). In conditions of temporal randomness, the intervals between arrow presentations randomly varied between 400 ms and 1,200 ms, around a mean interval of 800 ms. These manipulations were crossed to produce a total of four experimental conditions (i.e., predictable space – predictable time; predictable space – random time; random space – predictable time; random space – random time).

Participants underwent six trials in each condition in a counter-balanced order. Upon the completion of the eye-movement trials, participants completed a short questionnaire that required them to rank in order each of the four conditions in terms of the perceived difficulty and assign each condition an "effort score" ranging from 0 to 100.

Data analysis

Data analysis was based on the raw, unsmoothed eye-movement record to avoid the induction of spurious power-law like structure into the data (Coey et al., 2012). First, artifacts (i.e., when the participants blinked or the eye-tracker lost the eye) were removed, as were data points ±3 standard deviations (SDs) from the means and linear and quadratic trends, following the recommendations of Holden (2005) for the estimation of scaling relations. On average, 1.5 % of the data were discarded on these grounds. Lastly, each time series was then trimmed to the first 2,048 data points in order to compare participants' performance over the same period of time.

Scaling exponents were estimated across the eye movement record for each condition. To estimate scaling relations, the time-series data for vertical and horizontal coordinates for each trial was subjected to spectral analysis. The resulting power-spectral density was plotted on a log-log axis, and a least-squares line fitted to the log-log plot. The slope (S) of this line gives an estimation of the strength of the scaling relation (α) in eye-movement fluctuations, where $\alpha = -S$ (see Fig. 3).

To test the effects of predictability, the subjective ratings, the measures of eye movement performance, and the scaling exponents of eye-movement fluctuations were subjected to repeated-measures ANOVAs. To test the relations of subjective difficulty and eye movement performance with scaling exponents of eye movements, we used repeated-measures regression analysis (Lorch & Myers, 1990).

Results

Perceived effort

Participants' effort ratings for each task were subjected to two-way repeated-measures ANOVA with the factors temporal predictability (predictable, random) and spatial predictability (predictable, random). We observed a main effect of temporal predictability, indicating that participants perceived their performance as more effortful when the timing of the eye-movement cues was random ($F(1, 8) = 6.72$, $p = .016$, $= \eta^2 = .457$). Likewise, we observed a main effect of spatial predictability, indicating that participants perceived their performance as more effortful when the direction of the eye-movement cues was random ($F(1, 8) = 18.53$, $p = .002$, $= \eta^2 = .698$) (see Fig. 4). There was no interaction between the factors ($F = 0.48$, $p = .508$).

Saccade accuracy

To estimate the effect of spatial and temporal predictability of eye movement performance, we calculated the SD of saccade lengths and the SD of saccadic acceleration for each
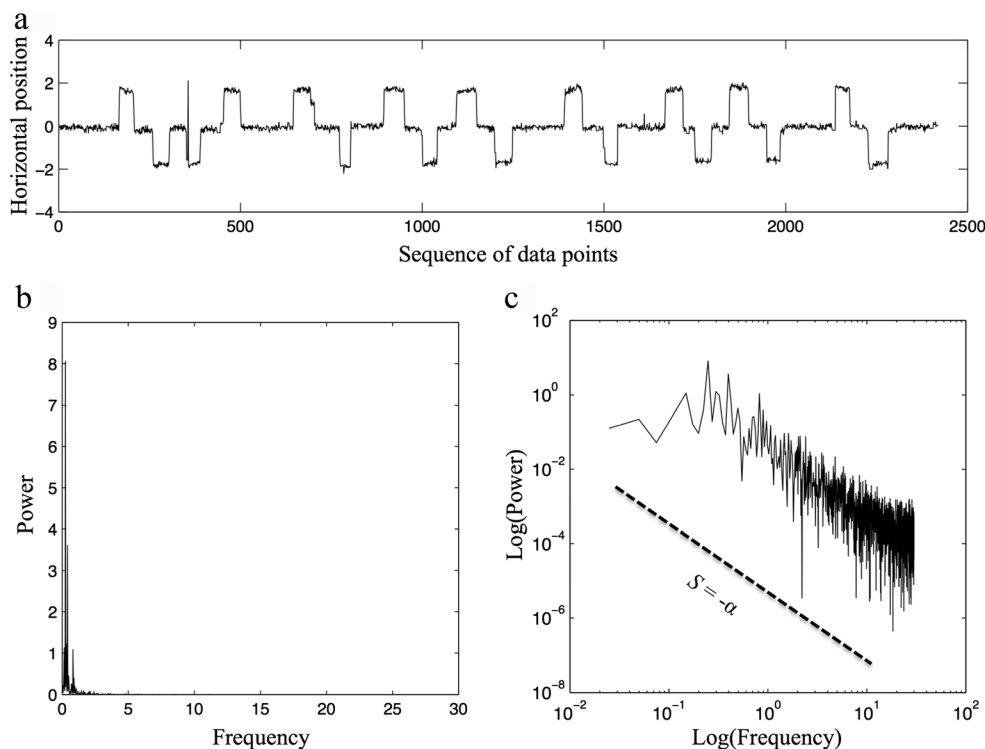
Fig. 3 Illustration of the calculation of scaling exponents. (**a**) The raw eye movement record from one participant's horizontal position series; (**b**) the associated power spectrum; and (**c**) the power spectrum when both axes (i.e., power and frequency) are on a logarithmic scale. If the plot in (**c**) conforms to a linear relation between power and frequency, the slope of a line that is fitted to the log-log plot estimates the scaling exponent of the fluctuations in the time-series displayed in (**a**), where the slope of the scaling exponent alpha (α) relates to the slope (S) of the regression line as $\alpha = -S$

