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ON THE CONTINUITY OF MIND: TOWARD A DYNAMICAL ACCOUNT OF COGNITION

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> It should be obvious by now that this minute inflow of stimulus energy does not consist of discrete inputs—that stimulation does not consist of stimuli. The flow is continuous. There are, of course, episodes in the flow, but these are nested within one another and cannot be cut up into elementary units. Stimulation is not momentary. (J. J. Gibson, 1979).

I. Introduction

In 1960, J. J. Gibson reviewed technical uses of the term *stimulus* and found that it did not have a consistent agreed-upon definition, but instead connoted several different conceptions of ‘‘stimulating'' an organism. Most of those conceptions did, however, have a property also found in the word's original uses: A stimulus is a temporally discrete, momentary happening in the life of an organism. Challenging this intuition, Gibson's ecological psychology assumes at its foundation the continuity of the stimulation in the surrounding environment. What this means is that the ‘‘flowing array of stimulus energy,'' as Gibson called it, is never presegmented into easily defined independent chunks, or ‘‘stimuli,''— even though we feel as though we perceive it that way.

Before Gibson, Dewey (1986) famously made a similar point in his influential critique of the reflex arc concept. The reflex arc concept was a relatively new idea, framing the questions of psychology in terms of causal arcs among stimulus, mental event, and response. Essentially, studying the causal arcs between just the former two, or the latter two, was considered a legitimate scientific enterprise in and of itself. In contrast, treating the

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progression of the three components as one continuous process, which naturally loops back on itself, was what Dewey influentially encouraged (Leahey, 1994). From his perspective, actions take place over time and they continuously alter the stimulus environment, which in turn continuously alters mental activity, which is continuously expressing and revising its inclinations to action. One of the most famous reactions to Dewey's criticism, behaviorism, found a long-standing solution by eliminating the second (mental) stage. But Dewey's critique still stands: Segmenting the natural life of an organism into discretely identifiable stimuli and responses is artificial and potentially misleading.

Although originally aimed predominantly at behaviorism, Gibson and Dewey's critiques echo into modern cognitive psychology. Essentially, cognitive psychology replaced behaviorism's emphasis on ''stimulus and response'' with an emphasis on ''stimulus and interpretation''—not really addressing the continuity problem. But if the environmental stimulation impinging on our sensory systems is almost always partially overlapping in space and continuous through time, why would our minds work in the staccato fashion of a digital computer, momentarily entertaining one discrete stable non-overlapping representational state, and then instantaneously flipping to entertain another one?

The goal of this chapter is to challenge the notion of discrete representational states. The mind, like Gibson's stimulation, exists in continuity, moving gradually between mental states, never standing still in time. Indeed, these ''mental states'' themselves are not really static states at all, but rather graded regions in mental state-space that are more or less interpretable than others and are briefly visited (or perhaps merely ''flirted'' with) by the mind during its continuous motion through this state-space. We offer the ''continuity of mind'' as a rubric for a psychological framework in which internal perceptual-cognitive processing exhibits continuous change in the salience of multiple simultaneously active representations. This framework forces one to rethink many representational and architectural assumptions that have persisted in cognitive psychology and poses as an ''intervention'' procedure to wean the cognitive sciences from their obsession with formal logical descriptions of mental representation. The continuity of mind attempts to replace the overidealized notion of discrete symbolic mental states, borrowed from antiquated artificial intelligence research, with distributed patterns of neural activation that are always partially consistent with multiple mental states. Most important, this framework focuses on the continuous temporal dynamics of these patterns of neural activation and the resulting consequences for descriptions of various perceptual-cognitive processes.

Of course, there exist several important precedents to this line of thinking. Kelso (1995), for example, explored how dynamic patterns in several perceptual and motor processes can be accounted for by the concepts of coordination and self-organization imported from synergetics (Haken, 1983). Port and Van Gelder (1995) offered a foundational collection of papers exploring a wide range of topics in which dynamical architectures and equations account for a wide variety of behavior. Thelen and Smith (1994) marshaled these dynamic-systems concepts in the service of explaining and predicting patterns in behavioral development. Even further back, Gregson (1983) offered a discussion of time series and recommended a radical reconceptualization of psychological explanation by invoking time as a crucial concern.

