1/f Dynamic in Complex Visual Search: Evidence for Self-Organized Criticality in Human Perception

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Consider the "search and select" problem we face each day. We constantly set goals for ourselves that require us to scan our environment until we find a target. Whether we are looking for a face in a crowd, our keys in a cluttered environment, or a tumor in an x-ray, we rely on this ability to search the environment. What type of process is involved? Most researchers argue that some form of memory serves as a guide to search. Attention also plays an important role (e.g., Kowler, Anderson, Dosher, & Blaser, 1995; McPeek, Maljkovic, & Nakayama, 1999), and is arguably what drives saccadic eye movements to be effective. For now, I will focus on the role of memory in guiding search. A popular view is that a record accumulates (e.g., Townsend, 1974) and persists across fixations to guide search (e.g., Irwin, 1992). Once items are visited they are tagged so as to inhibit unnecessary subsequent visits—a phenomenon known as inhibition-of-return (e.g., Posner & Cohen, 1984; Klein, 1988). Surely, search would be more efficient if we only needed to check each item once until the target was found. While this theory has empirical support (see Shore & Klein, 2000, for a review), views of what characterize this memory are widely varied, as are the experiments that attempt to test them (Irwin, 1992; Posner & Cohen, 1984; Klein, 1988; Treisman & Gelade, 1980; Wolfe, 1994). Moreover, and perhaps surprisingly, studies have shown that under some natural search conditions memory does not seem to play much of a role in guiding search (e.g., Ballard, Hayhoe, & Petz, 1995; Horowitz & Wolfe, 1998). Eye movements are often sloppy when scanning a natural environment with our eyes returning repeatedly to objects and locations that have already been visited (Ballard et al., 1995). Instead

of systematically retrieving information from memory, search may rely on the external world to serve as its guide (O'Regan, 1992).

RECONSIDERING HOW WE STUDY VISUAL SEARCH

To help reconcile why such widely varying search behavior has been seen in those different experiments, let us consider the different methodological approaches that have been taken. Typically, the analytical focus is on comparing performance speed, accuracy, or amount of information recalled across conditions (e.g., experimental and control). In studies of inhibition-of-return, for example, researchers are interested in the effect of prior exposure on subsequent search performance. Once the eyes fixate and "take note" of a particular item, there should be no need to revisit this item. Similarly, in priming experiments, the critical comparison is between "new" vs. "repeated" information. Positive priming experiments show benefits accrued from repeated exposure to target and distractor information, and negative priming produces interfering effects on search performance (e.g., Maljkovic & Nakayama, 1994).

In these traditional experiments, RTs and error rates are combined across trials of the same conditions. The variability of the behavior, which inevitably emerges in all conditions, is attributed to extraneous noise. That variability is isolated and removed from the purported impact of the independent variable. By contrast, similar to Gilden (1996) and Gilden, Thornton, and Mallon (1995), we focus on the variability over time. As is commonly done in the dynamical systems approach in psychology, we start by asking how a behavior changes over time (within a single condition). We no longer assume

erratic fluctuations are noise in the system (Gilden, 1996). Rather, these fluctuations may contain important information about how search history may have an important influence on future behavior. In this chapter I assess whether a dynamic is driving visual search by analyzing the temporal properties of eye movements. This approach may help us understand whether a simple iterative process is behind visual search.

PATTERNS OF SEARCH

Studying the pattern of search behavior is key to understanding what drives search, and it will help us understand essential characteristics of any mediating memory mechanism. An absence of memory will be signaled by random search. The opposing extreme of random search would be a highly systematic pattern of search, for example, looking sequentially from left to right and top to bottom. Such a systematic search guarantees coverage of the visual field until the target is located. Although this increases the likelihood of detecting a (fixed) target, there are costs involved. Perhaps most important is the substantial cost in time. A speedy search is imperative under many real world conditions, such as when the target is not fixed, its identity or context changes, when the perceiver is constrained by competing goals, or when an aggressive predator is pursuing the perceiver. Such time constraints need to be incorporated into any realistic model of human visual search.

Could a rapidly implemented, unsystematic, even haphazard search be better than a systematic one? Literature that documents examples of erratic yet effective search adds plausibility to this idea

(e.g., Ellis & Stark, 1986; Engle, 1977; Inditsky & Bodmann, 1980; Krendel & Wodinsky, 1960). Similarly, visual search has been found to be "nearly random" (Scinto, Pillalamarri, & Karsh1986), outright "random" (Groner & Groner, 1982; Horowitz & Wolfe, 1998), and a "random walk" (i.e., brown noise; Scinto et al., 1986). Likewise, studies focusing on the type of memory guiding search find little relation to the recall of objects (e.g., Melcher & Kowler, 2001; Ballard et al., 1995) or their locations in the scene (Zelinsky & Loschky, 1998). Contrary to what we might expect, and to what much conventional theorizing holds, visual search often is *un*systematic and not necessarily related to explicit memory for what and where our eyes have just visited.

Computational theory as well as empirical findings (e.g., Megaw & Richardson, 1979; Locher & Nodine, 1974) have begun to clarify these notions and illustrate how a pseudo-random search can afford better coverage and more efficient search than many systematic ones. As we will see, a long-term memory across fixations—one that does not necessarily contain explicit information about the identity or locations of objects—may be instrumental in driving behavior. Although the complicated search behavior appears inefficient, the efficiencies come in the form of significant cognitive savings. For instance, cognitive load may be reduced since complex long-memory search behavior may require minimal resources for coding, retrieval, and recall. As described later in discussion of the SOC model, the only cognitive load required involves iteration of a very simple set of rules.

PATTERNS OF SCALING, COLORED NOISE, & SELF-ORGANIZATION

When we look at the statistical properties of many systems' behavior we often find dynamics with well-defined scaling properties (e.g., Bak, Tang, & Wiesnfeld, 1988; Jensen, 1998). Scaling behavior (see Liebovitch & Shehadeh, Chapter 5, and Holden, Chapter 6) is a sign of long-term influences on system behavior and may be the product of a simple yet flexible process. The scaling behavior itself implies that no single characteristic scale is best suited to describe the behavior of the process. There is not just one time scale that controls the evolution of these systems; the means and variances change depending on the size of the sampling resolution. If given unlimited time, these "scale-free" distributions can stretch on indefinitely without encountering a cut-off. This stretching property is key to scaling and can be quantified by power laws. We can succinctly express some quantity N as some power (an exponent, e) of another quantity, s: $N(s) = s^{-e}$. Therefore, by examining the exponent of the power law we know how the distribution changes as a function of some underlying variable, which in this case is time.

Importantly, systems characterized by power laws often produce complex behavior that appears random. In a particular form of power scaling, one that emerges frequently in complicated behavior, slower (i.e., low-frequency) behavior dominates. The temporal phenomenon scales as the inverse of the frequency (f), or as *1/f noise*. Bak et al. (1987) suggested that these systems, with a power spectral exponent $\alpha = -1.0$ (i.e., f^{α}), consist of many interacting components, are ubiquitous in nature (see Bak et al., 1987 for examples), and,

under many conditions, are dynamical systems which organize themselves into a state with a complex structure. Self-organization (see, e.g., Kelso, 1995) implies that patterns develop without a need for a controlling agent. The patterns emerge from a decentralized set of interactions that are intrinsic to the system.