participant and condition. The SD of saccade lengths provides a measure of how much the manipulation of spatial and temporal predictability impact the spatial accuracy of eye movements: As the target distances in all conditions were the same, a higher degree of dispersion of saccade lengths would indicate a loss of aiming accuracy of the eyes.

Furthermore, we also investigated the SD of saccadic accelerations. Instead of looking at saccadic acceleration, the latency between cue-onset and saccadic initiation would have
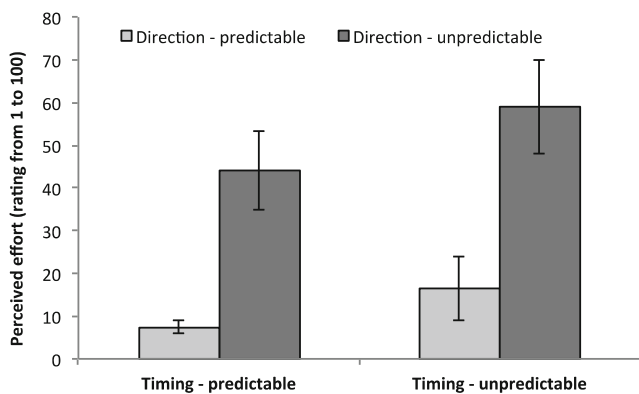

Fig. 4 Average perceived effort as a function of spatial and temporal predictability. Participants rated their performances as more effortful when the timing and direction of the cues were random and this effect was more pronounced for spatial predictability

been a preferred measure of the reliability of performance. However, as the stimuli were displayed via a set of timed PowerPoint slides, our data collection setup did not provide us with sufficiently accurate information about the relative timing of cue-onset and saccadic initiation. Hence, the SD of saccadic acceleration provides an indirect measure of the accuracy with which participants reacted in response to the target cues. The logic behind this measure is that under conditions of decreased cue predictability, participants will perform less accurately, sometimes fixating a cued position early and inhibiting the next saccade while waiting for the cue to appear, but sometimes being barely "just in time" to respond to an upcoming cue. Effectively, task performance under decreased cue predictability will lead to an increased mixture of prosaccades and delayed prosaccades, which are executed with different velocities (e.g., Edelman, Valenzuela, & Barton, 2006) and in turn lead to an increase of the SD in saccadic accelerations under conditions of decreased cue predictability. Hence, the higher the SD of saccadic accelerations, the less reliably participants performed saccades in response to cues.

Both measures were subjected to a repeated-measures ANOVA with the factors temporal predictability (predictable, random) and spatial predictability (predictable, random). For the SD of saccade lengths, the ANOVA revealed a main effect
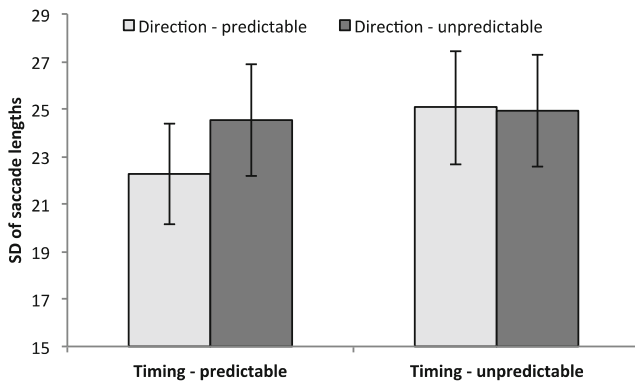
Fig. 5 Average standard deviation (SD) of saccade lengths as a function of spatial and temporal predictability. The SD of saccade lengths was increased when either spatial and/or temporal cues were randomized, compared to when both spatial and temporal cues were predictable

Fig. 7 Average scaling exponents as a function of spatial and temporal predictability. The data are collapsed across horizontal and vertical coordinates, as there were no differences between axes. Scaling exponents were greater when the direction and timing of the cues were random, although the effect for timing was marginal

of temporal predictability ($F(1, 8) = 5.76$, $p = .043$, $= \eta^2 = .418$), which was moderated by an interaction between temporal predictability and spatial predictability ($F(1, 8) = 12.98$, $p = .007$, $= \eta^2 = .619$): As can be seen from Fig. 5, the SD of saccade lengths was increased in all conditions that introduced either spatial and/or temporal predictability, compared to when cue posting and timing were completely predictable.

