

Research Article

FLUCTUATIONS IN THE TIME REQUIRED FOR
ELEMENTARY DECISIONS

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Abstract—*The nature of reaction time variability is analyzed in a suite of four experiments involving tasks, methodologies, and types of perceptual judgment commonly encountered in cognitive psychology. In every case, a substantial fraction of the trial-by-trial variability in reaction time latency is shown to be well described by a particular type of fluctuation known as 1/f noise. These results suggest that the time it takes to make and register a speeded decision reflects a kind of dynamic complexity that is seen in natural systems that self-organize at the boundary between order and chaos.*

Reaction time measurement has proven to be an enduring and effective tool in empirical studies of the nature of mental representation and cognitive process. There may be no area within cognitive science that has not been explored using methodologies that incorporate reaction time as a metric of thinking activity. In fact, reaction time is of such paramount importance that it has also been studied in its own right in order to better understand its measurement properties and the types of inferences it allows in the evaluation of theories and models (Townsend, 1990, Townsend & Ashby, 1983, Van Zandt & Ratcliff, 1995). Despite the practical and theoretical significance of this form of measurement, analyses of typical data sets suggest that much of what is in fact being measured has not been noticed. In this article, I show that reaction time fluctuations, which often account for 90% or more of the variance within a given observer's data, may exhibit the unique correlational structure of a $1/f$ noise, and so find an interpretation within the theory of complex systems.

The issues and analyses presented here require an appreciation that fluctuations come in varieties, and that these varieties have different meanings. The most common variety of fluctuation has uncorrelated increments and is referred to as white noise. Its power spectrum is flat with frequency (i.e., it falls off as $1/f^0$), signifying that there is equal power on all scales. White noise is the variety generally encountered in measurement, it is what random-number generators produce, it may appear in space or time, and it is what scholars generally are referring to when they speak of noise or random fluctuation. All other noises are essentially defined by the degree of correlation among their increments. A common type of correlated fluctuation arises as the successive sum of independent increments and is referred to as brown noise. Brown noises have spectra that fall off as $1/f^2$ and are frequently encountered as the fractals describing terrestrial landforms (Feder, 1988). Poised in the middle between white and brown noise is a statistically rare type of fluctuation whose power spectrum falls off inversely with frequency and is referred to variously as flicker, pink, or $1/f$ noise.¹ In the past quarter century, $1/f$ noise has been discovered

in the temporal fluctuations of an extraordinarily diverse number of physical and biological systems (Press, 1978, see articles in Handel & Chung, 1993, and references therein). Examples of its occurrence include fluctuations in tide and river heights, quasar light emissions, heart beat, and resistivity in solid-state devices. I have recently reported evidence for $1/f$ fluctuations in the patterning of successive judgments of spatial and temporal intervals (Gilden, Thornton, & Mallon, 1995). The fact that systems with no obvious connection can generate such a particular (and peculiar) temporal fluctuation has made the etiology of $1/f$ noise a central problem in theoretical physics. This effort has led to a deeper understanding of what kinds of systems produce $1/f$ noise, and there is now considerable evidence that its appearance is an identifying signature of dynamic complexity (Bak, 1990, 1992, Bak, Chen, & Creutz, 1989, Bak, Tang, & Wiesenfeld, 1987, 1988, Jensen, 1990).

MEASUREMENT OF REACTION
TIME VARIABILITY

I have measured reaction times in a sample of tasks that have been intensively investigated in the development of cognitive science: mental rotation, lexical decision, serial visual search, and parallel visual search. This selection is intended merely to illustrate the range of issues that have been fruitfully studied using reaction time as a dependent variable. Moreover, I do not wish to make arguments about the cognitive processes mediating attention, reading, or the imagination. The experiments, instead, have a purpose opposite to that which normally informs scientific activity. Rather than focusing the inquiry on the mean reaction times within different treatment conditions, I subtract out all treatment means from the data in order to describe what is usually regarded as the error. I wish to emphasize here that error in this context refers only to deviation from a mean and has no implications for accuracy.