Recognizing that difficult visual search tasks are often unsystematic, yet effective, has led to my belief that the oculomotor system uses subtle, self-organizing properties that produce erratic fluctuations in search behavior. Because the process involves very simple, iterated rules, only a minimal cognitive load is needed to carry out the complicated search behavior. The amount of information needed to be stored is reduced to a simple iterative function. This highly compact code may suffice to guide search. Evidence for such a self-organizing, complex system would reflect determinism inherent to the system and support the notion that a simple memory persists across fixations. It is a memory quite different from that of conventional thinking—the use of "memory" here does not imply "memory" in the everyday sense—and one that shares known properties of neurophysiology (e.g., spreading activation and inhibition).

SELF-ORGANIZED CRITICALITY AS A MODEL OF VISUAL SEARCH

One candidate model of visual search is Self-Organized Criticality (SOC[1]; Bak et al., 1987). In the SOC model, dramatic change,

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[1] Despite the controversy regarding Bak's original conception of SOC as a reliable model of 1/f dynamics, slight variants have proven to be reliable (Jensen, 1998). Alternative models maintain many similar properties including simple rules producing complex behaviors and self-organization. Thus, SOC or similar alternatives could account for described data trends.

or *criticality*, arises from the local interactions of the system's component parts. Such changes give rise to both the complex behavior as well as the *self-organization* within the system. The *simplicity* of the local rules according to which neighbors interact implies the cognitive load for driving eye-movements is minimal. In previous work, we have illustrated how SOC can easily be generalized to a neural network capable of evoking perceptual changes (Aks & Sprott, 2003). Here I describe how local interactions can occur through lateral inhibition and excitation across neurons. Together with simple threshold rules (as are typical in SOC models), these interactions can produce perceptual changes (i.e., Stassinopoulos & Bak, 1995). Similarly (as illustrated later in Figure 7.12 and the Discussion), we can conceive of eye movements being driven by the interaction of neurons across an underlying network of neurons.

Applications of dynamical approaches to other cognitive and perceptual phenomena (Gilden et al., 1995; Kelso, 1995; Port & Van Gelder, 1995; Pressing, 1999; Ward, 2002) show great promise for extending that approach to the visual search system. My proposal that a simple deterministic process may drive the human visual system has been tested in a challenging visual search task (Aks, Zelinsky, & Sprott, 2002). As described in the Method section in this chapter, our analysis focused on the impact of time on the resulting probability distributions and power spectra. We looked for scale-invariance in eye movements by evaluating whether the means and variances of those data distributions changed over time, and whether power laws emerged in the power spectra. Finding a scale-invariant perceptual system, characterized by a power law, would suggest that there is

determinism and compact coding of information in visual search (c.f. Voss, 1992). Furthermore, evidence of SOC or a similar such iterative mechanism in the perceptual system (as indicated by 1/f power laws) would present another illustration of a complex system with a simple underlying dynamic—one that can potentially account for the flexibility of our visual system in adapting to novel environments.

METHOD

The visual search task, illustrated in Figure 7.1, consisted of eighty-one 0.43° T shapes. Targets and distractors differed in orientation by 90°. Items were presented in a pseudo-random arrangement so that all locations had an equal probability of being searched. The participant's task was to search the array and press a hand-held button when the target was located.
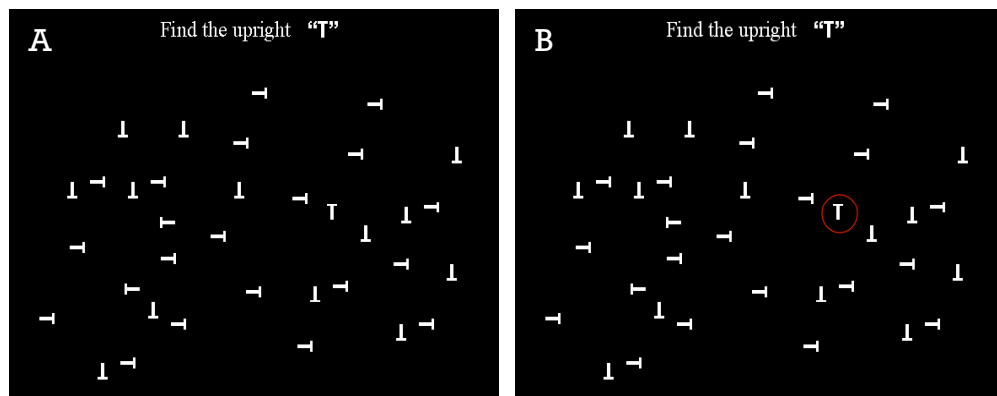
Figure 7.1. (A) Sample display from the search task. The subject searched for an upright 'T.' (B) The correct target is circled in red

The experiment consisted of 400 target-present trials and lasted approximately 2.5 hours. Every effort was made to emulate a

continuous search but factors such as fatigue and actual target detection forced brief discontinuities in the data series. The two types of discontinuities that occurred in this study were due to (1) inter-trial intervals between when the participant found the target and a new trial began, and (2) subdividing the trials into eight sessions separated by five-minute rest periods. Eye movements were sampled using a Generation V dual purkinje-image (DPI) tracker that was controlled by a computer.

The duration and x and y positions of the eyes were recorded at each fixation. Each measure was treated as a set of data points whose spatial and temporal properties were analyzed over the course of search. Additional parameters of the eye movements were used to map the trajectory of the eyes as they moved from fixation to fixation. These included differentiation of consecutive eye positions (e.g., $x_n - x_{n+1}$), eye movement distance $(x^2 + y^2)^{1/2}$, and eye movement direction [arctan (y/x)].

ANALYSIS STRATEGY

Many of the tools of complexity theory involve formalizing (with mathematical and visual representations) the interactions that occur within a network. A typical aim is to look for a statistical pattern that might emerge in data that have been collected over time. In our analysis of the eye fixations we looked for scaling and other patterns across data points in the series. Here I will focus on three sets of analyses—spectral analysis (FFT), power laws, and the Iterated Functions System (IFS) clumpiness test.

Spectral and Fourier analyses[2] are well-established methods to test for correlations within a time series. Jagged data series (appearing superficially as a random series) are often produced by natural complex systems. The data series can be described as a complex waveform best estimated by the composite of simple regular (sine) waves that span a range of frequencies. A Fourier transform involves first decomposing the observed series into simple waves and then plotting the power against frequency to describe what combination of waves best describes the observed waveform. The analysis in our study used a Fast Fourier transform (FFT; Press, Flannery, Teukolsky, & Vetterling, 1986) and the resulting plot of the power (mean square amplitude) against frequency. For an introduction to Fourier analyses see one of many tutorials, such as Peak and Frame (1994) and Sprott (2003).