The proposal herein pushes in some of the same directions as these preexisting dynamical theses but takes an important, different overall route. We will focus on processes at a specific time scale, perception and behavior on the order of hundreds of milliseconds, and how these processes importantly exemplify the continuity of mind. Mental activity at this time scale has been a battlefield of dispute between frameworks in cognitive science. For example, one possible modern target for Dewey's critique is the computer metaphor of the mind. This metaphor sees stages of cognitive processing as temporally discrete representational states (Dietrich & Markman, 2003). Not only does the approach recommend an analysis of the human mind in terms of temporally discrete representation, but supposes as an ontological matter that the mind entertains discrete representations and states. The processes at the time scale considered here have often involved heated debate between this and other explanatory frameworks. For years this traditional computational perspective has enjoyed a firm grip over the time scale, offering explanations for different processes in language and perception. The success of this paradigm permitted the computer metaphor to even trickle down into explorations of the properties of neural processes. For example, in the early years of cognitive science, there were a few who were inspired both by digital computing theory and by the physical processes of the human brain. These researchers invested quite a bit of intellectual stock in the idea that populations of spiking neurons would behave more or less the same as populations of digital bits (e.g., McCulloch, 1965; Von Neumann, 1958; Wickelgren, 1977; see also Barlow, 1972; Lettvin, 1995; Rose, 1996).

However, what we know now about real neurophysiological processes seems to suggest instead great promise for the continuity of mind rather than the digital computer metaphor. A great deal more has been learned in the past few decades about how populations of neurons work (e.g., Georgopoulos, Kalaska, Caminiti, & Massey, 1982; Pouget, Dayan, & Zemel, 2000; Sparks, Holland, & Guthrie, 1976; Tanaka, 1997; Young & Yamane, 1992), and it is nothing at all like the instantaneous binary

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flip-flopping from one discrete state to another that characterizes information processing in digital computers. In neuroscience, the closest thing to a classical mental representation is the population code. A population code is a sparse distributed representation comprised of a group of neurons that cooperate and resonate in response to a familiar perceptual input. Importantly, the individual neurons that make up a population code do not appear to update their states in lockstep to the beat of a single global clock. Population codes spend a substantial amount of their time in partially coherent patterns of activity. And thus the brain's state is often dynamically traversing intermediate regions of a state-space that contains what could be described as many meta-stable attractors.

Whether these population codes end up approximating discrete representations is an important question open to debate. The distant and tenuous connection between digital symbolic computation and distributed neural processing is nevertheless an attractive idea to some (cf. Marcus, 2001). According to this perspective, the activity of populations of neurons is sufficiently approximated by models that use rule-based operations on logical symbols, despite the fact that real neural hardware does not quite work that way.

There are two key properties of the representations instantiated by neural populations that we argue separate them from computer-like symbolic representations: (1) continuity in time and (2) continuity in space. Continuity in space has been dealt with elsewhere in roughly two different ways: (1) a contiguous high-dimensional state-space where proximity serves as similarity and prototypical representations exist as partially overlapping attractor basins (e.g., Aleksander, 1973; Edelman, 1999; Elman, 1991; Lund & Burgess, 1996; Pasupathy & Connor, 2002) and (2) a two-dimensional space based on sensory surfaces, in which the shape and layout of internal representations are roughly homologous to actual physical patterns of stimulation (e.g., Barsalou, 1999; Farah, 1985; Johnson-Laird, 1998; Kosslyn, Thompson, Kim, & Alpert, 1995; Langacker, 1990; Spivey, Richardson, & Gonzalez-Marquez, in press; Talmy, 1983). Continuity in time has also been dealt with elsewhere in two (at least superficially) different ways: (1) the continuous temporal dynamics of the neural connectivity patterns that constitute knowledge and intelligence changing over developmental time (e.g., Elman, Bates, Karmiloff-Smith, Parisi, & Plunkett, 1996; Spencer & Schöner, 2003; Thelen & Smith, 1994), and (2) the continuous temporal dynamics of representation and behavior in real-time processing (e.g., Kelso, 1994; Port & Van Gelder, 1995; Spivey, in preparation). This latter emphasis on continuous temporal dynamics in real-time processing is where this chapter will focus its arguments against digital-computational accounts of cognition.