Methods

Six experienced psychophysical observers participated in each study. No feedback was given on any trial. The studies were performed on a Quadra 950 with a 17-in Apple color monitor at a viewing distance of approximately 60 cm. Reaction time was measured as the latency between the presentation of a stimulus and a key press. Trials were sequenced so that the key press signifying a response on a given trial also reset the timer and initiated the subsequent stimulus display. Reaction times are accurate to about 4 ms in the mental rotation and lexical decision studies, and to about 8 ms in the

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¹ There is some potential confusion concerning what $1/f$ noise denotes. In the vision literature, investigators have recently taken to referring to brown noises as $1/f$ because they apparently prefer to identify noises by their ampli-

tude spectra, which are the square roots of the power spectra. The physics literature is quite uniform in referring to noises in terms of the power spectra, and that is the convention that I adopt here.

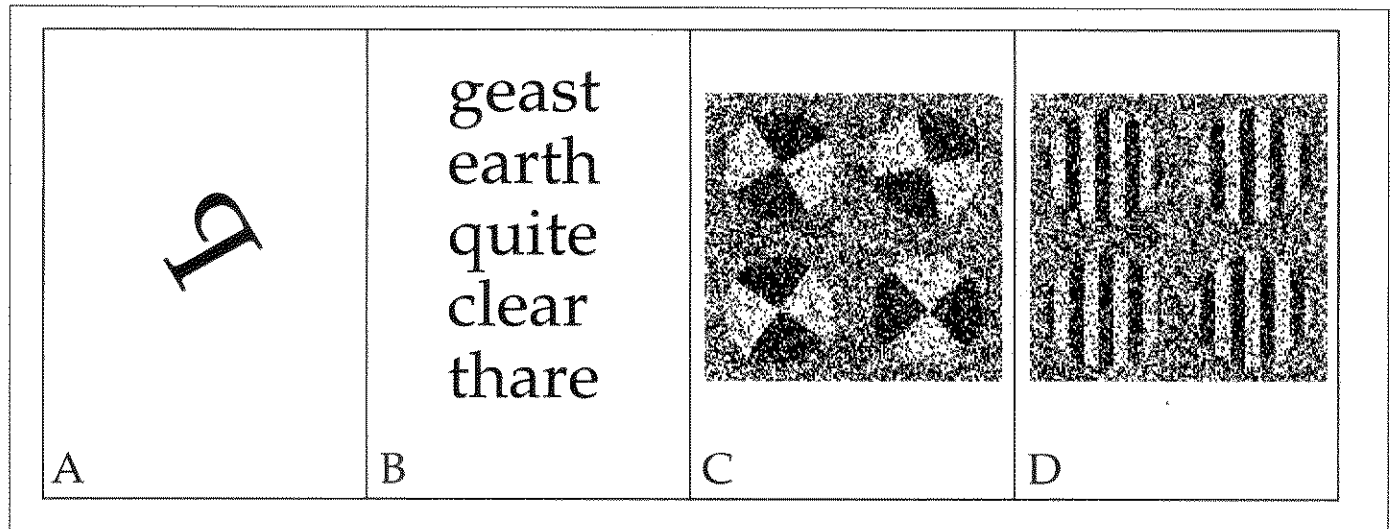


Fig. 1. Examples of the stimuli used in four reaction time studies: a stimulus from the mental rotation study (a), a stimulus from the lexical decision study (b), a single frame from a rotation animation sequence (c), and a single frame from a translation animation sequence (d).

studies of visual search.² Subjects were instructed to make their decisions as fast as possible without sacrificing accuracy. Each task was practiced for at least 200 trials before data were collected. Error rates in all studies were maintained below 5% to 10%, and trials on which errors were committed were not deleted from the data. Examples of the stimuli employed in the studies are given in Figure 1.

Mental rotation

One of three letters (*R*, *P*, *F*) subtending approximately 2° by 2° was presented at one of five orientations (0°, 60°, 120°, 240°, 300°) on each trial. On half of the trials, the letter was also mirror reversed. The subject's task was to decide whether the letter was mirror reversed or not. Each subject completed 1,056 trials.

