On the Intrinsic Fluctuations of Human Behavior

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Abstract

Human systems as well as other kinds of biological and complex systems have all been reported to exhibit the power law behavior known as 1/f noise. The coherence of 1/f noise contrasts sharply with the uncorrelated white noise that is typically assumed to be the background noise in human behavior. In this chapter, the authors discuss ideas that arise in thinking about the origins of 1/f noise in human behavior. The general theme is built around the fact that 1/f noise is a power law scaling relation in time. This fact helps to guide the discussion through numerous examples of power law scaling relations in the behaviors of many biological and complex systems, leading up to 1/f noise in human behavior. One of the core conclusions is that observations of 1/f noise in human behavior are most robust when the same behavior is repeated with minimal perturbation from extrinsic factors such as unpredictable changes in task. This conclusion leads to the proposal that 1/f noise is a property of dynamics that are general to human behavior, and revealed in the intrinsic fluctuations of human behavior. This idea is elaborated in the context of other more mechanistic accounts of 1/f noise in human behavior.

Introduction

What do rivers, quasars, ecosystems, economic markets, computer networks, and humans all have in common? These complex systems all exhibit a statistical pattern in their behavioral fluctuations known as pink or 1/f noise. Why do they all produce this particular kind of pattern? The systems appear to share little in common except that they are all complex in some loosely defined sense. This commonality has driven researchers to search for general theories of complex systems that might explain the ubiquity of 1/f noise. But there has been relatively less empirical work to complement this search, partly because many complex systems are difficult to experiment with.

One of the most pertinent empirical questions in this line of research is, what are the conditions for observing 1/f noise in complex systems? A comprehensive answer is not possible at this point, but the human system provides a good case study for addressing the question because human systems afford experimental manipulation. By contrast, very large-scale systems like ecosystems, economic markets, and quasars, are not susceptible to direct experimental manipulation. Experimental manipulations can be used to test hypotheses about the conditions for observing 1/f noise in human behavior, and the results can contribute to the study of complex systems in general.

When one looks over the reports to date on 1/f noise in human behavior, it appears to be a rather generic phenomenon. For instance, 1/f noise has been reported in finger tapping (Chen, et al., 2001; Ding, et al., 2002), visual search (Aks, 2002), simple reaction times (Gilden, 1997; Van Orden, et al. 2003), memory load (Clayton, 1997), and ratings of self-esteem (Delignieres, et al., 2004). The recurrence of 1/f noise across such diverse tasks and behaviors has led researchers to speculate that 1/f noise is a ubiquitous property of human behavior. But exactly what this means is currently open to debate.

In this chapter, we review the literature on 1/f noise in complex systems and in human behavior, with the aim of formulating an explanation for its ubiquity. We begin with an overview of power law behavior in which examples from complex systems are used to illustrate and explain 1/f noise. We then review the reports of 1/f noise in human systems, with the aim of showing that they are all consistent with the intrinsic fluctuation hypothesis. This hypothesis states that 1/f noise is ubiquitous specifically to the intrinsic fluctuations of human behavior. Much of the chapter is devoted to elaborating on the intrinsic fluctuation hypothesis, with some time at the end for a discussion of the theoretical implications of ubiquitous 1/f noise.

Power law behavior

In order to appreciate the phenomena of 1/f noise, it is helpful to first define its mathematical properties. 1/f noise is a kind of power law scaling relation that occurs in time series. In a power law scaling relation, the value of some function f(x) is proportional to some power of x,

$$f(x) = x^{\alpha}.$$

It turns out that both complex systems and non-equilibrium systems have a known tendency to produce power law behavior. Research has focused mostly on one of two different kinds of power laws, power law distributions and 1/f noise.

In power law distributions, f(x) is the frequency of occurrence of some measured value, expressed as a power of the value itself. Perhaps one of the best known examples of power law distributions in natural systems comes from plotting the distribution of earthquakes according to their size, as seen in Figure 1. The relationship between the frequency of an earthquake and its size follows a power law distribution: for each increase in order of magnitude there is a corresponding decrease in its frequency of occurrence. If the data are plotted on log coordinates, as in Figure 1, the result is nearly a straight line. The classification of earthquakes on the Gutenberg-Richter scale reflects this power law scaling relation. For example, earthquakes of size 7 on the Richter scale occur one order of magnitude less frequently than earthquakes of size 6.

Insert Figure 1 about here

Power law distributions reflect one kind of power law relation. 1/f noise is the other kind that is often found in complex systems. For 1/f noise, f(x) is spectral power expressed as a function of spectral frequency,

$$P = 1/f^{\alpha}.$$

To explain this function, let us first consider the two series of measurements plotted in Figure 2. The top time series shows fluctuations that are characterized by white, Gaussian noise. White noise means that each measurement is sampled independently from some distribution (the normal distribution in this case). This independence appears as a time series with random, uncorrelated fluctuations. Fluctuations refer to the time-dependent variability in a series of measurements that are taken from a particular system.

Insert Figure 2 about here

The bottom time series is characterized by 1/f noise. Measurements show long-range dependence, which means that the autocorrelation function decays very slowly, i.e., as a power of the correlation lag. Dependencies in this time series can be seen by the naked eye as prominent, low-frequency fluctuations. Because it is 1/f noise, there are actually higher-frequency, lower-amplitude fluctuations nested within the lower-frequency, higher-amplitude fluctuations. For true 1/f noise, this nesting occurs across all time scales; if more and more measurements are collected, one would continue to find larger and larger fluctuations that nest the smaller ones. Conversely, if measurements are taken with finer and finer temporal resolution, one would continue to find smaller and smaller fluctuations nested inside the larger ones, within the limits of the system being measured. The nesting of fluctuations across all measurement scales highlights the scale invariant property of 1/f noise.