Power Laws in Spectral Analyses

Can the eye movement data be described by a power law, and do the data possess scale invariance associated with a self-organizing complex system? A linear function on a double-log plot produced by FFT indicates the presence of a power law. The regression slope of this function, denoted by α, is the power exponent. When the exponent of the power spectrum is $\alpha = -1.0$ (as shown in the middle

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[2] Spectral analysis is a linear method that can be effectively used to characterize a nonlinear (fractal scaling) process. A linear method can be very useful in detecting correlated structure in noisy data regardless of the process that produced it. For example, the eye movement data that we have analyzed can be the output of either a linear or nonlinear process. I argue that the 1/f structure—estimated by FFT spectral analysis—may suggest that a SOC-type process drives eye-movements. SOC is a simple nonlinear process (iterated many times over) which can operate in a neural network—perhaps to produce complicated eye movements. The linear Fourier analysis is an effective tool to uncover (and estimate) correlated structure regardless of whether it has emerged from a linear or nonlinear process.

Dominant Frequencies
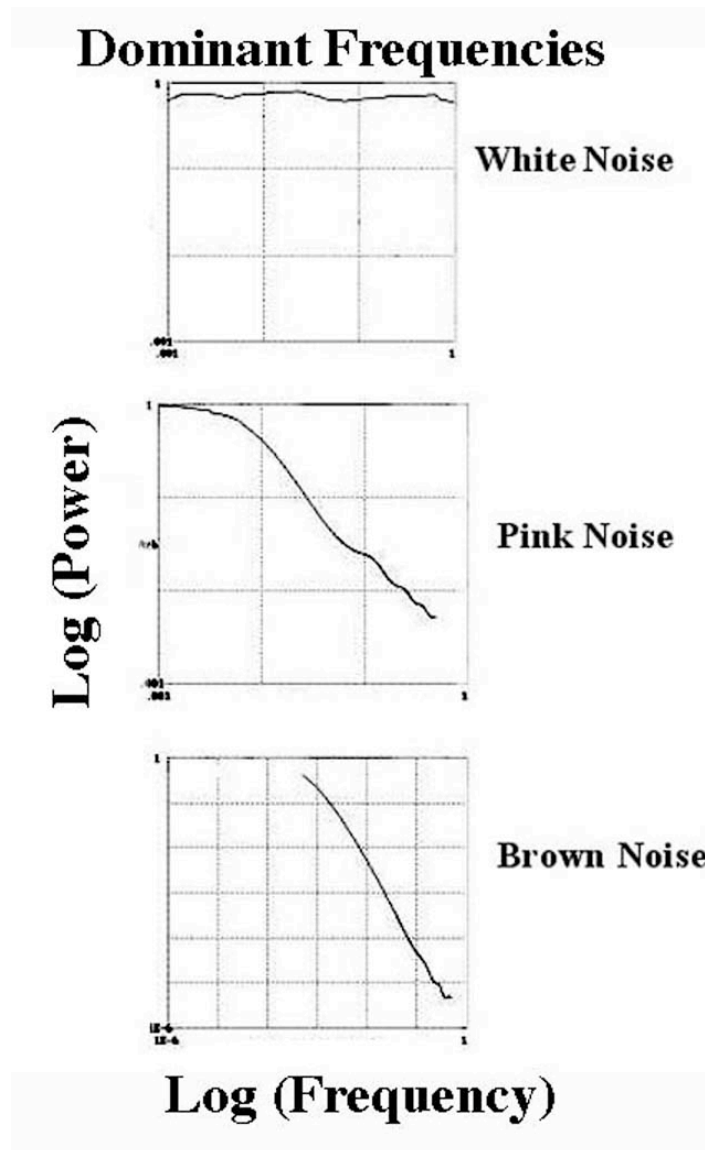
Figure 7.2. Spectral analysis of three types of colored noise. White ($1/f^0$) noise with a flat spectrum indicates no correlation across data points; Brown ($1/f^2$) noise has a steep slope indicating short-term correlation; and Pink ($1/f$) noise has a shallow slope indicating extremely long time correlation. The white noise is a Gaussian distribution of scores with all frequencies equally represented. Sprott and Rowland (1995) included this sample data set in their *Chaos Data Analyzer* software. Brown noise is a simple integration of the white noise. To generate the pink noise I took the Fourier transform of the white noise data to isolate the frequency domain, multiplied the amplitude of the frequency components by 1/f, and performed an inverse Fourier transform. See also Equations 9.35 and 9.36 in Sprott (2003).

panel of Figure 7.2), the given temporal phenomenon scales as the inverse of the frequency (f), or as 1/f noise. In this particular form of scaling, fluctuations occur in the same proportion at all scales (i.e., they are self-similar and scale invariant), and there exists a great deal of fine structure in the data.

An important aspect of spectral analysis is that it serves as a useful measure of the strength of memory across the system. Revealing temporal correlation is important not only in assessing whether memory exists across eye-movements, but the magnitude of the exponent also quantifies memory strength. The steepness of the slope (on a log-log scale) reflects the duration of memory (i.e., correlation across points). As shown in Figure 7.2, Brown ($1/f^2$) noise has a steep slope, indicating short-term correlation. Pink ($1/f^1$) noise has a shallow slope, indicating extremely long time correlation, and white ($1/f^0$) noise, with its flat spectrum, indicates no correlation across data points. Implications for these trends are described in the Discussion section, including how pink noise hints at a process that has important self-organizing properties.

Iterated Function Systems (*IFS*) provides an interesting alternative to determine whether temporal correlations exist across fixations (Peak & Frame, 1994; Jeffrey, 1992; Sprott & Rowlands, 1995; Mata-Toledo & Willis, 1997). This technique is used to create a pattern that helps to visually characterize the color of noise. It does so by producing clumped patterns for colored noise while producing homogeneously filled spaces when the data are uncorrelated. At a minimum we learn whether our data deviates from a random pattern, but there is also the potential for learning about the degree of

correlation present in noisy data. The different degrees of temporal correlation correspond to the different forms of coloring to the noise. As can be seen in Figure 7.3, white ($1/f^0$), pink ($1/f^1$, or $1/f$), and brown ($1/f^2$) noise are easily distinguishable. White noise produces a pattern that uniformly fills its representation space. At the other extreme, brown ($1/f^2$) noise produces a pattern in which the dots accumulate over the diagonals and some of the sides of the square, leaving most of the representation space empty. Pink ($1/f$) noise produces self-similar repeating triangular structures of different sizes, and accumulates, albeit in a dispersed way, near the diagonals. These examples illustrate how to visualize the fine structure of time series using the IFS test to help distinguish the color of noise in a system.

The IFS Procedure

First, take either the x or y fixation series (or some derivative as shown in Figure 7.4), and sort the data from the minimum to the maximum value. Then, subdivide the series into four quartiles, in such a way that each group contains the same number of points. The original unsorted data set is then normalized and grouped into one of four values, 1 to 4, representing the quartile to which the data belong.