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By describing demonstrations, in psycholinguistics and in visual perception, of representations that are analog (rather than digital), partially overlapping, and change gradually over the course of hundreds of milliseconds, we hope to convince some readers that symbolic accounts of cognition that do not accommodate such continuous temporal dynamics are missing a crucial aspect of an accurate description of the mind. Such graded mental states appear to be more than just temporary transitions between discrete mental representations but instead may be the modus operandi of the mind. Therefore, we suggest that approximating patterns of neural activation, and the continuous temporal dynamics of these patterns, with a metaphor of discrete symbolic computation, is not merely a stretched analogy, but in fact a misleading one. Although the conversion of a continuous trajectory through a high-dimensional state-space into a string of emitted symbols is a powerful mathematical concept, it faces statistical problems with regard to the exact placement of symbolic partitions (Bollt, Stanford, Lai, & Zyczkowski, 2000), it faces representational problems with regard to how a discrete perfectly repeatable logical symbol is implemented by an inherently noisy and distributed neural system, and it faces architectural problems with regard to an unrealistic degree of modularity required of the systems to and from which these symbol strings are being sent. Instead of pretending to be able to chop time into chunks that are associated with individual nonoverlapping symbolic representations, we argue that patterns of brain and behavior inevitably exhibit temporal and representational continuity and that adopting this perspective can help predict and explain a considerable database in the study of cognition.

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II. Continuously Changing Graded Representations

A. Probabilistic Versus Pure Mental States

Before evaluating support for continuity in language and vision, we present some simple illustrations that may help further limn our perspective. First, consider a very simple demonstration of how we might visualize continuous change in neural population codes. Readers familiar with dynamical metaphors will doubtless find this example highly simplistic. Nevertheless, it will help solidify the predictions about temporal dynamics that are made by the continuity of mind thesis.