Lexical decision

A list of five real words and pronounceable pseudowords (taken from Juola, Ward, & McNamara, 1982) was presented on each trial. They consisted of five letters each and subtended about 1° by 4°. The five words and pseudowords in each list were stacked vertically, as shown in Figure 1. The number of real words was either one, two, three, or four in each list, and the subject's task was to identify this number. Each subject completed 1,280 trials.

Serial visual search

A trial consisted of the display of one, two, or four disks rotating at about 1 revolution/s in a field subtending 5° by 5°. Half of the trials contained at least one clockwise rotation, which was defined as the

target. Portions of the stimulus where disks were absent were filled with random dynamic noise. When the set size was less than four, the disks were positioned at random in the four locations indicated in Figure 1. The subject's task was to decide whether at least one target was present in the display. Each subject completed 1,152 trials.

Parallel visual search

The design and stimulus arrangement were the same in this experiment as in the one involving clockwise rotation search except that translating gratings were used and the subject's task was to decide whether at least one rightward moving grating was present. Grating speed was about 2°/s, and the motion was periodic within the apertures displayed in Figure 1. Each subject completed 1,152 trials.

Results

Figure 2 presents the results from the four reaction time experiments in terms of separate means and error analyses. The means analysis, displayed in the top row, is what is generally presented in experimental work, and it is summarized by the location and magnitude of the error bars depicting the standard error of the mean. Note that these error bars do not describe the real variability observed in the experiment; they depict only the precision with which the mean can be placed. In each of these studies, the mean was highly localized, yet the treatment effects accounted for relatively small proportions of the total variance. The average percentage of variance accounted for by the treatments within individual subjects was 11% in mental rotation, 3% in lexical decision, 17% in clockwise rotation search, and 7% in rightward translation search. The remaining variance in these studies was error in the sense that it was not explained by treatment effects.

The mean analyses are not without interest and would normally be the focus of psychological experimentation. Figure 2a shows the expected tent-shaped mean reaction time function indicating that people make mirror inversion judgments by mentally rotating the letter to its upright position (Finke & Shepard, 1986; Shepard & Cooper, 1982). Figure 2b shows that the time required to count real words is a non-monotonic function of the number of real words in the list. Although this experiment was originally contrived simply to generate lexical

2. Although it is possible to measure reaction time to greater precision than I do here, the tolerances set by the equipment are of minor importance. Not only are the tolerances small compared with the size of observed fluctuations, but regardless of the tolerance magnitude, the equipment does not generate correlated error and is not a spurious source of $1/f$ fluctuation. I have performed numerous timing experiments that are not expected to produce $1/f$ noise and do not. Examples include synchronized tapping to a metronome and speeded response to the presence of a stimulus (Gilden et al., 1995).