For the SD of saccadic acceleration, the ANOVA revealed a main effect of spatial predictability ($F(1, 8) = 8.29$, $p = .021$, $= \eta^2 = .509$), indicating that SDs of saccadic accelerations decreased with the introduction of spatial predictability (see Fig. 6). No other effects were apparent (all $F < 0.15$, all $p > .379$).

Scaling exponents

Again, scaling exponents for each participant and condition were calculated for horizontal and vertical coordinates separately and were subjected to a repeated-measures ANOVA with the factors temporal predictability (predictable, random), spatial predictability (predictable, random), and position axis
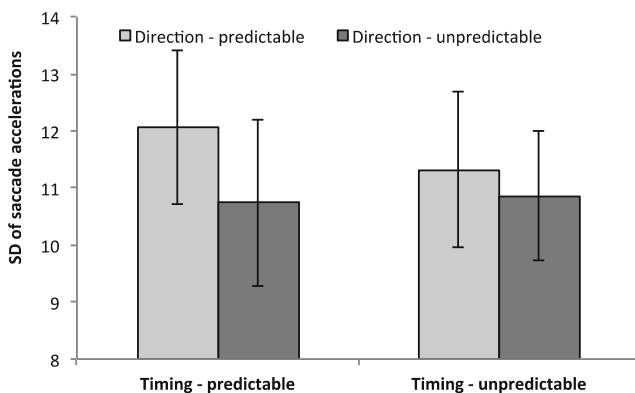

Fig. 6 Average standard deviation (SD) of saccade acceleration as a function of spatial and temporal predictability. The SD of saccade acceleration was lower when spatial cues were random
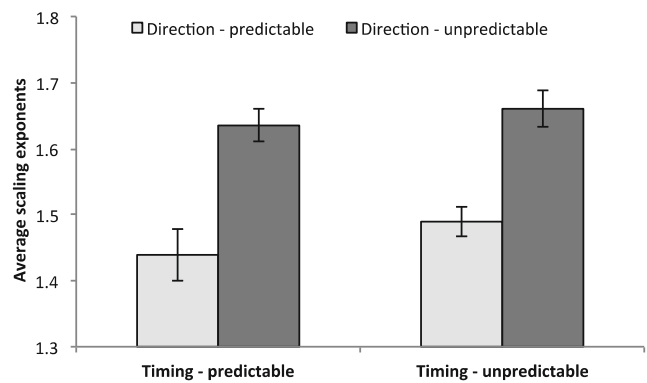
(horizontal, vertical). The ANOVA revealed a significant main effect of spatial predictability ($F(4, 64) = 63.12$, $p < .001$, $\eta^2 = .798$), indicating that the scaling exponents of eye-movement fluctuations increased when the direction of the movement cues was random. There was also a statistical trend for temporal predictability ($F(4, 64) = 2.00$, $p = .091$, $\eta^2 = .109$), indicating a tendency for scaling exponents to increase when the timing of movement cues was random (see Fig. 7). There were no effects for position axis (horizontal vs. vertical) and no interactions between the factors (all $F < 1.18$, all $p > .294$). Figure 8 displays the average scaling plots for all four experimental conditions.

Effort and eye movement characteristics

To test whether the observed increases in scaling exponents were indeed related to increases in effortful voluntary control, we conducted a repeated-measures regression analysis predicting each participant's effort ratings from eye movement characteristics: scaling exponents of eye-movements, SD of saccade lengths, and SD of saccade acceleration. The resulting regressions showed a strong positive relationship between effort ratings and scaling exponents, a comparatively weak negative relationship between effort ratings and the SDs of saccade accelerations, and no substantial relationship between effort ratings and the SDs of saccade lengths (see Table 1).