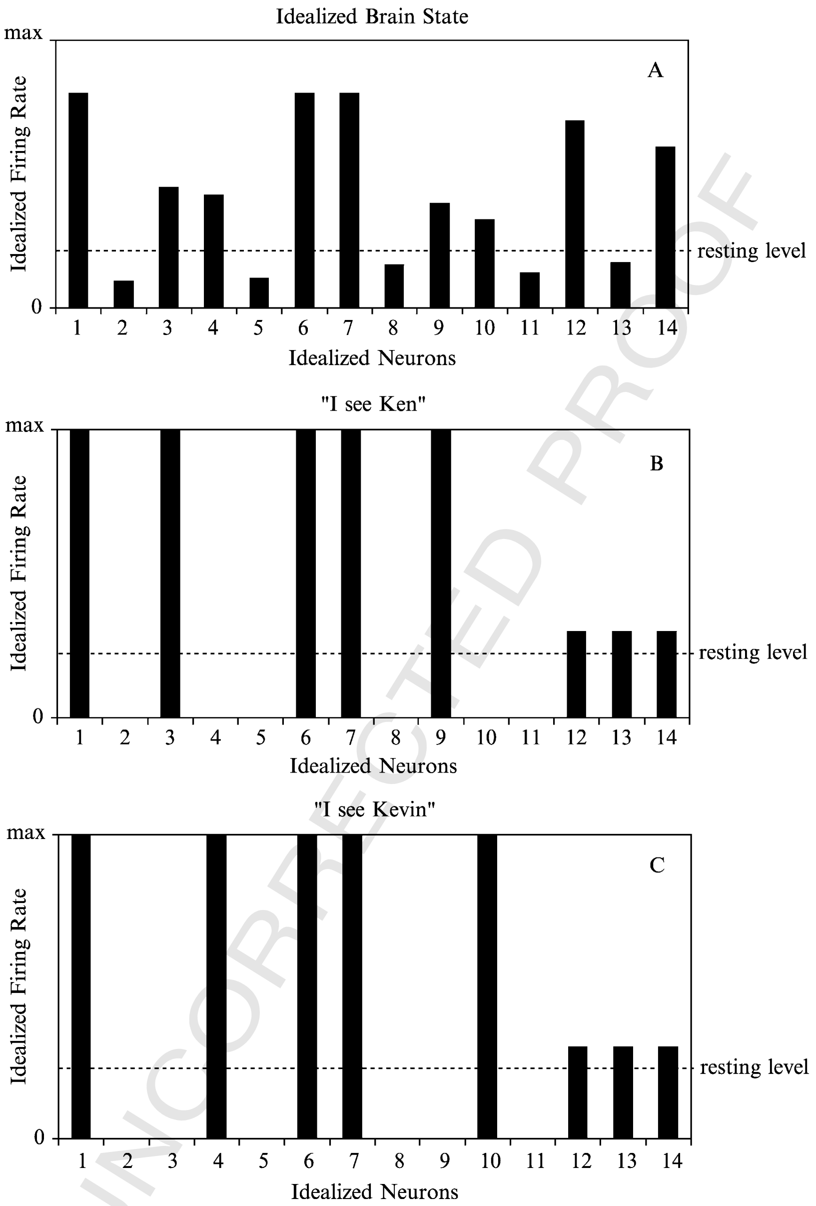
Imagine you've taken over a sturdy stool at the bar of your favorite pub, awaiting a close friend. Call him Ken. He's late. After a couple beers, you continue to keep your eye out for him, noting various faces as they enter the pub. Imagine catching glimpses of someone you think might be Ken among an entering crowd. In that brief period of time, before being certain of this person's identity, your brain will exhibit patterns of activity that are partially consistent with a number of alternative people. Figure 1A is a cartoon illustration of a 100-ms time slice of that brain state—that uncertain, fuzzy state—if one were measuring a mere 14 of your cortical neurons (out of about a billion).

In the idealized brain state in Fig. 1A, a few neurons are excited near their maximum firing rate, several neurons are moderately above their resting level of activation, and several neurons are conspicuously inhibited below their resting level. (As these are firing rates and not action potentials, this "state" is obviously an average over the 100-ms time slice.) Although this pattern of neural activation can be treated as a discrete location in the space of possible brain states, it does not correspond to a discrete, pure, mental state. That is, we have devised this demonstration such that the pattern of neural activity in Fig. 1A corresponds to a brain state that is partially consistent with two different identifiable mental states (Fig. 1B and C; the surface similarity in the two names here is irrelevant for our purposes).

Imagine we had the capacity to record previous moments in which you perceived Ken and another friend Kevin, and could establish which specific set of neurons corresponded to this identification, averaged over many instances. Figures 1B and C depict the pattern of neural activity that would emerge in the situations, "I see Ken" and "I see Kevin," respectively. In Fig. 1B, one can see that neurons 1, 3, 6, 7, and 9 compose the population code of "I see Ken." Partially overlapping with this, in Fig. 1C, it becomes clear that neurons 1, 4, 6, 7, and 10 compose the population code "I see Kevin." Due to the complexity of multiple sensory inputs, the nonlinear dynamics in neural processing, and noise in neural activity, these "pure" ideals of interpretation (Fig. 1B and C) are practically unattainable, but they are regularly approximated by the brain's actual pattern of activity.