True 1/f noise is scale invariant over all time scales, which means that the power law extends to infinitely high and low frequencies. But only a finite range of frequencies can be measured in any given experiment, due to limitations in temporal resolution and the amount of data that can be collected. For example, in reaction time experiments with human participants the measurement equipment and the task itself limits the rate at which measurements can be taken. These limits place an upper bound on the frequencies that can be measured. There are also practical limits on the amount of data that can be collected in any one experimental session. These limits place a lower bound on the frequencies that can be measured.

The features that separate white noise from 1/f noise can be seen more clearly by converting the signal from the time domain to the frequency domain, as in a power spectrum. A power spectrum decomposes a series of measurement into a set of frequency (sine wave) components, each with an associated level of power (amplitude). This is analogous to the way that a prism separates light into its component colors. In figure 3, spectra are plotted for the white noise and 1/f noise fluctuations that are shown in figure 2. Power and frequency are both plotted on log scales.

Insert Figure 3 about here

For white noise, one can see that power is constant as a function of spectral frequency, which indicates that fluctuations have equal power across all time scales. By contrast, the power spectrum of 1/f noise shows a negative linear trend. This trend in log-log coordinates depicts the nesting of high-frequency fluctuations within low-frequency fluctuations that was mentioned earlier. This nested structure can be quantified by the slope of a regression line fit to the power densities (as depicted). In fact, the slope of this line is equal to the parameter α, as can be seen when the logarithm of *P* is taken,

$$\log P = -\alpha \log f.$$

For ideal 1/f noise, α is equal to 1. However, the special properties of scale invariance and long-range correlation hold for $0 < \alpha < 1$, which is the range that α typically falls in for most observations of 1/f noise. As α approaches zero, we can say that the spectrum is “whitened” relative to ideal 1/f noise, because an α of zero corresponds to pure white noise. Thus, α can be used as a measure of the clarity with which 1/f noise is observed, provided that it is between 0 and 1. We will later address how the effect of whitening, as seen by the changes in α, plays an important role in delineating the conditions that manifest 1/f noise.

1/f noise in complex systems

The statistical pattern of 1/f noise is intriguing because it suggests the presence of processes that are self-similar and organized in relation to each other across all time scales. It is curious to find such organization in any one system, but is truly mysterious to find this organization again and again across so many different systems and phenomena. Hundreds of articles have been published on the topic across a wide range of scientific disciplines. The phenomena has been reported from very small-scale phenomena such as DNA sequences (Li & Holste, 2005) all the way to very large-scale phenomena such as celestial bodies (Matthaeus & Goldstein, 1986). A common denominator appears to be that 1/f noise is found in the global behaviors of complex systems.

The term “complex system” is not well-defined, despite many years of use throughout the physical, biological, and social sciences. Most researchers would agree that complex systems are not just composed of many components (i.e., not just “complicated”). In order to be complex, a system must have components that interact with each other. Moreover, the interactions are typically nonlinear. The consequence of nonlinearity is that the global behavior of a complex system may not be deducible from knowledge of how the components interact.

In the biological and social sciences, complex systems are most apparent when there are identifiable agents (components) with observable interactions. For instance, consider an ecosystem in which species interact with one another and their physical environment. If each organism is viewed as a component of the system, then interactions among components would take the form of predator-prey relations, parent-offspring relations, symbiotic relations, and so on. The global consequences of these interactions can be measured in the fluctuations of population levels for each species over time. Inchausti and Hailey (2001) analyzed time series data for the population levels of 123 different species from a variety of ecosystems across multiple geographic locations. The time series spanned 46.5 years on average. The authors found evidence of 1/f noise in the patterns of fluctuations for each species. Specifically, regression lines were fit to the log-log spectral densities estimates for each time series, and the slopes of the regression lines all fell in the range $0 < -\alpha < -2$ (noise in the lower half of this range is classified as brown noise instead of 1/f noise). The average slope across all 123 time series was -1.022, where -1 is ideal 1/f noise.

Just as organisms interact with each other and their environment to form ecosystems, so do buyers and sellers interact with each other and their business environment to form marketplaces. There are even obvious analogues between the kinds of interactions found in ecosystems and those found in marketplaces (consider again the examples of predator-prey, parent-offspring, and symbiotic relations). If 1/f noise is a general property of complex systems, then it should be observable in measures of the global behaviors of marketplaces that are analogous to population levels in ecosystems.

To draw this analogy further, let us first equate species with business sectors. On this view, if population levels are considered to be a measure of how much a given species is thriving in its environment, then the value of a business sector provides an analogous measure of how well that sector is thriving. The business value of public companies and corporations is determined primarily by stock markets. Therefore, fluctuations in stock prices should provide a global measure of the marketplace that is analogous to fluctuations in the population levels of species.

Liu et al.(1999) analyzed the time series of stock prices over a 13 year time period. Consistent with the analogy that we have set up, the authors found evidence of 1/f noise in the fluctuations of the S&P stock index. This index is a conglomeration of business values (stock prices) across a range of sectors. The authors computed the autocorrelation function of the S&P time series, and they found that correlation coefficients decayed as a power of the autocorrelation lag. Power law decay in the autocorrelation function is evidence of the long-range memory that characterizes 1/f noise. Liu et al. also conducted spectral analyses of fluctuations in individual stock prices over a period of 1.5 days, and they found spectral slopes consistent with the range of 1/f noise. Both of the autocorrelation and spectral analyses suggest that, by virtue of being a complex system, the global behaviors of marketplaces fluctuate as 1/f noise.

Yet another kind of ecosystem is the internet. Server and client computers take the place of species or business sectors, and data transmission becomes the measure of how much a given computer is "thriving" in the cyberspace environment; indeed, the advertising value of a website is an explicit function of its traffic. On this analogy, the global measures of population levels and sector values are replaces with global measures of internet traffic.