Discussion

In this study we sought to experimentally control scaling relations in eye-movement fluctuations by manipulating the predictability of when and where to look on a simple stimulus layout. The purpose of this experiment was to examine current hypotheses about the role of power-law scaling in human behavioral performance, namely, that decreases in cue
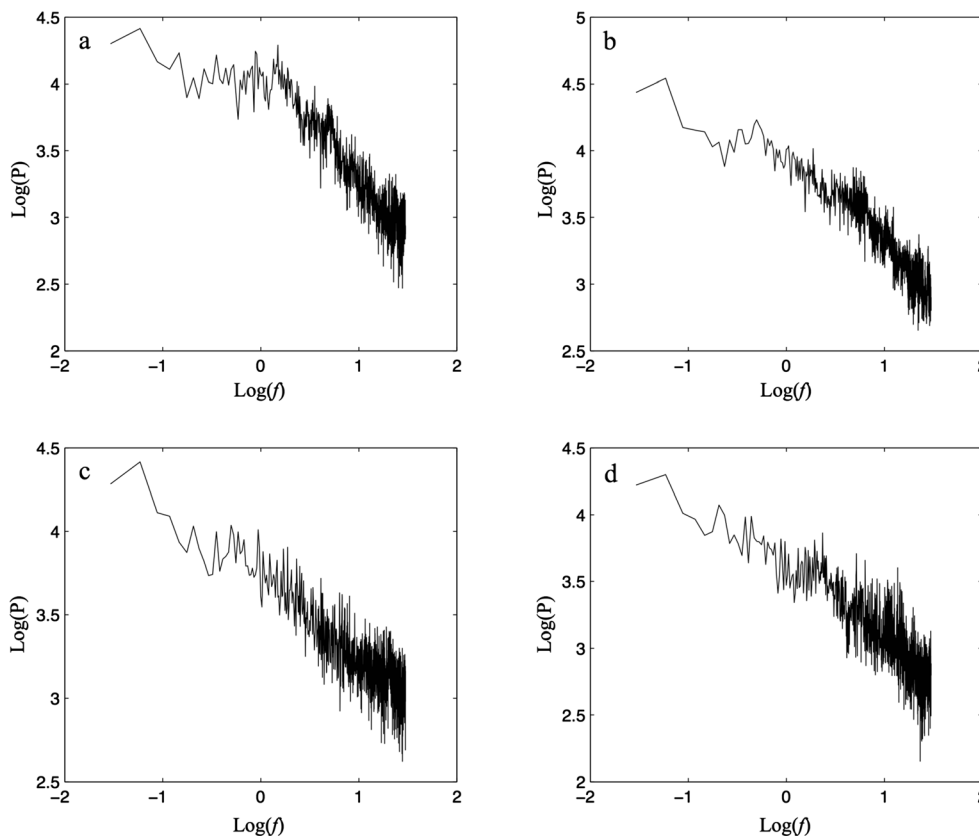
Fig. 8 Average scaling plots of the logarithm of power versus the logarithm of frequency of the eye movement records for (**a**) predictable timing and location, (**b**) random timing and predictable location, (**c**) random location and predictable timing, and (**d**) random timing and location. Plot (**a**) shows some deviation form linearity at the lowest frequencies. Nevertheless, all four plots yielded satisfactory linear fits of comparable magnitude: $r = -0.826$, $r = -0.896$, $r = -0.903$, and $r = -0.849$, respectively. (See the appendix for additional analysis that demonstrate that the observed scaling relations were not biased by exponential behavior or inflection points, as well as additional tests that determined that the observed differences in scaling relations between conditions was not a simple artifact of the different task conditions)

predictability would lead to increases of power-law scaling exponents and that these increases in scaling exponents are reflective of effortful, voluntary control processes. As expected, the degree of predictability led to changes in scaling relations observed in the eye movements and the scaling exponents were indeed strongly related to the perceived effort.

Our findings are at odds with the proposal that increases in task difficulty necessarily result in decreases in scaling exponents (Grigolini et al., 2009). Instead, our findings

Table 1 Prediction of subjective effort from eye movement characteristics

Predictors	T	B	R^2	P
Scaling exponents α	8.07	.794	.630	< .001
SD saccade acceleration	−2.03	−.357	.127	= .038
SD saccade lengths	−0.94	−.240	.057	= .187

Note. The associated DF for the *t*-values were DF = 8. The predictors were tested individually

SD = standard deviation

demonstrated that when the involuntary task constraints are held relatively constant there is a positive relationship between scaling exponents and task difficultly, as well as the participants' perceived effort. In other words, our findings are consistent with the proposal that scaling exponents reflect the *relative* demand of voluntary control in a cognitive task, rather than task or information-processing difficulty per se (Kloos & Van Orden, 2010). Tasks demanding vigilant control necessitate the coordination of many different processes operating on different timescales (attentional, motivational, perceptual, and motoric). Theoretically, power-law scaling is reflective of the coordination of processes across timescales (Van Orden et al., 2003), and tasks demanding more effortful control of behavior might be expected to increase scaling exponents. Again, this interpretation is consistent with our findings, where the scaling exponents for eye movements increase with the need to exercise vigilant control (i.e., low predictability) and are positively correlated with subjective effort ratings.