Let us simplify further and assume that each neuron in these population codes is encoding some small feature about Ken and Kevin. Figure 2 shows the same pattern of neural activity as in Fig. 1A, but with pretend interpretations for what each neuron represents. Of course, individual neurons probably encode far finer details than those depicted in Fig. 2. The term *microfeatures* has been used to refer to the properties of the sensory input to which individual neurons respond (Hinton, 1981). Often times, these individual microfeatures are not easily deciphered, either in artificial neural networks or in biological neural networks.

By comparing the actual neural pattern of microfeatures in Fig. 2 to various "pure" population codes (such as those in Fig. 1B and C), we can calculate the actual neural pattern's Euclidian proximity to these "pure" population codes, normalize those proximity values so that they sum to 1.0,



Idealized Brain State

"I see Ken"

"I see Kevin"

Fig. 1. Idealized neural patterns that correspond to a graded brain state (A), and two example “pure” states (B & C).

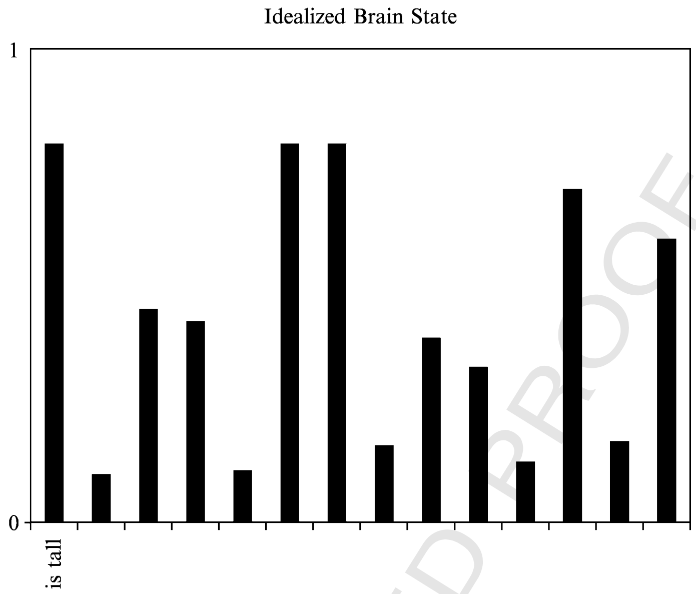


Fig. 2. Idealized labels for each neuron in the graded brain state.

and thus generate a rough probability distribution over possible interpretations of the person who is entering the pub. See Fig. 3. In this way, a neural pattern can be seen as a probabilistic mental state, represented in the form of its proximity to idealized pure (discretely interpretable) mental states, instead of mere activity levels of individual neurons. In contrast, a supposed pure mental state refers to an ideal precise pattern of neural activation that—due to the complex and noisy dynamics of a brain with billions of neurons and trillions of synapses—is never actually perfectly instantiated. In this framework, a pure discrete (i.e., symbolic) mental state is an abstract concept. It is a useful construct for theory development, but we argue that an actual physical instantiation of a symbolic mental state never comes into being. Rather, a fuzzy region of state-space broadly encompassing the specific coordinates that correspond to a “pure” mental state (i.e., the basin of attraction that surrounds an individual attractor point), is what gets briefly visited by the trajectory defining the system’s state as a function of time. The precise set of coordinates corresponding to that “pure” mental state (i.e., the idealized identifiable population code) is never quite reached. Nonetheless, the labels attached to these “pure” mental states are extremely helpful in understanding the probabilistic mental states (cf. Barber, Clark, & Anderson, 2003; Zemel, Dayan, & Pouget, 1998). Without the descriptive