As shown in Figure 7.5, the representation space is a square that provides a 2-D picture of the correlation structure present in the trajectory of eye movements. The four corners are labeled 1 to 4 in a clockwise direction (starting in the lower left corner) to represent the quartile of that fixation. The first fifteen fixations from Figure 7.4 are used here to demonstrate the IFS procedure.
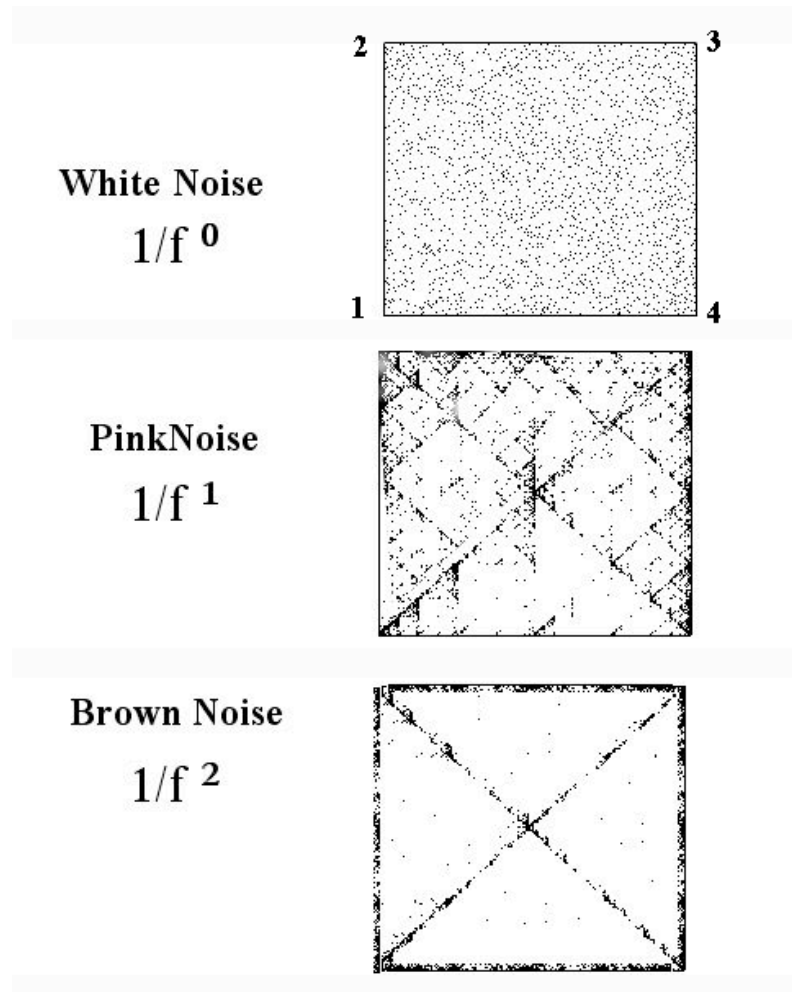
Figure 7.3. Output of the IFS test performed on white, pink, and brown noise (the same simulated data used in the analysis of Figure 7.2). Each case is easily distinguishable. White noise uniformly fills the representation space. Brown noise produces a pattern in which the dots accumulate over the diagonals and some of the sides of the square, leaving most of the representation space empty. 1/f (pink) noise produces self-similar, repeating, triangular structures of different sizes, and accumulates, albeit in a dispersed way, near the diagonals.

Because previous points determine the position of each subsequent point, the plot represents a trajectory of the eye movements. Each point gives a short-term history of eye movements, since the influence of previous fixations diminishes over time. The

Fixation Series

	Y diff	Quartile
1	-31.0	2
2	-62.0	1
3	-33.0	2
4	14.0	3
5	-12.0	2
6	20.0	3
7	-98.0	1
8	-10.0	2
9	-82.0	1
10	-34.0	2
11	-42.0	2
12	12.0	3
13	56.0	4
14	62.0	4
15	60.0	4

**Figure 7.4.** The first 15 data points for the difference across the y coordinate of each fixation. In the right column is the quartile to which each data point belongs.

result is a scattering of points in the plane as shown in Figure 7.3. Any departure from a uniform distribution of points is evidence for correlated structure and possibly a deterministic mechanism driving the behavior. Clustering along the diagonals in the figure reveals the short-term, highly correlated pattern associated with brown noise. The additional fractal microstructure reflects longer-term, but weaker, correlations often associated with pink noise.

RESULTS

Visual search produced, on average, 24 fixations ($SD = 15$) per trial, with each trial lasting 7.6 s ($SD = 6.9$ s). Mean fixation duration was 212 ms ($SD = 89$ ms) with 10,215 fixations across the complete search experiment. The number of fixations decreased from 1888 to 657 across eight sessions, with the average duration increasing from
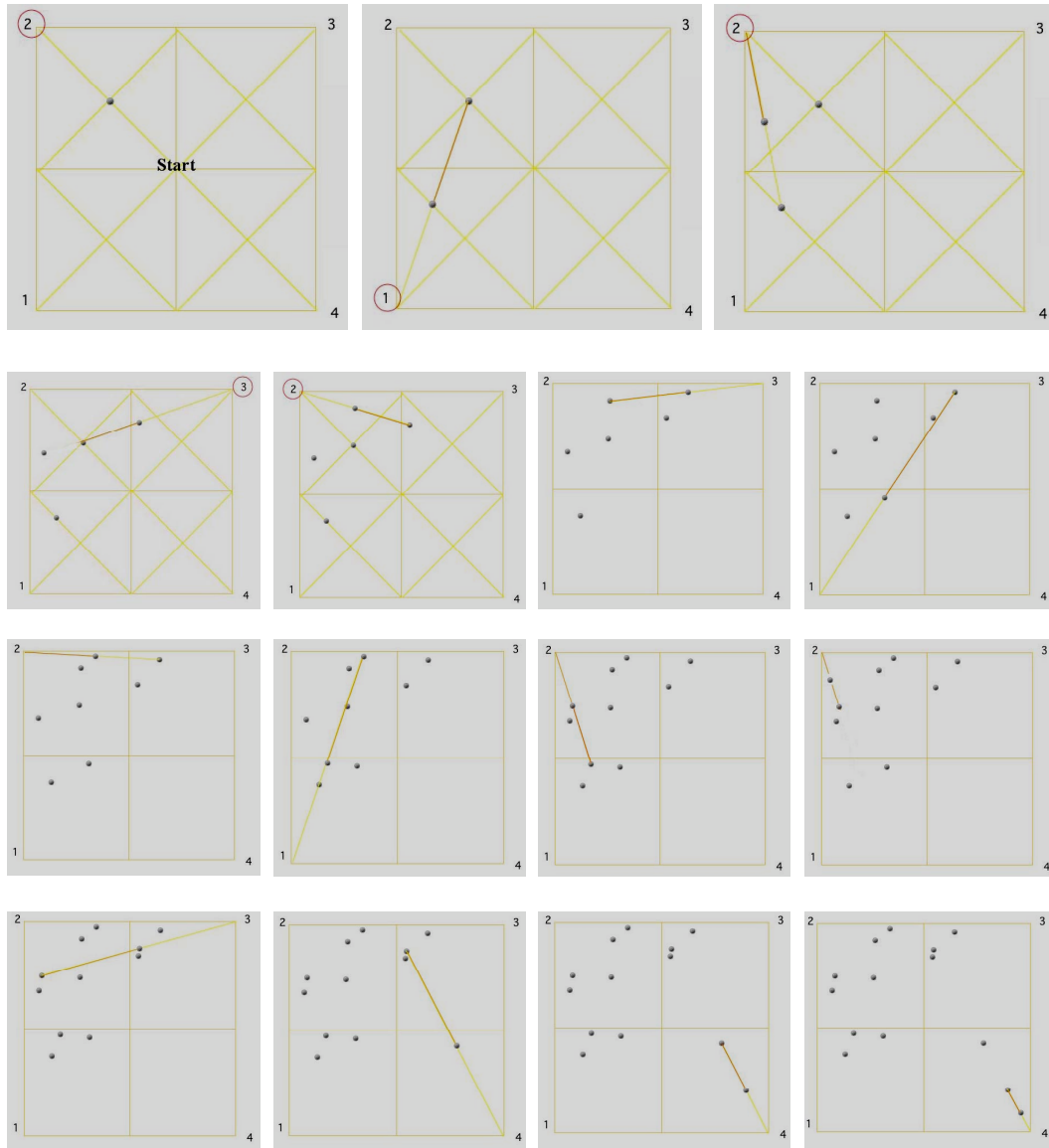
Figure 7.5. (A; top-left) A point is plotted halfway between the center of the IFS square and the quartile of the first point of the series. The first point falls into the 2nd quartile of the full data series. The quartile of the data point is circled in red. (B; top-middle) A second point (falling into the 1st quartile of the full data series) is plotted halfway between the first plotted point and the second point in the fixation series. (C; top-right) A third point (falling into the 2nd quartile) is plotted halfway between the second plotted point and the third point in the series, and so forth. (D)-(O) (smaller panels, from top-left to bottom-right) show the remaining evolution of the IFS map when applied to the first fifteen trials.