Moreover, scaling exponents in eye-movement fluctuations were a stronger predictor compared to other process measures, such as the SD of saccade accelerations or the

SD of saccade lengths. Interestingly, the SD of saccade lengths was primarily different between the conditions of full cue-predictability compared to all other conditions. Hence, the accuracy of saccades seems to have been compromised with any kind of in cue-predictability, showing a detrimental impact of the absence of predictability on eye movement performance (see also Doherty, Rao, Mesulam, & Nobre, 2005). This was not so, however, for the SD of saccade accelerations. The decreases in cue predictability led to more consistent acceleration performance. This effect seems to reflect the need for a consistent level of eye movement acceleration in conditions of decreased cue predictability, as not moving one's gaze fast enough to the next location results in missing the crucial information that is provided by the next cue – a pressure that is absent under conditions of high cue-predictability, where the information provided by the cue is less relevant and failure to fully perceive the cue is not so detrimental for task performance. The SD of saccadic accelerations was also predictive of effort ratings. This points to the possibility that acceleration under conditions of decreased predictability is one of the aspects of eye movement performance that demands for voluntary control to allow for successful task performance.

However, the effects of predictability on the SD of saccadic accelerations, as well as scaling exponents, was only observed for changes in spatial, but not temporal cue predictability. As explained above, where to look is very crucial for this task. In contrast, predictability of the time intervals might not have been of equally high importance. In hindsight, this might be due to the fact that even the shortest of the randomly presented intervals between fixations (i.e., 400 ms) were too long to pose a challenge to eye-movement control. Humans can initiate a saccade easily within 150 ms after stimulus onset (Altmann, 2011). Thus, participants in our study had a relatively comfortable time window to respond, even in the most challenging case of 400 ms. Another explanation of the spatial-temporal discrepancy might be that processing of spatial-directional properties are enhanced through several levels of visual processing in the nervous system, which may bias the attention towards spatial characteristics in guiding behavior (Doherty et al., 2005; Hillyard, Vogel, & Luck, 1998).

This prompts the question about how changes in scaling exponents in behavioral measures relate to changes of scaling exponents in the nervous system remains. It has been observed that attentionally demanding visual tasks lead to changes in the participating time-scales of neural activity, particularly resulting in an increased allocation of neural activity to the faster time-scales (Correa, Lupiáñez, Madrid, & Tudela, 2006). These findings seem to fit with research on scaling in neurophysiology showing that scaling exponents in EEG decreased with task difficulty (Grigolini et al., 2009) and that scaling exponents in fMRI records decrease when participants went from rest to a cognitive task (He, 2011). Moreover,

decreasing scaling exponents in neurophysiological activity may also reflect connectivity, indicating a recruitment of cognitive processes (Stam, 2005). In sum this seems to indicate that scaling relations in behavioral and neurophysiological activity do *not* follow the same pattern, and while increased scaling in behavior might be reflective of the demand for voluntary control, the opposite might be the case for measures of neural activity (cf. Van Orden, Hollis, & Wallot, 2012). This question, however, can only be answered by future research that studies the time course of neurophysiological and behavioral measures together.

Limitations

Our study only incorporated (behavioral) measures of eye movements, and thus cannot directly speak to the link between behavioral and neurophysiological properties of power-law scaling. Also, future research should incorporate non-subjective measures of effort, such as heart-rate, respiration, or skin conductance (e.g., Brookhuis & de Waard, 2010) to cross-validate the current findings that were based on self-reports. Furthermore, it remains to be seen whether the effects of effort on power-law scaling that we observed in the present study are generalizable to other task setups, or whether they are specific to the current task with its emphasis on successive to-and-fro movements between fixed coordinates on a plane. In that respect, a replication of the observed effects in simpler, as well as more ecological task setups would be desirable.

Conclusion

We used spatial temporal predictability to manipulate scaling exponents in eye-movement fluctuations. Unpredictability increased scaling exponents in eye-movement dynamics, and this increase of scaling exponents was strongly related to the subjective ratings of effort. Taking other, seemingly opposing findings into account (e.g., Mirman et al., 2012; Wallot, Coey, et al., 2015), a consistent explanation for the divergent findings might be that scaling exponents capture the *relative* demand for voluntary control in a task, not so much the overall increase or decrease of task difficulty (Kloos & Van Orden, 2010). However, neurophysiological evidence for the relation between scaling and aspects of task difficulty that are related to voluntary control cannot be easily subsumed under this explanation (e.g., Grigolini et al., 2009; He, 2011). Further research employing behavioral and neurophysiological measures is needed to investigate whether measures of the degree of voluntary control are involved in a task can bridge the gap effects of scaling found in behavioral end neurophysiological data.