Reaction Time

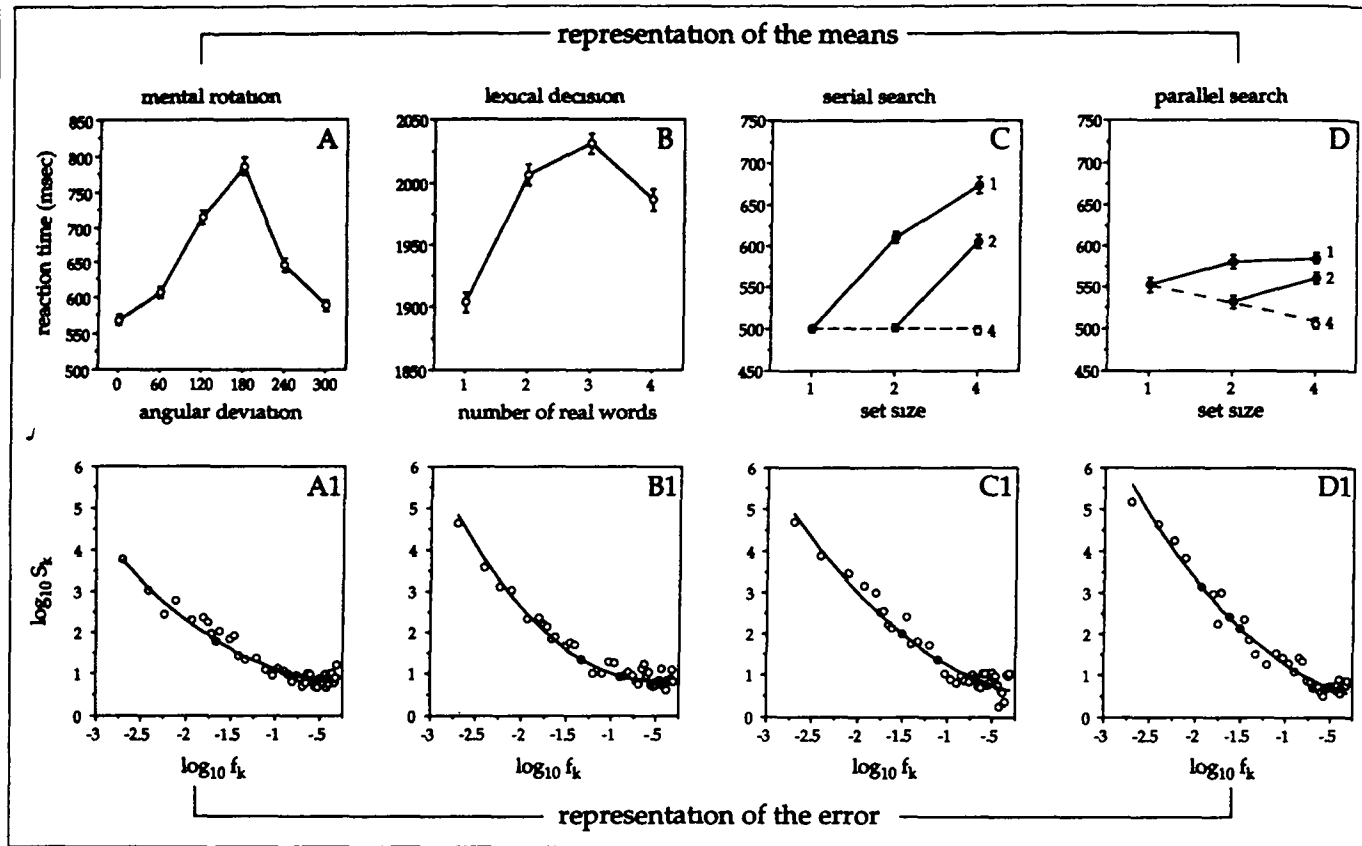


Fig. 2. Results from the four reaction time studies. The top panels show the means for studies of mental rotation (a), lexical decision (b), serial search (rotation direction) (c), and parallel search (translation direction) (d). Error bars depict the standard errors of the mean. In (c) and (d), the number alongside each track denotes the number of targets, the dashed lines are for trials in which all stimuli were targets. Each panel on the bottom shows the average spectral power densities, S_k , of the trial-by-trial residual error, $error_n$, for the experiment whose means are shown directly above. The curves in (a1) through (d1) illustrate best fits to the spectral power densities from the dual-source noise model described in the text and in Table 1.

decision fluctuations, this result is interesting in itself for it suggests that the information entropy of the lists influences reaction time (i.e., if we let real word = 1 and pseudoword = 0, reaction time is roughly proportional to the number of distinguishable permutations in the binary strings representing the five decisions that are made on a trial). In other words, reaction time in this task appears to be proportional to the uncertainty of the list conceived of as a pattern with alternatives (Garner, 1962). Figure 2c shows the mean reaction times for clockwise rotation search. The dashed line (for trials in which all stimuli were targets) has a slope of zero, evidence that targets are isolated individually in a serial search (van der Heijden, 1975, see Townsend, 1990, for a discussion of the subtleties in distinguishing serial from parallel processes). Figure 2d shows the mean reaction times for rightward translation search. The dashed line here has a significantly negative slope ($F[2, 10] = 5.1, p < .03$), indicating that multiple targets influence the decision that a target is present, evidence that translation direction search is conducted in parallel. These results on rotation and translation search are consistent with earlier studies of perceptual segmentation on the basis of motion direction (Julesz & Hesse, 1970, Nakayama & Silverman, 1986).