As a simple measure of internet traffic, Csabai (1994) recorded fluctuations in the transfer rates between two computers in separate countries that sent data packets back and forth to each other. We can assume that transfer rates reflected the summed amount of traffic (among other factors) along the data route between the two computers. Recordings were taken over a period of two weeks, and transfer rates were found to fluctuate as 1/f noise. Specifically, spectral analyses revealed a negative linear trend in log-log coordinates, with a slope of -1.12.

1/f noise in human physiology

Ecosystems, marketplaces, and computer networks are transparent examples of complex systems because they are comprised of identifiable agents with plainly observable interactions. But the components of a complex system do not have to be agents *per se*, and their interactions do not have to be anthropomorphized as predator-prey relations, exchanges of goods, and the like. At a greater level of abstraction, the hallmark of a complex system is the emergence of global behavior that is driven primarily by the interdependencies among its components (Van Orden, Holden, & Turvey, 2003).

In this light, the human organism can be seen as a vast and intricate layering of complex systems nested within complex systems, with global behaviors emerging at every level (Simon, 1973). Cells interact to coordinate the relatively global behaviors of organs, organs interact to coordinate the relatively global behaviors of physiological systems (e.g., circulatory, respiratory, nervous, digestive, etc.), and physiological systems interact to coordinate the relative global behavior of the individual.

The nesting of these complex systems is most apparent in terms of their spatial organization; networks of cells comprise organs, networks of organs comprise physiological systems, and networks of physiological systems comprise the human organism. But there is also a temporal nesting to these complex systems that may be relevant to 1/f noise. Growth and decay of the human organism is governed by the relatively faster interactions among physiological systems. Growth and decay of physiological systems is governed by even faster interactions among the organs. And likewise for organs with respect to cells. Loosely speaking, this temporal nesting is analogous to the nesting of fluctuations that defines 1/f noise. It is therefore intriguing that 1/f noise has been found across all of these levels.

With respect to the level of cell networks, the most salient case study is the brain. Neurons appear to transmit information along synaptic connections, just as computers transmit information along internet connections. If electrical activity is the currency of information in the brain, then one might expect it to fluctuate as 1/f noise. Linkenaer-Hansen, et al. (2001) measured the fluctuations in electrical activation of the brain using magnetoencephalography (MEG) and electroencephalography (EEG) across the entire scalp of human participants. During measurement participants were at a resting state either with their eyes open or closed. Neural fluctuations were measured over the course of 20 minutes at a rate of 300 Hz. In all conditions, the neural activity of participants exhibited 1/f noise. This was demonstrated by the data being subjected to several tests of 1/f noise, including spectral analysis.

Jumping up to the level of organ networks, 1/f noise has been measured in the circulatory system via the heart. Goldberger et al. (2002) measured the amount of time between beats of healthy humans while they were at rest. The heart rate measurements showed self-similar scaling, indicative of 1/f noise, over periods of 30 minutes. Interestingly, the authors compared the heart rates of healthy individuals with those of individuals with histories of heart failure. The “unhealthy” heart rates lacked the property of self-similar scaling, in that they showed either excessive regularity or uncorrelated randomness compared to healthy heart rates. Goldberger, et al. interpreted this finding as evidence that healthy hearts tend to operate near critical states in their dynamics. We return to the concept of critical states in the General Discussion.

We finally turn to the human organism as a whole. There are an unlimited number of human behaviors that one could examine for evidence of 1/f noise. To narrow down the search, it makes sense to focus on behaviors that reflect the intrinsic dynamic of the human organism itself. The intrinsic dynamic refers to the trajectory of changes in the state of the human organism as it unfolds over time, with no perturbations from outside the organism. If perturbations occur, then one’s measurements of human behavior will reflect those perturbations, rather than the fluctuations of the human organism “by itself”. In practice the problem of perturbations is a matter of degree; weaker perturbations result in a clearer picture of intrinsic fluctuations.

A candidate behavior for measuring intrinsic dynamics is self-paced walking on a straight line along flat and unobstructed ground. Any fluctuations in pacing would have to come primarily from the human organism itself, and not some feature of the environment. Hausdorff et al. (1996) measured the time intervals between successive movements of the same foot while walking. The authors found that these intervals exhibited the long-range dependence that is characteristic of 1/f noise. In summary, the studies reviewed in this section provide evidence that 1/f noise can be found at all levels of the human organism, which is consistent with the idea of complex systems nested within complex systems.

1/f noise in human cognition

Our review thus far illustrates the range of empirical domains in which 1/f noise has been reported. But it is informative to note that none of these studies provided a mechanistic account of 1/f noise. They did not provide models that simulate how 1/f noise is hypothesized to be generated. These studies have value nonetheless because they document the ubiquity of 1/f noise in nature. Documenting its ubiquity is important, if only because 1/f noise is so difficult to explain mechanistically. In fact science as a whole is still waiting for a mechanistic theory of 1/f noise to be accepted as a general explanation of its ubiquity. There is currently only one viable candidate (see General Discussion), but it has been criticized on numerous fronts (for example see Wagenmakers, Farrell, & Ratcliff, 2005).

The development of theory in this case might be helped along if we had more information on the experimental conditions that do and do not manifest 1/f noise. To gather this information, let us again consider the idea that, in order to find 1/f noise in human behavior, one should try to measure the intrinsic dynamics of the human organism. While there is currently no mechanistic theory of intrinsic dynamics, the idea can still be used to delineate the experimental conditions that should manifest or obscure 1/f noise in human behavior. Simply put, 1/f noise should be observed most clearly when a behavior is repeated with minimal perturbation from extrinsic factors that vary unsystematically from one measurement to the next. These conditions allow one to attribute any fluctuations in measurement to the system being measured, rather than factors varying independently of the system. Conversely, 1/f noise should be obscured when events drive behavior in an unsystematic fashion from one measurement to the next.

It turns out that this simple delineation does a good job of characterizing all of the reports of 1/f noise in human cognition that we know of. To start with, let us consider the studies in which 1/f noise was simply found to be present in cognitive performance. One of the earliest of these studies also provides one of the best examples of how to measure intrinsic dynamics.