Appendix

This appendix details complementary analyses that were conducted to validate the findings with regard to the following three questions:

Question 1. The average scaling plots for eye-movement fluctuations presented in Fig. 8 show varying degrees of bending/flattening for the lower frequencies (especially for the condition where timing and location were predictable – see Fig. 8a). The question was whether this visual impression indicates that the underlying scaling relation was better captured by an exponential, rather than a power-law function.

Question 2. The average scaling plots also suggested that the empirical functions might exhibit inflection points, and that those inflection points were systematically different for the different conditions. Hence, it needs to be clarified as to whether the scaling exponents (and the resulting inferential statistics) were bias by the presence of these (potential) inflection points.

Question 3. Finally, we also examined whether the differences in scaling exponents between conditions were not reflective of a differential performance of participants, but rather were simply a direct consequence of the predictability manipulation.
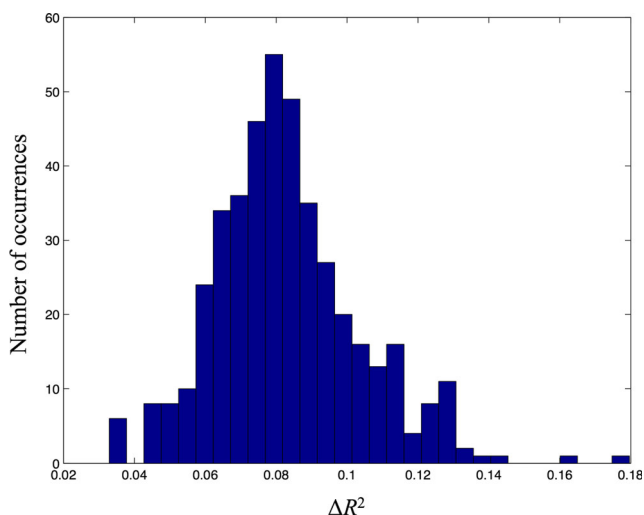

Fig. 9 Histogram of ΔR^2 ($R^2_{power-law} - R^2_{exponential}$) for the individual power spectra

Validation 1. In order to test whether the visual impression of a bend in the scaling plots is indicative of exponential function, rather than a power-law function, we tested the goodness-of-fit (R^2) for an exponential function versus a power-law function for the individual power-spectra of participants' eye movements. Figure A1 presents the histogram of the differences in R^2 ($R^2_{power-law} - R^2_{exponential} = \Delta R^2$). Positive values indicate that the power-law fit explained more variance than the exponential fit, and negative values indicate that an exponential function provided a better fit. As can be seen, all values are positive. Therefore, a power-law function provided a better data fit in each case.

Validation 2. In order to test whether the experimental results regarding the relation between scaling exponents and the experimental conditions are a function of a systematic difference in the distribution of inflection points and whether this difference biased the slopes of the scaling plots, we used a change-point algorithm (Jensen, 2013) to extract the frequency from each of the empirical log-log scaling functions with the highest probability of being classified as an inflection point. We then tested whether the extracted frequencies yielded effects on the predictability manipulations in our study by subjecting them to a repeated-measures ANOVA with the factors of temporal predictability (predictable, random) and spatial predictability (predictable, random). The ANOVA yielded no significant main effects of temporal or spatial predictability, and no interaction between those factors (all $F < 0.96$, all $p > .194$).

Furthermore, we correlated the extracted frequencies with their corresponding scaling exponents and effort ratings to test whether they could explain the effects of regressing effort ratings onto scaling exponents (within-participant analysis as described in the manuscript). Consistent with the ANOVA results reported in the previous paragraph, the repeated-measures regression analysis did not yield a significant relationship between the extracted frequencies ($\beta = .103$, $p = .584$) and the scaling exponents. Likewise, we found no substantial relationship between the extracted frequencies and the effort ratings ($\beta = .235$, $p = .091$). Hence, the potential influence of inflection points on the scaling plots seems to be responsible neither for the effects of cue predictability on scaling exponents, nor for the correlation between scaling exponents and effort ratings.