206 to 217 ms. Mean deviation from last trial fixation to new target location was 0.4°. indicating a high degree of accuracy in actual target detection.

Figure 7.6 shows a representative sample of the first differences across eye position ($y_{n-1} - y_n$). These erratic trends were similar for x- and y-coordinate positions, except for the overall direction in which the eye position changed over time. While differences across y positions gradually increased over time, differences across x positions tended to decrease over time. The same trends occurred with relative dispersions (*SD/M*), a measure which reflects system contingencies as function of sampling resolution (Liebovitch, 1998). These changes in mean and variance with fixation duration are characteristic of fractal structures and scale-invariant systems.
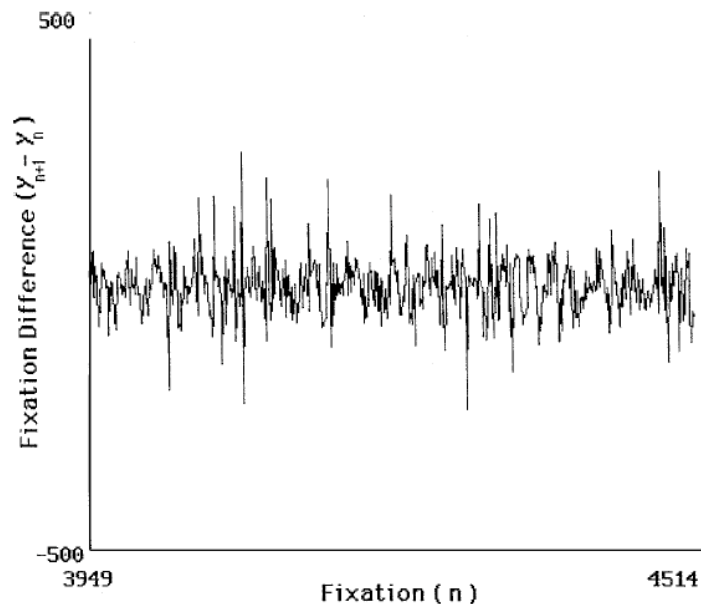

Figure 7.6. Representative fixation series for the first differences of eye position ($y_{n+1} - y_n$). Only fixations along the vertical coordinate are shown. The erratic pattern in the fixation series is similar for horizontal eye positions. The spikes are typical of 1/f behavior.

The first method to assess temporal correlations (i.e., memory) in search involved FFT and power spectral analysis. The mean regression slope of the power spectra for the x and y eye-position coordinates was $\alpha = -1.7$ (i.e., brown noise). Differentiated (x and y) data showed reduced regression slopes, $\alpha = -0.23$. The spurious low-frequency regions of the spectra flattened the slope. In the high-frequency region of the curve $\alpha = -0.7$ (for y, $\alpha = -0.7$; for x, $\alpha = -0.6$). An example of the 1/f trends is illustrated in Figure 7.7.
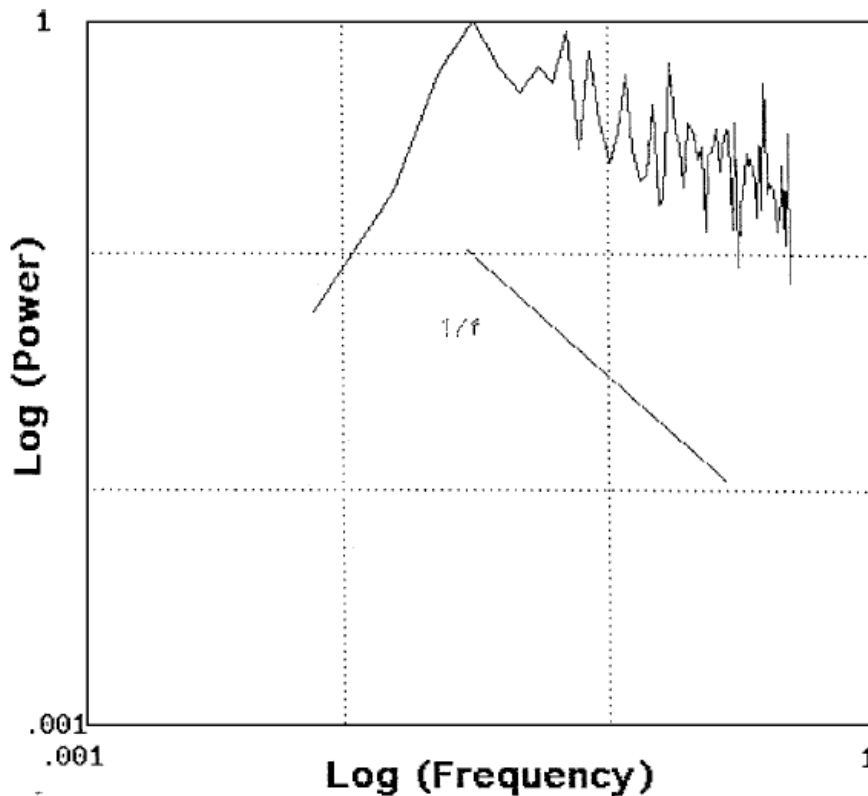
Figure 7.7. Power spectra of first differences of x and y fixation series produced pink (1/f) noise. Spectra of differences across y fixations are shown here. Mean regression slope of the y-difference power spectrum is $\alpha = -0.7$ in the high frequency region. Also shown is a line depicting an exact 1/f power spectrum.