The focus of these studies is on the time development of fluctuations about the cell means within the natural ordering of trials. The reaction time latency on the n th trial within a given sequence of trials

may be decomposed into two components: a part reflecting the experimental design and a part denoting that any individual latency contains error.

$$RT_n = \mu(\text{treatment cell})_n + error_n$$

In this equation, " $\mu(\text{treatment cell})_n$ " refers to the cell mean appropriate to the trial in question and is computed as the average latency over all trials in the sequence belonging to that cell, " $error_n$ " is the deviation from the cell mean that occurred on the n th trial. The values of $\mu(\text{treatment cell})_n$ varied randomly throughout the sequence because treatments were randomly interleaved in the experimental designs. This equation serves merely to define the error term and is standard in the formulation of regression models (Hays, 1988).

The main results from these experiments derive from a Fourier analysis of the residual error, where trial succession defines the data ordering. The spectral power density, S_k , was estimated for each detrended error sequence, $error_n$, using overlapping samples of $N = 2m$ data points (Press, Teukolsky, Vetterling, & Flannery, 1992) at the frequencies $f_k = (k - 1)/(2m)$, for $k = 1, 2, 3, \dots, m$. A block of trials completed by a given subject defines a sequence in this analysis. Trends up to second order were filtered from each data sequence so as to remove spurious low-frequency power that may derive from global

effects such as perceptual learning over the course of a trial block. Leakage from adjacent frequency bins was minimized by multiplying the error series by a Bartlett window. Individual differences in the overall spectral trends with frequency were not important in any of the studies presented here, and the bottom panels of Figure 2 show the average spectral densities for the four experiments, all plotted on the same scale and with equal weight given to all sequences. Note that in this treatment, frequency has the units of inverse trial number.

Figures 2a1 through 2d1 show that the residual error terms have power spectra that rise monotonically upward at low frequencies. Such spectra imply that the residual error fluctuations are positively correlated on all scales of trial number, and that each level of structure is nested within structure of larger scale. Only in this way can the spectral density continuously increase with scale. In contrast, if the errors were uncorrelated, then the spectral densities would be independent of frequency or scale. It should be noted that in these experiments, it was not strictly necessary to subtract the cell means from the data. Treatment effects accounted for so little of the variation in observed latencies that essentially the same power spectra were realized when the Fourier transform was computed from the raw reaction time data.

ANALYSIS OF REACTION TIME FLUCTUATION

Spectral analysis is distinguished from the type of analysis generated by an experimental design in several important respects. Foremost, experimental designs rarely account for all of the variance, but a spectral analysis necessarily does. The integrated spectral power density mathematically sums to the total variance. In this sense, the discovered structure displayed in Figure 2 gives a complete account of the error fluctuations. However, this last statement would have been true regardless of what was produced by the Fourier analysis, so it has no theoretical content in itself and clearly requires further definition. The apparently lawful behavior of the power spectra suggests that such definition may exist, that there is some deeper principle that explains why the spectra have the common shape that they do. The point of view that I develop here identifies these error sequences with a pattern of variation found within a certain class of dynamic systems that is well-represented in nature. In other words, I attempt to establish that the error fluctuations are part of a *natural kind*.

I have constructed a dual-source model of reaction time in which the error term comprises two kinds of fluctuation. One is associated with processes of perception, discrimination, and choice, and generates a signal with spectral power proportional to $1/f^\alpha$, $\alpha > 0$. Evidence for this association comes from studies of reaction time to the mere presence of a stimulus. If the stimulus does not have to be identified, then the reaction time fluctuations are uncorrelated (Gildden et al., 1995). The second type of fluctuation is a white ($1/f^0$) noise defined by independent samples from a normal distribution. There may be several sources of white noise that collectively appear in reaction time. Motor fluctuations in key-press response naturally occur and have been successfully modeled as additively contributing white noise to reaction time (Gildden et al., 1995; Wing, 1980; Wing & Kristoferson, 1973). Cognitive activity associated with perception and judgment may also contribute a component of white noise. Although the relative amplitudes of these two white components cannot be determined because they cannot be distinguished in terms of their spectra, we can identify a colored ($1/f^\alpha$) source of fluctuation associated with the decision pathway.