Validation 3. Finally, in order to gauge the effect the task-design might have had on the power-spectra, we modeled the dynamics inherent in the task design and subjected the model-output to spectral analysis. The model was a simple model composed of the positions on the screen over time (P) as prescribed by the visual cues for
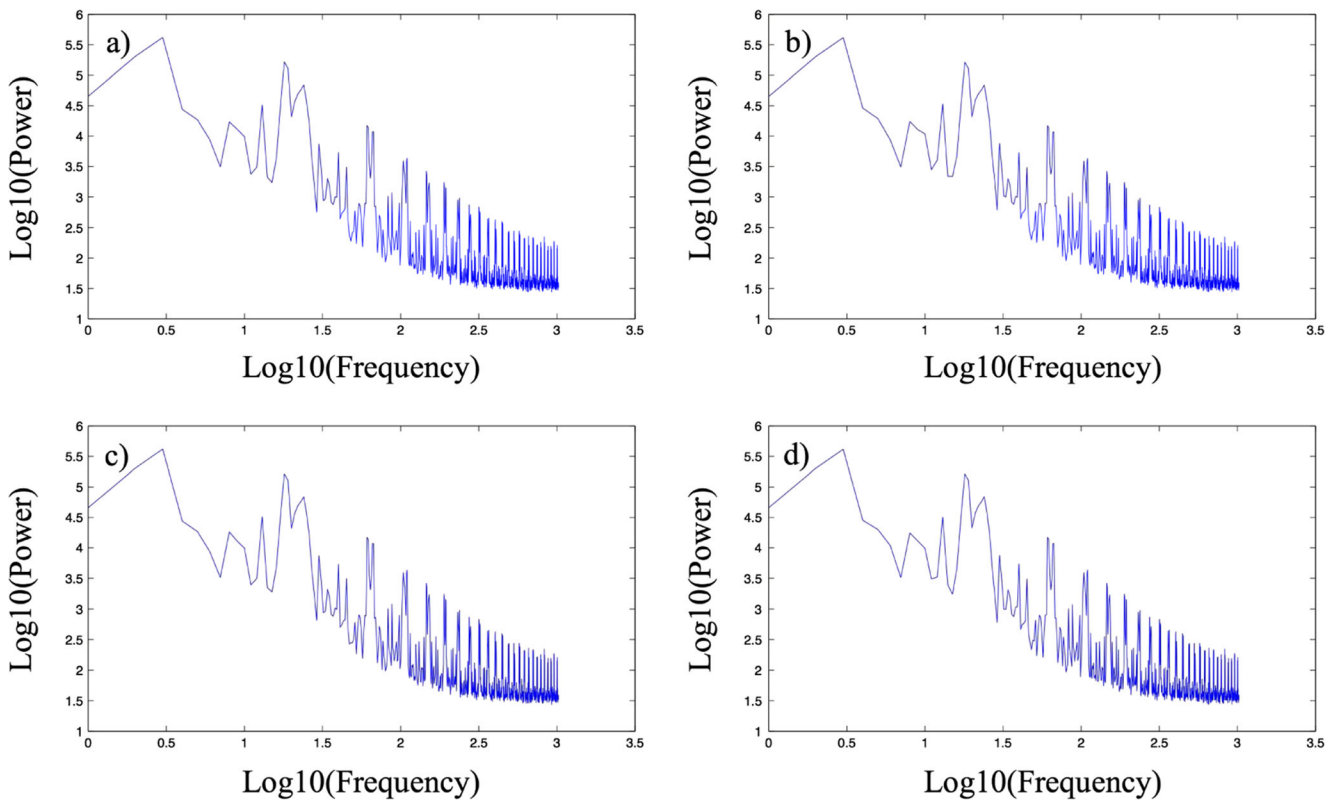
Fig. 10 Log-log scaling plots of the power-spectra of the task dynamics according to the white-noise model (M_w) for (**a**) the fully predictable cue, (**b**) the time-randomized cue, (**c**) the location-randomized cue, and (**d**) the fully randomized cue
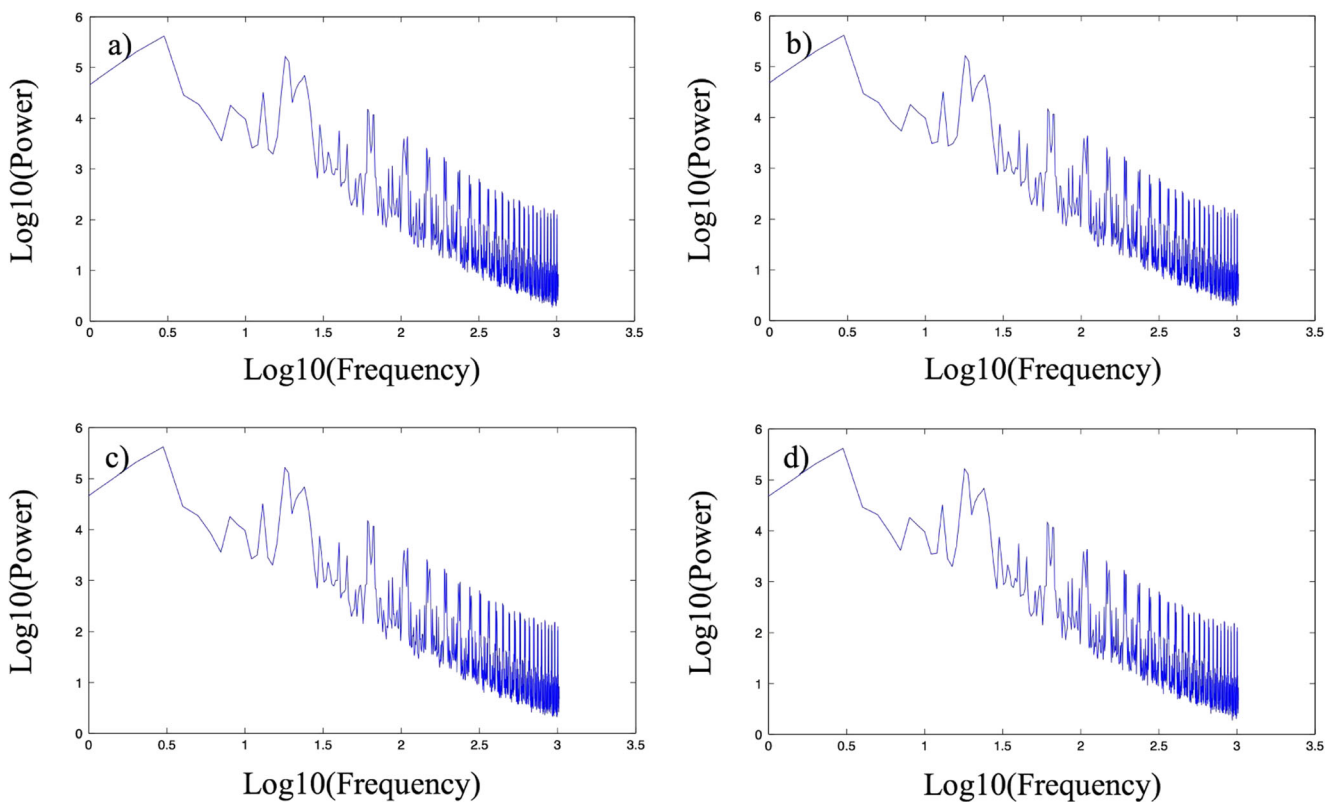