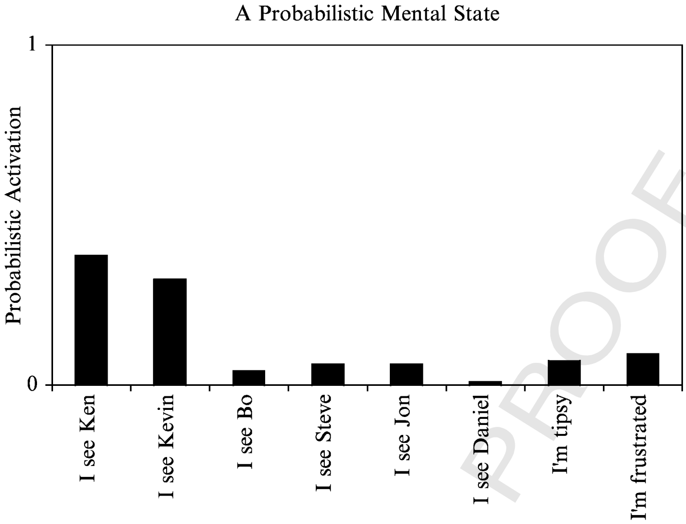


Fig. 3. An idealized pattern of normalized proximities (treated as probabilities) to various "pure" states in the space of possible mental states.

conveniences of the labels along the abscissa in Fig. 3, a probabilistic mental state would be essentially uninterpretable.

Our talk of "states" could imply that this specific pattern of activation is stable for a certain period of time. The continuity of mind suggests, however, that it would be continuously moving toward some interpretable population codes and away from others. When the activations of these neural patterns are tracked over time, they change gradually and nonlinearly. In Fig. 4, a time course plot of probabilities of different interpretable population codes is illustrated. In the particular settling algorithm used here, it is guaranteed that the probability value that starts out higher will be the eventual winner, but this will not be true with all settling algorithms.

Although this scenario quaintly displays the multifarious character of graded mental states changing over time, its simplicity reveals theoretical flaws in the form of what might be called "edge effects" in time. Figure 4 assumes that this process occurred in a contextual vacuum, involving no new informative events while it was settling, and involved no action. It simply gravitated to a stable corner (attractor basin) in its state-space. In real life, no such event is free of some context, new information is constantly arriving, and we are often producing continuous motor actions during perception. Thus, by the time your brain state has approached a location in state-space that is roughly consistent with only one pure population code, such as .8

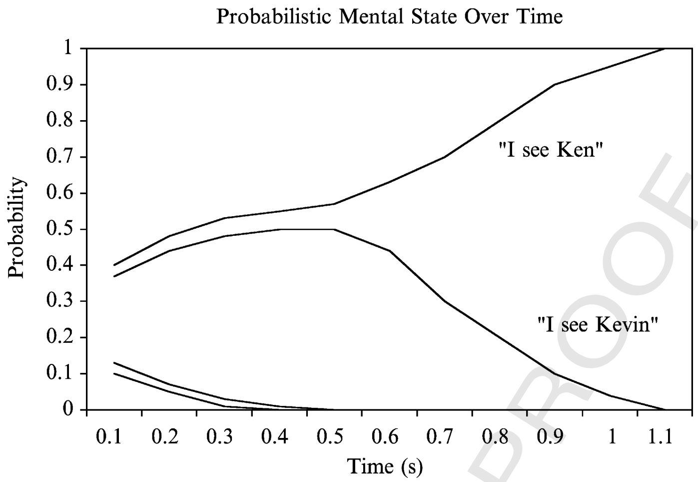


Fig. 4. An idealized evolution of these probabilistic activations (or normalized proximities) depicting a dynamic graded mental state over the course a several hundred milliseconds.

activation for "I see Ken," changes in the environment and your own behavior will alter the brain state such that it travels back into "unlabeled" regions in state-space, preparing for another near settling event where it gets just close enough to another pure mental state to elicit appropriate action and perhaps then veers off once again. This more ecologically valid perspective of continuous change in natural behavior gives considerable bite to the continuity of mind proposal: It means that the vast majority of the mind's time is spent in between identifiable mental states rather than in them.