Gilden et al. (1995) gave participants spatial and temporal intervals (e.g., one inch or one second) to reproduce from memory over and over again, for more than 1000 trials. For example, participants would repeatedly reproduce a one second time interval. Importantly, participants were not given any stimulus cues or feedback during the experiment. The lack of stimuli and feedback meant that estimates were not intentionally perturbed from one trial to the next. The authors measured fluctuations in the recorded series of estimates, and the measurement series were subjected to spectral analyses. Regression lines were fit to power density estimates in the lower frequency range, and the slopes of these regression lines varied between -0.9 and -1.1. The upper frequency range was excluded from analyses because it is “whitened” by unsystematic variation due to measurement error and limitations inherent to measurement. If one imagines fluctuations to be characterized by a mixture of white and 1/f noise, whitening refers to a greater proportion of white noise. Whitening corresponds to spectral slopes that are relatively closer to zero.

In a subsequent set of experiments, Gilden (1997) analyzed series of reaction times for a number of tasks that are representative of the reaction time experiments used to study cognition. These tasks included mental rotation, lexical decision, serial visual search, and parallel visual search. As in Gilden's (1995) previous study, participants were not given any feedback regarding their performance from trial to trial. To most clearly observe the intrinsic dynamic in these tasks, the experimental effects were partialed out of the reaction times (e.g., degree of object rotation, frequency of word, and stimuli search characteristics). For example, any variations associated with the degree of object rotation in the mental rotation task were removed from the analysis. The results were striking because not only was 1/f noise found in the remaining "error" variance, but the total variance contained a greater proportion of 1/f noise compared with the experimental effects. Similar results have since been found in studies of choice reaction time (Wagenmakers et al., 2004), visual search (Aks, 2002), word naming (Van Orden et al, 2003), and reports of self-esteem, (Delignieres et al., 2004).

The studies of cognitive performance reviewed thus far demonstrate how 1/f noise is manifested when experimental conditions facilitate the measurement of intrinsic dynamics. But to more solidly support the idea that 1/f noise is associated with intrinsic dynamics, it is equally important to demonstrate that 1/f noise is whitened when the measurement of intrinsic dynamics is obscured. Such obscuring should occur when experimental manipulations add unsystematic variations from one measurement to the next.

A memory experiment by Clayton and Frey (1997) provides a hint of how 1/f noise can be whitened. Two experimental conditions were created to manipulate memory load. The low load condition was a discrimination task in which participants only needed to keep two stimuli in memory for the duration of a single trial. The high load condition required discrimination between a current stimulus and one that was presented two trials back. Both conditions introduced unsystematic variation by varying the stimuli randomly from one trial to the next. But this variation should be greater in the high load condition because the stimuli should have a greater impact on performance due to the greater difficulty of the task. Spectral analyses of the reaction time series showed that 1/f noise was relatively whitened in the high load condition, but the difference in spectral slopes across conditions was not statistically reliable.

Gilden (2001) provided a more robust demonstration of how unsystematic variation can whiten 1/f noise in human behavior. Participants were given tasks in which they had to classify objects according to their shape and color. In a pure block condition, all trials were either shape or color classification. In a mixed block condition, shape and color trials were randomly interspersed, which added a source of unsystematic variation to series of reaction times. Spectral analyses showed that 1/f noise in reaction times was whitened in the mixed block condition compared with the pure block condition. Gilden interpreted this result as indicating that 1/f noise is more robust when the mental set is consistent across measurements. From our perspective, unsystematic task switching in the mixed blocks had obscured the measurement of intrinsic dynamics.

The ubiquitous nature of 1/f noise in cognitive performance

Experiments with cognitive performance provide clear support for the association of 1/f noise with intrinsic dynamics. The most natural next step for a cognitive psychologist is to formulate a mechanism that generates intrinsic dynamics with 1/f fluctuations. But in this case we can make predictions before taking this step, solely on the basis of associating 1/f noise with intrinsic dynamics. We do not yet need to make a commitment to mechanism. The association of 1/f noise with intrinsic dynamics suggests that 1/f noise can manifest in all aspects of behavior, so long as the same behavior is repeated consistently with minimal perturbation. Perturbations may come from stimuli and any other task parameters that change unsystematically over the course of measurement.

Kello, Beltz, Holden, & Van Orden (2005) tested this general prediction in a series of experiments using simple and choice response tasks (see also Beltz & Kello, 2004). In the simple response tasks, a single cue appeared periodically on a monitor, and participants pressed a key as soon as they saw each cue. In the choice response tasks, one of two cues appeared and participants responded by pressing one of two corresponding keys. Reaction times were measured as usual, that is, as the time from cue onset to the time that a key made contact with its sensor. But the authors also recorded a second, unusual measure of the key-press response: the time from contact to release of the key. The authors referred to the latter as key-contact duration.

If 1/f noise can potentially manifest in all repeated behaviors, then it should be able to manifest in both reaction times and key-contact durations. The idea that key-contact durations can manifest 1/f noise is rather curious, given that they span a very brief period of time (100-150 ms), they are completely automatic, and completely irrelevant to the task. Why would such a behavior exhibit the long-range correlation and fractal structure of 1/f noise? Whatever the answer to this question might be, it is exactly what is predicted by the association of 1/f noise with intrinsic dynamics.

Kello et al. (2005) created conditions for measuring intrinsic dynamics by making the response cues predictable. In the simple response task, each predictable cue was presented exactly 1000 ms after the key-release from the previous response. In the choice response task, cues were made predictable either by presenting them in a simple, constant pattern from trial to trial, or by previewing them 1000 ms prior to the time to respond. All of these predictable conditions were designed to minimize unsystematic changes in stimuli or task parameters from trial to trial.