Fig. 11 Log-log scaling plots of the power-spectra of the task dynamics according to the pink-noise model (M_p) for (**a**) the fully predictable cue, (**b**) the time-randomized cue, (**c**) the location-randomized cue, and (**d**) the fully randomized cue

each of the four conditions accordingly. This position vector was sampled at the same rate as eye-movements in the experiment. Furthermore, this position vector, P, was smoothed with an equal-weight moving-average of lag5 (m-5) to account for the non-instantaneous acceleration and deceleration within a saccade (leading to a "saccade" duration of roughly 100 ms). Finally, a noise term (e) was added to the smoothed positions vector, $P_{m\text{-}5}$, where the magnitude of e was 33 % of the overall saccade length and the scaling properties of e where $1/f^0$, i.e., white noise.[1] This resulted in the model $M_w = P_{m\text{-}5} + e_{\alpha=0}$.

Figure A2 displays the average log-log scaling plots for our four conditions based on an amount of iterations equal to the number of trials in our study. As can be seen in comparison to Fig. 8 (i.e., the original plots of participants' performance), the spectra are qualitatively different, with the modeled data exhibiting strong cyclicity evident in the spikes in the spectrum, as well as the general downward bend of the spectrum, both of which are absent in the empirical data.

If instead of a white noise error term a pink-noise error term is used (i.e., $e_{\alpha=1}$, $1/f^{-1}$), resulting in a pink-noise model $M_p = P_{m\text{-}5} + e_{\alpha=1}$, the bending of the plot is somewhat decreased, but the cyclicity remains (see Fig. A3).

Moreover, the goodness-of-fit for the least-square line is generally lower across the conditions for the simulated data (R^2 = .599, .610, .610, and .614 for the white noise-model, and R^2 = .624, .632, .634, and .640 for the pink-noise model) compared to the original plots (R^2 = .682, .803, .815, and .721). Also, the observed slopes of the regression lines for the simulated data (S = −1.10, −1.10, −1.11, and −1.11 for the white noise-model, and S = −1.67, −1.68, −1.68, and −1.68) differ from the empirical results (S = −1.44, −1.50, −1.63, −1.66) with regard to the different conditions.

Together, the results of these additional analyses provide further evidence that the fluctuations of the raw position records exhibit power-law behavior and that the changes in the power-law structure across conditions reflected physiological and behavioral changes in effortful, voluntary eye-movement control, and are were not merely an artifact of the employed experimental conditions.

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[1] The size of the moving average and the magnitude of the noise term were inferred from the variability of participants' eye-movements in our task to approximate the average participant variability and saccade duration in the task.

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