The second method, the IFS clumpiness test (Jeffrey, 1992), evaluates memory in complex search (i.e., temporal correlations and deviations from randomness). Clustering along the diagonals reveals short-term, highly correlated consecutive data points typically found in brown noise. Such a pattern was observed in the analysis of raw eye fixations for the x and y coordinates. Additional fractal microstructure appeared in the IFS test when fixation differences were analyzed. This trend, shown in Figure 7.8, reflects long-term, but weaker, correlations often associated with pink noise.
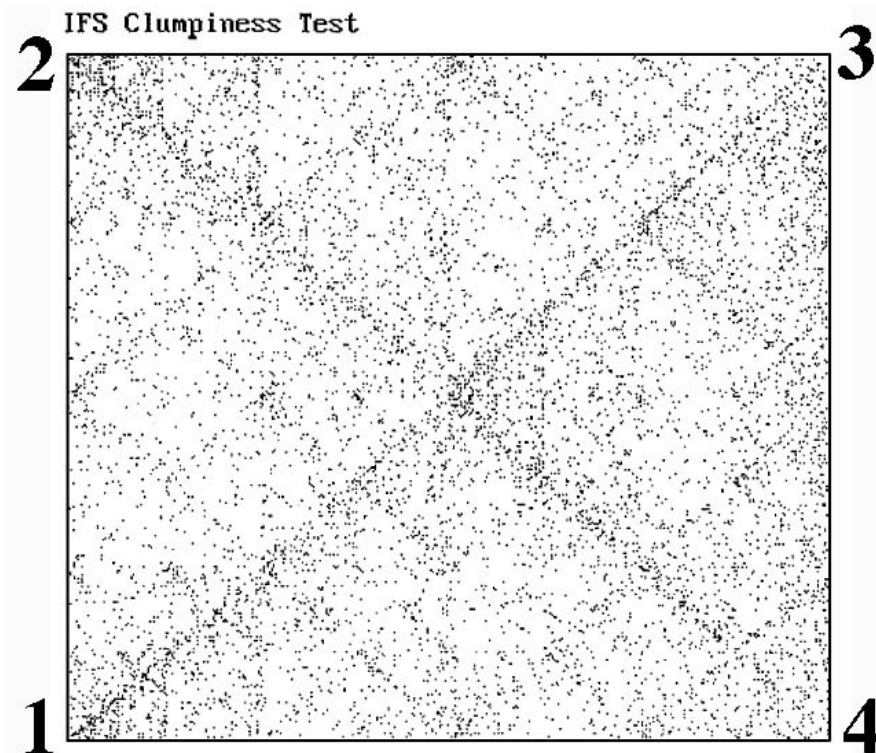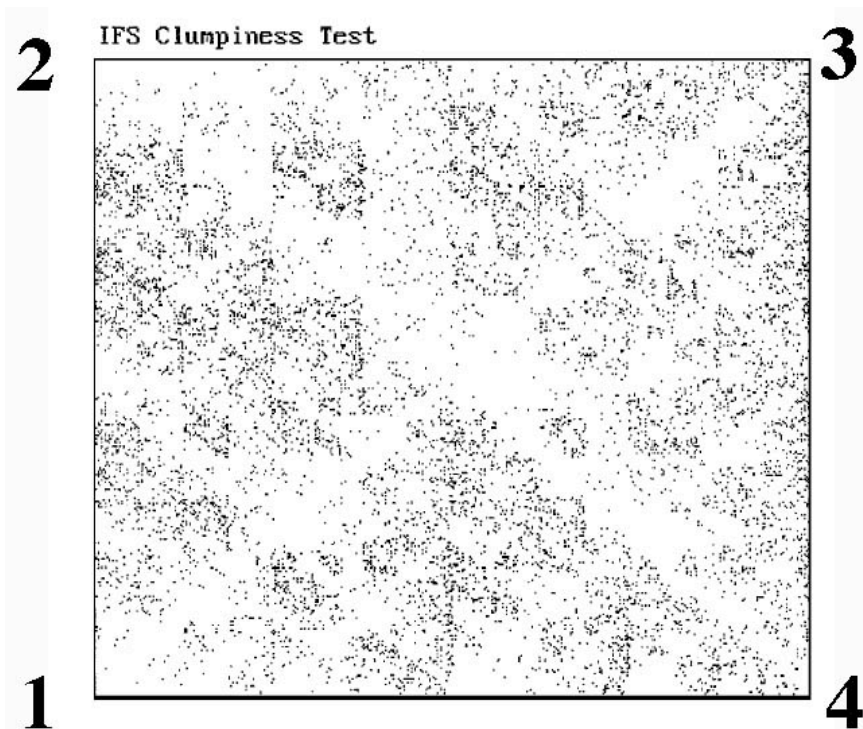

Figure 7.8. Results of the IFS clumpiness test of differentiated vertical (y) fixations. A similar pattern emerged for horizontal (x) fixations. The diffuse fractal microstructure reflects longer-term correlations appearing weaker than those in the raw data. Both cases resemble patterns associated with pink noise.

A combined measure of distance across eye fixations (Δx^2 + $\Delta y^2)^{1/2}$ produced power spectra with 1/f trends dominating the lower frequency range and $1/f^2$ trends dominating the high frequency range (Mean α = –0.47; see Figure 7.9). The corresponding IFS test, shown in Figure 7.10, produced a clear but distinct colored noise pattern with more diffuse clustering of data points than those found in the raw and differentiated data sets. Random shuffling of x, y, and distance data sets produced white noise. Thus, differences in these fixations possessed a potentially important, long-term dynamic characterized by ~1/f pink noise.
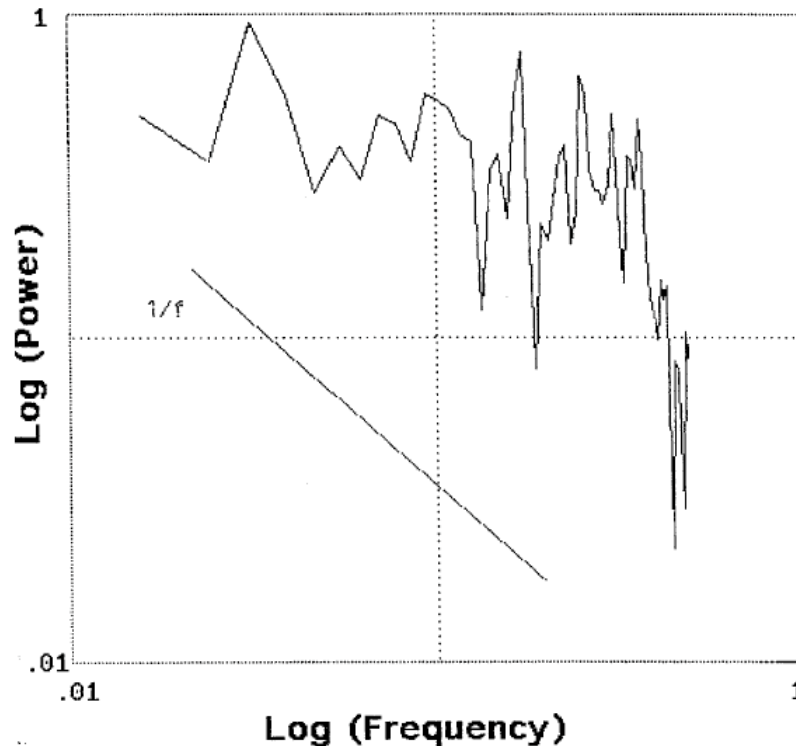
Figure 7.9. Power spectra of distance across eye fixations (Δx^2 + $\Delta y^2)^{1/2}$. Pink (1/f) trends were dominant in the lower frequency range, and $1/f^2$ trends were dominant in the high frequency range (mean α = –0.47). Also shown is a line depicting an exact 1/f power spectrum.