The results from these predictable conditions are summarized in Figure 4, with reaction time analyses shown on the left and key-contact duration analyses shown on the right. Power spectra were computed for each individual measurement series in each condition, and the power density estimates were averaged across participant. Figure 4 shows regression lines that were fit to the averaged estimates in the lower half of the frequency range in each condition. The slopes of the regression lines indicate that both measurements of reaction times and key-contact durations exhibited robust 1/f noise. The average slopes for reaction times and key-contact durations were -.58 and -.59, respectively.

Insert Figure 4 about here

Upon seeing these results, one might ask whether the 1/f noise found in key-contact durations is only a byproduct of the 1/f noise found in reaction times. Indeed it is theoretically possible that the fluctuations in key-contact durations are driven by the same “1/f source” that drove the fluctuations in reaction times. If so, the two dependent measures would be correlated, but analyses showed that the mean correlation coefficient, averaged across subjects for each condition of each experiment, ranged between 0 and -0.2. This lack of correlation means that the responses to predictable cues had manifested two independent streams of 1/f noise. It therefore appears that reaction times and key-contact durations each had their own intrinsic dynamic that fluctuated as 1/f noise.

Kello et al. (2005) further pursued the independence of reaction times and key-contact durations by creating experimental conditions that were hypothesized to perturb the former but not the latter. In particular, cues were made unpredictable by either timing them randomly in the simple response task or sequencing them randomly in the choice response task. Random cues should add unsystematic variation to reaction times because the cues themselves are unsystematic from one to the next. They should not however affect key-contact durations because key-contact durations are defined independently of the cues; the time from key-contact to key-release does not make reference to the cue. Therefore, if the 1/f noise in reaction times is independent of the 1/f noise in key-contact durations, then the unpredictable cues should whiten the former but not the latter.

As summarized in Figure 5, results from the unpredictable conditions provided further evidence that 1/f noise in reaction times was independent of 1/f noise in key-contact durations. Unpredictable cues had the predicted effect of whitening of 1/f noise in reaction times, as can be seen in the shallower slopes of the regression lines compared with Figure 4. The reaction times to unpredictable cues had an average slope of -.24 compared to -.58 for the predictable cues as noted previously. By contrast, unpredictable cues had no detectable whitening effect on the 1/f noise in key-contact durations, as can be seen in the comparable slopes between Figures 4 and 5. The average slope for key-contact durations in responses to unpredictable cues was -.55 compared to -.59 in responses to predictable cues. Thus the dissociating effect of cue predictability provides further evidence that two different dynamics were reflected in reaction times and key-contact durations. While it remains to be determined how these dynamics were dissociated, the results provide strong support for the idea that 1/f noise is inherent to the intrinsic dynamics of human behavior.

Insert Figure 5 about here

General Discussion

The apparent ubiquity of 1/f noise throughout complex systems is both striking and mysterious. The mystery is that there is no known mechanism to explain how 1/f noise is injected into so many behaviors. The idea that 1/f noise is inherent to intrinsic fluctuations does not provide such a mechanism, but it does go a long way towards clarifying the conditions that manifest 1/f noise. The idea was formulated and tested in the context of human cognitive performance, but it fits quite well with all of the results discussed herein: 1/f noise is manifest when a complex system is allowed to fluctuate “on its own”, and measurement is not perturbed by extrinsic factors.

But we are still tasked with seeking out a mechanistic explanation, because this is the agenda set by the information processing framework that drives the fields of cognitive psychology and cognitive neuroscience. It is therefore worthwhile to briefly review the kinds of mechanisms that have been proposed to explain observations of 1/f noise in human behavior. As we shall see, while each kind of mechanism yields potential insights, none have been formulated to the point of providing a satisfying account of the data.

It turns out that the summation of white noises or short-range dependent processes can, under certain parameterizations, produce the appearance of 1/f noise within a finite range of frequencies (Granger, 1980). Some researchers have proposed that what appears as 1/f noise in human behavior is actually the results of processes that are not truly scale invariant.

For instance, Ding, Chen, and Kelso (2001) proposed that long-range correlations in human behavior may be the result of short-range dependencies that are hypothesized to be widespread in neural network dynamics. If human behavior always reflects the summation of many such short-range dependencies, then indeed one might expect to see long-range correlations in behavioral measurements. Along similar lines, Ward (2002) proposed that when three distinct timescales of the brain are summed together they can produce 1/f noise. The timescales are based on different cycle frequencies of neurons and roughly correspond to preconscious, unconscious, and conscious cognitive processing. Each distinct timescale is governed by a relaxation equation that can vary in the amount of white noise it exhibits over time.

These “summation” accounts of 1/f noise may be appealing because they demystify the phenomenon by applying well-understood mathematical models. But these models have limitations that make them unviable as general explanations of observed long-range correlations. The most severe limitation is that parameters must be fit post-hoc to each measurement series. Outside a given parameterization, the models generate white noise instead of the power law scaling relation that defines true 1/f noise. If behavior is characterized by true 1/f noise, then the summation accounts can be disproven by showing that the power law continues into lower and lower frequencies as more and more measurements are taken. Indeed Van Orden and his colleagues (2005) reported reaction time results in which the power law extended into lower frequencies as more measurements were taken. The post-hoc nature of the summation accounts also limits their ability to explain the apparent ubiquity of 1/f noise in biological and complex systems; why would the behavior of so many different systems be driven by white noises or short-range dependent processes that just happen to be parameterized appropriately to give the appearance of 1/f noise every time a system is measured, regardless of the level at which it is measured?

Another way to mimic 1/f noise is based on the idea that a non-stationary process can generate behavior similar to the stationary process of 1/f noise. In the context of human behavior, Wagenmakers and his colleagues (2004) proposed that non-stationary shifts in strategy can lead to fluctuations in cognitive performance that mimic 1/f noise. To illustrate, imagine an arithmetic task in which problems can be solved using a number of different arithmetic strategies. A participant might switch among strategies over the course of a trial series of problems to be solved. This switching might show up in the data as a series of “plateaus” embedded in the measurement series. Each plateau would correspond to one run of a given strategy, and each strategy would be associated with its own mean level of performance. For instance one arithmetic strategy might allow for quick and dirty answers, another might be more slow and tedious, and third strategy might be some compromise of the first two. Wagenmakers et al. showed that, under certain parameterizations, a model that switches among different strategies will mimic the long-range dependence that characterizes 1/f noise.