The model of reaction time error groups all sources of white variation together and represents the error on the n th trial as being embedded in an ordered sequence of the following form:

$$\text{error}_n = (1/f^\alpha)_n + \beta N(0,1),$$

where $(1/f^\alpha)_n$ is the n th term in a $1/f^\alpha$ noise scaled to have zero mean and unit variance, $N(0,1)$ denotes a sample from the normal distribution with zero mean and unit variance, and β is a constant free parameter that determines the relative contributions of the two types of variability. For each experiment, I have spectrally synthesized a continuous family of $1/f^\alpha$ noises and computed the values of α and β that provide the best fit to the average spectral densities in the least squares sense. The optimal models are shown as curves in the bottom panels of Figure 2.

Explicit fitting parameters for the dual-source model are given in Table 1. In each case, the model provides an excellent fit to the data ($r^2 \geq .92$ in all cases), and the colored source of fluctuation has a common exponent, α , close to unity; that is, the cognitive component may be considered a $1/f$ noise. Furthermore, the model demonstrates that the $1/f$ source always makes a substantial contribution to reaction time variability, a contribution that exceeds that of the treatment effects by generally a factor of 3 or more. The proportion of residual variance in the model due to $1/f$ noise is given by $1/(1 + \beta^2)$ and is listed in the final column of Table 1. Given that the treatments accounted for about 10% of individual subject variability, it is evident that 25% or more of the average variability in reaction time measurement may arise from $1/f$ -type fluctuations independent of the particular decision that is being rendered.

PHYSICAL INTERPRETATIONS

Thus far, I have given a purely empirical demonstration that the error terms in reaction time latency are correlated as a mixture of white and $1/f$ noise independent of decision domain. Recognizing that the error terms dominate the data and appear to have a universal form, we have a real problem to consider, and I focus now on what these noises can tell us about cognition. Cognitive psychology is not framed within a formalization that can guide us in this matter. The processes and mechanisms that are presumed in theories of memory, attention, and lexical decision, for example, have not contemplated scenarios in which the important structure is contained in the error. Perhaps the only relevance that these results have for current cognitive theory is the adjustment of Fisher's F statistic to encompass sampling distributions with correlated error. I do not consider this implementation to

Table 1. Theoretical models

Experiment	Model parameters		Variance explained	
	α	β	r^2 (model)	$1/f^\alpha$ proportion
Mental rotation	.7	2.0	.94	.20
Lexical decision	.9	2.0	.95	.20
Serial search	.7	1.4	.92	.33
Parallel search	.7	1.3	.93	.39

Reaction Time

exhaust the issues raised by the findings. In order to make progress, we must look to disciplines that have the requisite formalism and referential structure to discuss cognitive activity abstractly as a dynamic system.

Chaos theory provides both the language and the practical techniques for investigating the underlying structure in noise. In this domain, the primary issue is whether the error is produced by a relatively simple deterministic mechanism. If so, then the error sequences may be embedded as an orbit in an attracting set of low dimensionality, and we might be able to model the error in terms of meaningful psychological constructs. Analyses of this sort are rife in economics, biology, physics, astronomy, and medicine, and the methods for ascertaining the existence of (strange) attractors are well known. I have pursued this line of investigation to some depth by estimating the correlation dimension, testing for false nearest neighbors, and predicting my data using nonlinear forecasting methods (Abarbanel, Brown, Sidorowich, & Tsimring, 1993; Sugihara & May, 1990; Tsonis & Elsner, 1992). These analyses are somewhat difficult to do in practice because correlated noise can masquerade as an attracting set by virtue of the fact that correlations per se cause data to occupy restricted regions of the appropriate embedding spaces. In fact, early reports of strange attractors in psychological data (e.g., in electroencephalograms) are now regarded as erroneous identifications of what is probably correlated noise (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992). A careful analysis requires the construction of surrogate data sets that mimic various statistical aspects of the data to be modeled, and yet are themselves not examples of orbits on strange attractors (Theiler et al., 1992). I have constructed surrogate data sequences and have found the power spectrum of the observed data sequences and have shared the surrogates and the data to be indistinguishable on all measures: correlation dimension, unfolding of nearest neighbors, and nonlinear predictability. There appears to be no simple deterministic mechanism that creates the observed structure in reaction time latency.