Figure 7.10. Results of the IFS clumpiness test on the time series of distances between fixations $(\Delta x^2 + \Delta y^2)^{1/2}$. A unique colored noise pattern emerged with more diffuse clustering of data points than those found in the raw and differentiated data sets.

DISCUSSION

I examined complicated eye movements to gain insight into the underlying mechanism guiding visual search. Using a challenging conjunction search task, we generated and then analyzed the resulting eye movements (Aks et al., 2002). My focus on the dynamic of the fixation series offers a unique perspective to the broader study of eye movement behavior. It contributes new insights to the debate in the visual-cognitive literature on whether memory plays a role in guiding visual search (e.g., Horowitz & Wolfe, 1998; Kristjansson, 2000; Melcher & Kowler, 2001; Ballard et al., 1995; Shore & Klein, 2003).

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According to conventional theory and common sense, visual search utilizes information from previous fixations to guide subsequent search. Memory models of visual search incorporate mechanisms such as inhibitory tagging (Klein, 1988) or identification of previously searched items (e.g., Irwin, 1992; Jonides, Irwin, & Yantis, 1981). Horowitz and Wolfe (1998) is a recent example of research that challenges the assumption that search is guided by memory from previous fixations. Doubts about a memory-based guidance emerge from their findings of RTs being unaffected by randomly repositioned items, together with recent research showing that visual memory is often surprisingly poor (Melcher & Kowler, 2001; Rensink, O'Regan, & Clark, 1997; Simons & Levins, 1997) and that the visual system retains little information about the locations (or identity) of objects over time. Instead, the visual system seems to act on fleeting neural representations that are overwritten by a change in the visual scene. Horowitz and Wolfe's (1998) claim that visual search does not keep track of previously searched locations comes from their examination of overall RTs to complete visual search. However, relying on such a coarse measure of behavior means that subtle contingencies in scanning behavior can be overlooked. Direct analyses of the eye movements revealed a less obvious form of memory.

The key finding that a sequence of fixations can be represented by a power law function confirmed our prediction that search might be guided by a memory of previous fixations. Contrary to Horowitz and Wolfe (1998), we found that search behavior was *not* random and that contingencies did in fact exist across fixations. While much cognitive theory implicates search mechanisms such as tagging and inhibition of

return (to previously visited items), the form of memory we have found involves general contingencies across fixations. The 1/f power law is a signature of these contingencies. The power law further indicates that the system has scale-invariant properties typically associated with a system optimized to adapt to a changing environment. Since systems characterized by power functions are known to be flexible, this suggests that the contingencies guiding search may play an important role in selection of appropriate information in an array of constantly changing environmental information. The IFS clumpiness tests confirmed the results of the power spectral analyses, showing that differences across fixations revealed pink (1/f) noise. These results suggest a long-term memory is maintained across complicated search in a manner that may involve the use of a simple set of rules with self-organizing properties (i.e., variants of Bak et al., 1988; Jensen, 1998).

IMPLICATIONS OF 1/f NOISE

Simple neuronal interactions can produce complex, self-organizing behavior. To understand how simple rules can produce complex eye movements let us consider Bak's SOC model in the context of a neural network. Figure 7.11 depicts such a network that could be used by the human visual system to represent a scene. Activation of different neural sites on the network can serve both as a means to represent the scene and a means to guide eye movements.

Figure 7.12 shows how the network is represented as a two-dimensional grid of interacting cells. Each cell possesses a certain degree of activation represented by a numerical value, $Z(x,y)$. Activity
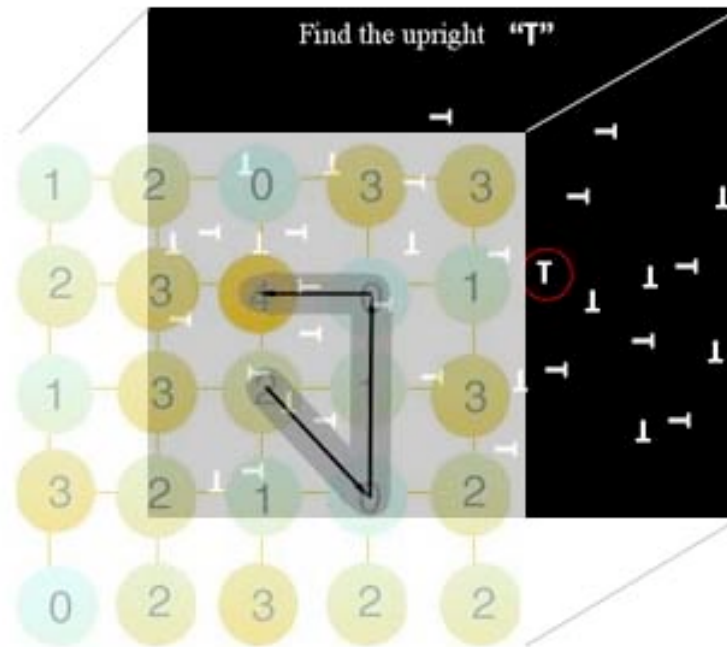
Figure 7.11. Representation of a visual search scene mapped onto a neural network. The scene is depicted in the top-right portion of the figure and shows one search display used in the experiment. Shifting attention to a particular stimulus produces an increase in the activation at the corresponding site on the neural net. Each node's numbers and colors represent the level of neural activation at that site. Nodes with the highest activation pull the eyes to that location. The resulting path of the eye movements is shown as a shifting black line superimposed on the network.