As with the summation accounts, the strategy-shifting account of 1/f noise gives little insight into the apparent ubiquity of 1/f noise in biological and complex systems; why would the behavior of so many different systems be governed by non-stationary processes that just happen to be parameterized to give the appearance of 1/f noise? Another limitation of the strategy-shifting account is that it cannot readily explain the existence of separate streams of 1/f noise that come from two different measures of the same behavior. We are specifically referring to the reaction time and key-contact duration results reported by Kello and his colleagues (2005). Recall that they found evidence of independent streams of 1/f noise in the downward versus upward motions of a key-press response. How could two independent strategies exist to govern two adjacent and interleaved measures of what appears to be a unified key-press behavior?

We seem to need a mechanism for which 1/f noise is a general and robust consequence of processing. Only one such mechanism has been general enough to generate widespread interest and investigation across the physical, biological, psychological, and social sciences. Bak, Tang, and Wiesenfeld (BTW; 1987) introduced a simple model of interacting nodes that they claimed to exhibit self-organized criticality. The term criticality refers to a system that is poised at a state at which local perturbations can have system-wide effects. For the BTW model, criticality means that a perturbation at one node can potentially have almost immediate effects on the states of all nodes in the system. Criticality is key because physicists have known for some time that systems at or near critical states tend to exhibit true power law behaviors such as 1/f noise. The term self-organized is intended to mean that the model parameters do not need to be fine-tuned to achieve the critical state. Instead the model is supposed to intrinsically poise itself at the critical state.

The general idea behind the BTW model is that each node has an activation value, a threshold, and a set of neighboring nodes. Activation values are increased slowly over time due to some external driving force. When the activation of any given node crosses threshold, the node relaxes by distributing its activation to its neighbors and returning to baseline. An "avalanche" occurs when the relaxation of one node sets off a chain reaction of relaxations across other nodes. Bak and his colleagues (1987) reported that for a range of parameterizations, the sizes of avalanches followed a power law distribution, and the time series of avalanches fluctuated as 1/f noise. It later came to light that the claim of 1/f noise was erroneous, but subsequent versions of the model did in fact exhibit 1/f noise (Jensen, Christensen, & Fogedby, 1989)

It is not clear how the BTW model can be used to directly simulate cognitive processes or human behavior (Wagenmaker, et al, 2005). However the model does have obvious parallels with neural networks, and in fact it has been used to address results from studies of neural behavior (Beggs & Plenz, 2003). One could speculate that the power law behavior observed in neural networks is responsible for the 1/f noise that is observed in human behavior, but the connection remains to be established. Nonetheless, as it stands now, the model proves that it is at least possible to formulate a mechanism for which 1/f noise originates from a general property, rather than a specific, isolable process. The BTW model may thus provide the basis for understanding the ubiquity of 1/f noise throughout human behavior, as well as throughout biological and complex systems. Future research will need to investigate how a model that exhibits self-organized criticality can shed more direct light on the nature of cognition and human behavior.

References

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

Bak, P. (1996). *How nature works*. New York: Springer-Verlag.

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

Beggs, J.M., & Plenz, D. (2003). Neuronal Avalanches in Neocortical Circuits. *The Journal of Neuroscience*. *23(35),*11167-11177

Beltz, B. C. & Kello, C. T (2004). The effect of cue predictability on long range dependencies in response times versus response durations. *Proceedings of the 26th Annual Meeting of the Cognitive Science Society*. Chicago, IL.

Chen, Y., Ding, M., & Kelso, J. (2001). Origins of timing errors in human sensorimotor coordination. *Journal of Motor Behavior, 33*(1), 3-8.

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

Csabai, I. (1994). 1/f noise in computer network traffic. *Journal of Physics A, 27*, L417-L421.

Delignieres, D., Fortes, M., & Ninot, G. (2004). The fractal dynamics of self-esteem and physical self. *Nonlinear Dynamics, Psychology, and the Life Sciences*.*8(4),* 479-510.

Ding, M., Chen, Y., & Kelso, J. (2002). Statistical analysis of timing errors. *Brain & Cognition, 48(1)*, 98-106.

Gilden, D. (1997). Fluctuations in the time required for elementary decisions. *Psychological Science, 8(4)*, 296-301.

Gilden, D., Thornton, T., & Mallon, M. (1995). 1/f noise in human cognition. *Science, 267(5205)*, 1837-1839.

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

Goldberger, A. L., Amaral, L. A. N., Hausdorff, J. M., Ivanov, P. C., Peng, C. K., & Stanley, H.E. (2002). Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Science of the United States of America, 99(1)*, 2466-2472

Granger, C. W. J., & Joyeux, R. (1980). An introduction to long-memory models and fractional differencing. *Journal of Time Series Analysis, 1*, 15-29.

Hausdorff, J. M., Purdon, P. L., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: Stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology, 80(5)*, 1448-1457.

Inchausti, P. H., John. (2001). Extinction risk and the 1/f family of noise models. *Science, 293*, 655-657.

Jensen, H. J., Christensen, K., & Fogedby, H. C. (1989) 1/f noise, distribution of lifetimes, and a pile of sand. *Physical Review B 40*, 7425-7427

Kello, C., Beltz, B., Holden, J., & Van Orden, G. (2005) 1/f noise is generic to the intrinsic fluctuations of human behavior. *Manuscript submitted for publication*.