This negative result does not imply that mental chronometry cannot be understood in terms of a physical mechanism. It simply means that mental chronometry cannot be reduced to a set of processes whose action is definite, and that we must inquire generally into what types of stochastic systems produce $1/f$ noise. This turns out to be a rather deep problem in theoretical physics. Although one can easily create recipes, algorithms, for producing $1/f$ noise, it is much more difficult to render a prescription for their occurrence in nature.

Physical theories of $1/f$ noise often begin with the patent observation that natural systems fluctuate when subjected to random perturbations about an equilibrium state (Dutta & Horn, 1981). Under quite general conditions, the fluctuations accompanying the return to equilibrium follow a Langevin equation. Solutions to the Langevin equation have a Debye-Lorentz power spectrum that goes as $S(\omega) = \tau/(1 + \tau^2\omega^2)$, where $\omega = 2\pi f$ is the circular frequency and τ is the time-scale for the system to reestablish equilibrium. This spectrum is decidedly not $1/f$ but rather is white ($1/f^0$) at low frequencies and brown ($1/f^2$) at high frequencies. In order for $1/f$ noise to be realized perturbatively, there must be additional structure imposed on the system architecture. Consider, then, a system composed of an ensemble of independently relaxing subsystems that collectively add into a fluctuating output that forms the measured signal. For the summed output to have a $1/f$ spectrum over a significant range of frequency, the ensemble must satisfy two constraints: The relaxation timescales have a large range, $\tau_{\max}/\tau_{\min} > 1,000$, and the probability

density of relaxation times varies as $1/\tau$. This particular distribution function is quite special because it has the physical significance of being scale free; the collection as a whole is not characterized by any time or length scale.³ The phenomenon of scale freedom is well known and is observed in thermodynamic systems undergoing a phase transition. Bak has suggested that we view the transition between order and chaos in thermodynamic terms (Bak, 1990, 1992; Bak et al., 1987, 1988), and has identified a class of complex systems that naturally self-organize and maintain themselves in this scale-free critical state. When perturbed, self-organized critical systems fluctuate and produce $1/f$ noise.

Neural models based on self-organizing metastable systems have shown that simulated neurons can exhibit self-similar firing rates between 20 and 800 ms leading to $1/f$ power spectra (Usher, Stemmler, Koch, & Olami, 1994; Usher, Stemmler, & Olami, 1995). These results are consistent with fractal firing patterns observed in single-unit recording (Teich, 1992). It is, however, not clear how these physiological data can explain $1/f$ fluctuations in reaction time latency as a perceptual decision is not likely to mirror the behavior of single neurons. The same simulations that produced $1/f$ spectra in single units also showed that firing patterns in the aggregate were highly nonfractal (Usher et al., 1994), displaying rather a prominent 40-Hz peak in the collective power spectrum, reminiscent of oscillations observed in primary visual cortex of awake monkey (Eckhorn, Frien, Bauer, Woelbern, & Harald, 1993). That fluctuations in cognitive activity resemble those seen in complex physical systems at least suggests a common set of constraints. The notion that the formal structure of cognition has evolved to internalize natural constraints has been proposed by Shepard (1981, 1984, 1994), and the demonstrated existence of $1/f$ fluctuations in reaction time may provide a substantive example of how such embodiments occur.

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3. The number of subsystems that are relaxing on timescales between τ and $\tau + d\tau$ is proportional to $d\tau/\tau$. Note that this ratio is dimensionless as it stands, which it must be in order to represent a pure number (i.e., the number of systems . . .). Any other probability density must be accompanied by a timescale in order to create the dimensionless quantity of number. Does a timescale acts as the signature of the ensemble and is precisely what does not exist in systems that emit $1/f$ noise.

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