can be induced by any of a number of factors such as a salient visual feature, shifting attention to a feature of interest, or random activity that is produced even at rest. Neural activity can also be triggered by movement of the eyes to different locations. As individual neurons are activated beyond a threshold of, say, 4 arbitrary units, the activity in the original site is dispersed to surrounding cells, incrementing the activity in these regions by 1, $\{Z(x,y) \rightarrow Z(x,y) + 1\}$, thus depleting the activity in the original site to zero, $Z(x,y) \rightarrow Z(x,y) - 4$. In the
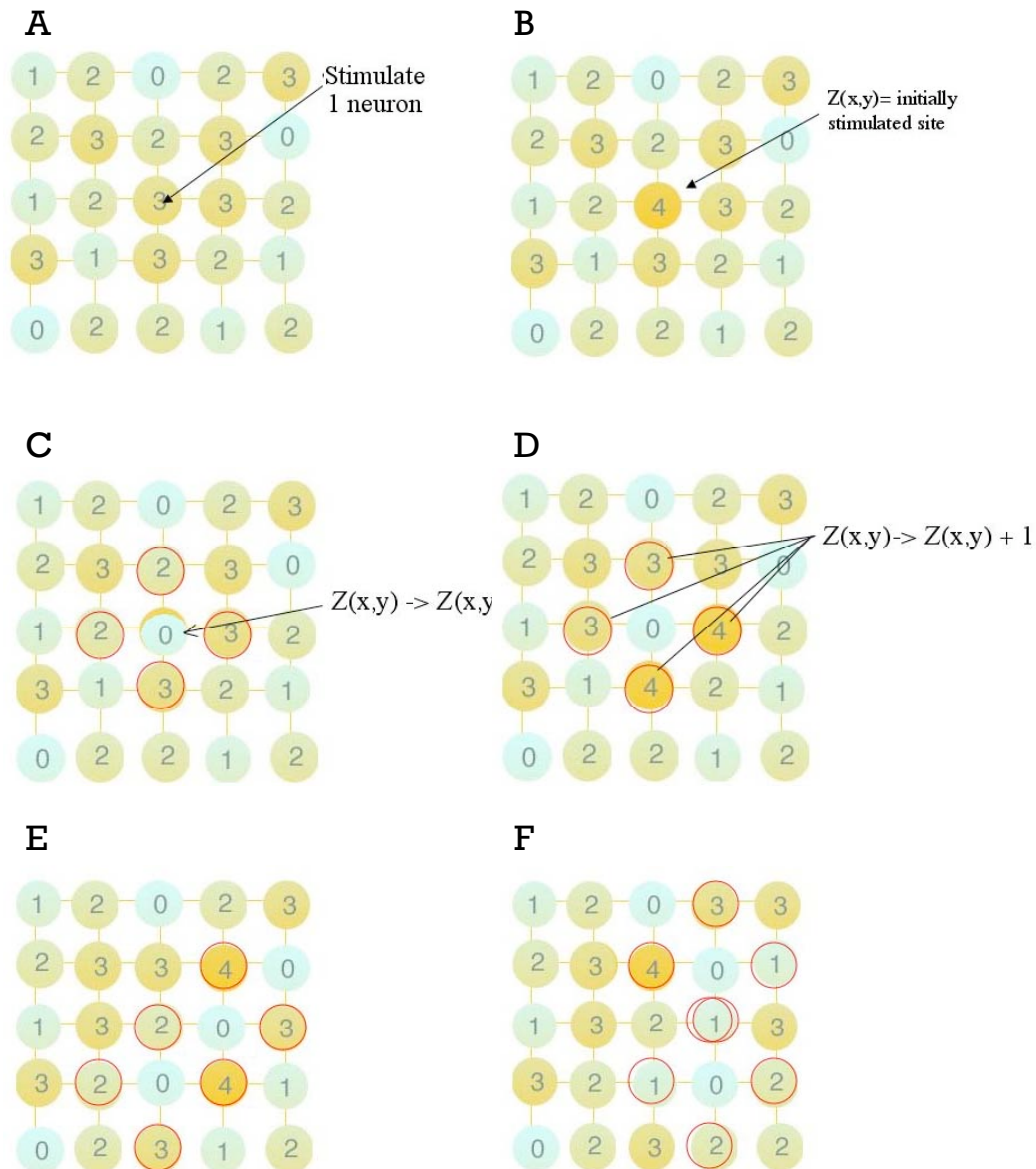
Figure 7.12. (A) A neural network. Numbers and colors indicate the relative activation of neurons. High numbers and orange colors indicate a high level of activity. Low numbers and blue colors indicate low levels of activity. (B) A one-unit increment in neural activity at the central site. This increase in neural activity can be due to any one of a number of factors, including the appearance of a salient feature, shifting attention to a feature of interest, or random activity that is produced at rest. (C) Neural activity in the original central site is depleted to zero after the threshold of 4 activation units is reached. (D) Neural activity in the immediately surrounding sites is increased by one unit. (E)-(F) Neural activity in subsequent surrounding sites is increased by one unit.

absence of useful environmental information during visual search, the eyes may be guided to sites that contain the highest level of activity among immediately surrounding cells, and evade local sites depleted of neuronal activity. The global result can be a complicated search pattern that could easily be mistaken for a random search (see Figure 7.13).
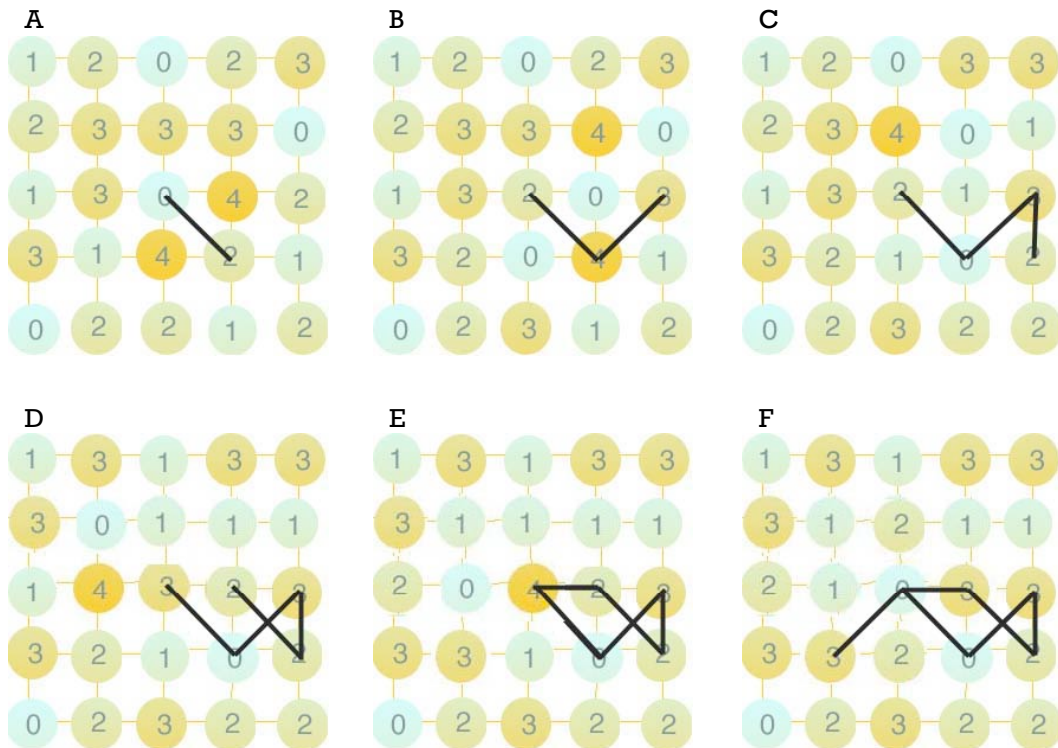
Figure 7.13. Eye-movements being pulled to sites of greatest neural activity, following the same progression of neural activity in Figure 7.12. When two sites have an equal level of activity (a tie), as in (A), the eyes traverse an intermediate path. (B) and (F) show another example of tied activity, but here the tie is on opposing sites. Rather than remaining fixed, the eyes are pulled to the site where the prevailing activity surrounding the recipient site is greater. Aside from these cases of equal activity, the general rule is that eyes are pulled to a single adjacent site of greatest activity.

The key finding of 1/f noise in eye movements has some important implications. First, we know that search is not random. Instead the eyes are guided by their history. A simple form of temporal memory exists across the sequence of eye movements. It is possible that the 1/f search pattern is produced from guidance of eye movements by changes in the intensity of neuronal activity across a network of neurons. These changes may be best described as the output of iterating a simple set of threshold-based rules such as those associated with SOC models.

The 1/f eye movements may also involve a cognitive mechanism such as attention-based sampling and selection of useful information from a complicated environment. It is an open question whether neuronal interactions and their spread of activation drives this selection process. Could this process produce the rapid and effective search known to occur in humans? The answer may relate to the general finding that 1/f systems offer an optimal compromise between efficient recovery of information and the tendency to err (Voss, 1992). The significance of these complex yet adaptive behaviors remains open to future scientific inquiry.

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