Li, W., & Holste, D. (2005) Universal 1/f noise, crossovers of scaling exponents, and chromosome-specific patterns of guanine-cytosine content in DNA sequences of the human genome. *Physical Review E 71*, 041910

Linkenkaer-Hansen, K., Nikouline, V. V., Palva, J. M., & Ilmoniemi, R. J. (2001). Long-range temporal correlations and scaling behavior in human brain oscillations. *Journal of Neuroscience, 21(4)*, 1370-1377.

Liu, Y., Goprikrishnan, P., Cizeau, P., Meyer, M., Peng, K.C., & Stanley, H.E. (1999). Statistical properties of the volatility of price fluctuations. *Physical Review E, 60(2)*, 1390-1400

Matthaeus , W.H., & Goldstein, M.L. (1986). Low-frequency 1/f noise in the interplanetary magnetic field. *Physical Review Letters 57(4)*, 495-498

Simon, H. A. (1973). The organization of complex systems. In H. H. Pattee (Ed.), *Hierarchy theory: The challenge of complex systems* (pp. 1-27). New York: George Braziller, Inc.

Thornton, T. L., & Gilden, D. (2005). Provenance of correlations in psychophysical data. *Manuscript submitted for publication*.

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

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General, 132(3)*, 331-350.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of l/f alpha noise in human cognition. *Psychonomic Bulletin & Review, 11(4)*, 579-615.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2005). Human cognition and a pile of sand. *Journal of Experimental Psychology: General, 134(1)*, 108-116.

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

Figure Captions

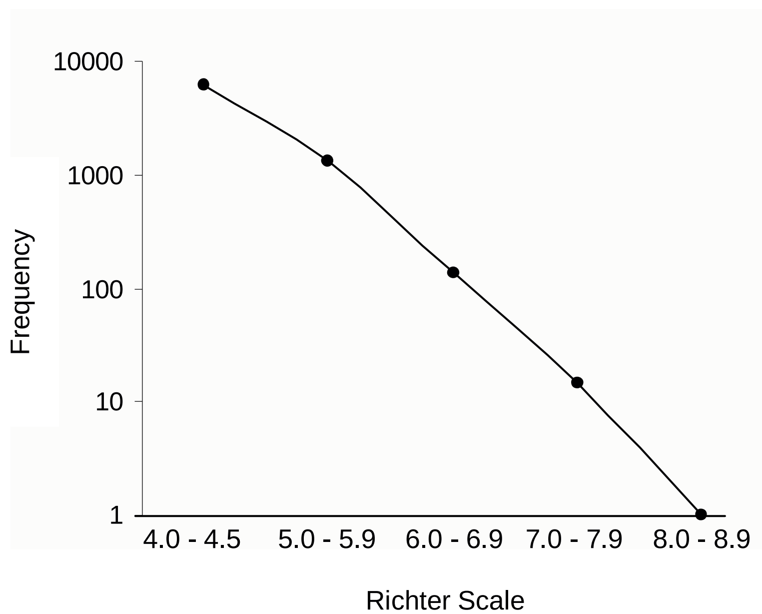
Figure 1. Average number of earthquakes by size, United States 1990-1999 Source: U.S. Geological Survey

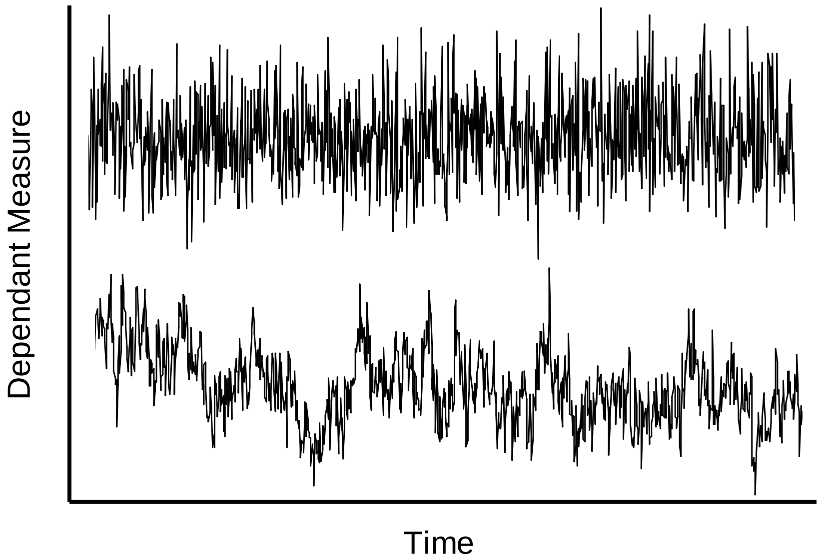
Figure 2. White noise (top) and 1/f noise (bottom).

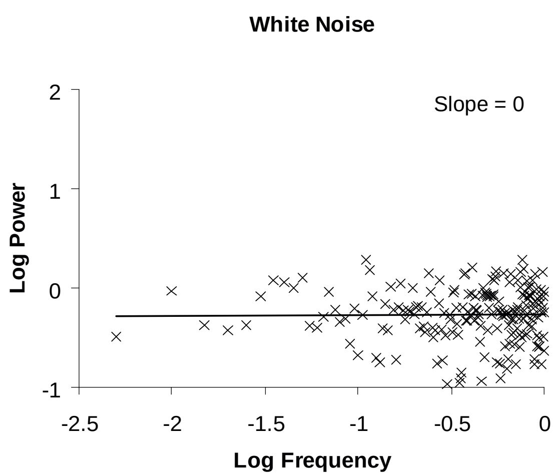
Figure 3. Spectral analysis of time series from Figure 2 showing the linear relationship between log frequency and log power. White noise (top) and 1/f noise (bottom).

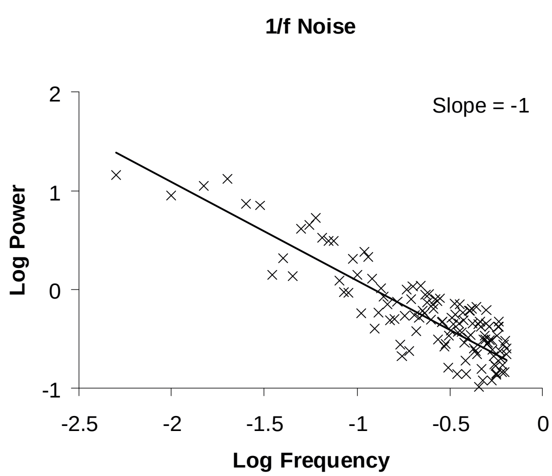
Figure 4. 1/f noise in the response times (left) and key-press durations (right) for predictable conditions in Kello et al (2005). In the choice reaction time tasks, the two possible cue identities (left or right) were made predictable by following a consistent pattern or by being previewed for 1 second before a response was required.

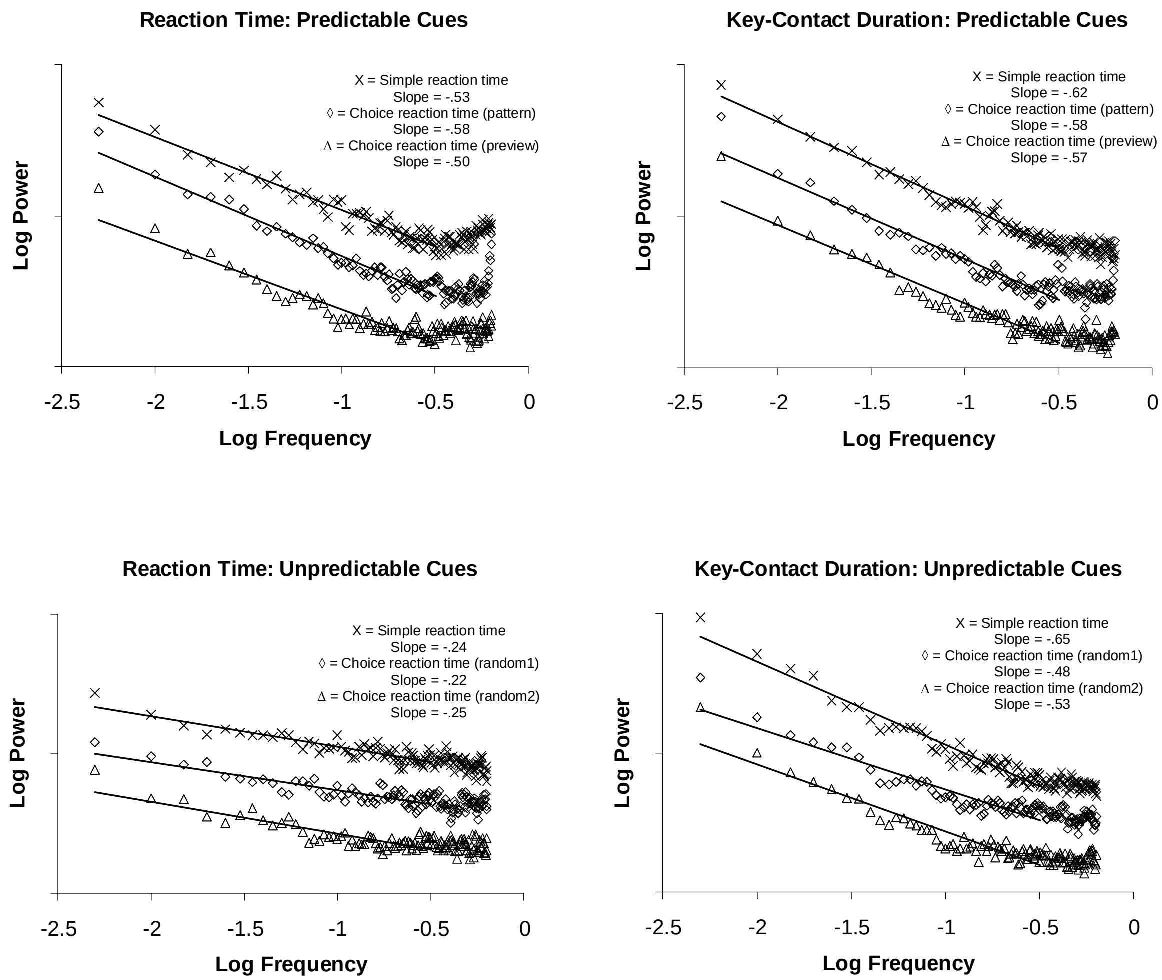
Figure 5. 1/f noise in the response times (left) and key-press durations (right) for unpredictable conditions in Kello et al (2005). In the choice reaction time tasks, the two possible cue identities were randomly selected each trial.




Dependant Measure
Time


White Noise
Slope = 0
Log Power
2
1
0
-1
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency


1/f Noise
Slope = -1
Log Power
2
1
0
-1
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency


Reaction Time: Predictable Cues
X = Simple reaction time
Slope = -.53
◊ = Choice reaction time (pattern)
Slope = -.58
Δ = Choice reaction time (preview)
Slope = -.50
Log Power
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency
Key-Contact Duration: Predictable Cues
X = Simple reaction time
Slope = -.62
◊ = Choice reaction time (pattern)
Slope = -.58
Δ = Choice reaction time (preview)
Slope = -.57
Log Power
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency
Reaction Time: Unpredictable Cues
X = Simple reaction time
Slope = -.24
◊ = Choice reaction time (random1)
Slope = -.22
Δ = Choice reaction time (random2)
Slope = -.25
Log Power
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency
Key-Contact Duration: Unpredictable Cues
X = Simple reaction time
Slope = -.65
◊ = Choice reaction time (random1)
Slope = -.48
Δ = Choice reaction time (random2)
Slope = -.53
Log Power
-2.5
-2
-1.5
-1
-0.5
0
Log Frequency