It is perhaps tempting to think of achieving one briefly relatively stable state for one temporal portion of sensory stimulation (such as that in the later time period of Fig. 4) as producing a symbollike representation that could somehow persist in some mental arena, and that when the system then gravitates to other attractors in state-space this mental arena could somehow accumulate accurate renditions of these symbollike representations that are visited in the continuous state-space (but cf. Bollt et al., 2000). This perspective has much in common with the way a digital computer might shunt one symbol into a working memory buffer and then shunt another and another, thus giving the system several complete representational entities to work with at the same time. In fact, there are hybrid theoretical frameworks for cognition and language that implement this kind of temporally dynamic accrual of activation for competing representations in a first stage, with the winning symbolic representation then becoming part of a discrete rule-driven computational system in a second stage (e.g., Anderson &

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Lebiere, 1998; Budiu & Anderson, 2004; Stevenson, 1994; see also Hummel, 2001; Marcus, 2001; Pinker & Ullman, 2002). Such frameworks hypothesize a rather drastic schism between one part of the mind that functions in ways that are consistent with the temporally continuous ebb and flow of neuronal population codes and another part of the mind that functions in ways that are substantially inconsistent with the neurophysiology.

This tempting notion of ‘‘accumulating symbols’’ after their attractors are visited necessarily requires this problematic schism. Where else could those accumulated symbols be stored but in a separate additional system? If one accepts that this neural state-space can pose as a description of the activation of every neuron in the brain, then such a description would have no room for an additional separate system in the brain that could be a repository for such an accumulation of symbols. The only sense in which these semistable population codes—which may act something like fuzzy (nondiscrete) symbols—could accumulate, in this account, is if they continue to reverberate their coherent activation pattern while new population codes also become coherently active. Note, however, that this still requires the coordinates describing the state of the system in this space to move away from their original location near that first attractor and now find a location that is roughly equidistant from the previous attractor and the new one. Thus, if one endeavors to describe the entire state of mind as a system with one state-space (and not as collection of independent noninteractive systems with separate state-spaces), then one cannot accumulate complete unchanged symbols as the state of the system travels from one attractor to another. Hence, dealing with the fast and complex temporal sequence of sensory stimulation that occurs in normal everyday circumstances (although not necessarily in the cognitive psychologist's laboratory), and the spatiotemporally contiguous movement in state-space that this instigates, forces the behavior of the system to be best described by its continuous trajectory (spending much of its time in intermediate unlabeled regions of state-space) rather than by an enumerated list of the interpretable attractors it visits.

B. Continuity in Categorization?

To offer a more substantive demonstration, we further exemplify this continuity by considering a particular realm of research in cognitive psychology. The study of categorization has been at the core of psychology, and especially cognitive psychology, for many decades (cf. Harnad, 1987). A continuity account, similar to that cartooned in Fig. 4, would naturally predict that categorization tasks often show quite different results from speeded responses than from nonspeeded responses (e.g., Lamberts, 1995, 1998, 2000; Lin & Murphy, 1997; Nosofsky & Alfonso-Reese, 1999; see also Brownell & Caramazza, 1978; Medin & Smith, 1981). This prediction derives from the idea that a speeded response forces an unsettled trajectory to select among multiple nearby attractors in an unsystematic fashion (e.g., perhaps stochastically). The results can allow one to infer partial activation of multiple competing ''interpretations'' of the stimulus array. Unfortunately, as noted by Lamberts (2000), it is still somewhat new and unusual for categorization studies to give consideration to temporal dynamics. The bulk of the literature over the past few decades has focused almost exclusively on the outcome of categorization rather than the process. This tradition may miss the fact that by examining the continuous time course of online categorization, one can tease apart various theoretical accounts that would never have been rigorously tested by outcome-based offline experimental measures.

For example, one theoretical account of the process of categorization, which is generally consistent with Lamberts' (2000) information accumulation theory, can be idealistically demonstrated by a very simple neural network architecture called normalized recurrence (McRae, Spivey-Knowlton, & Tanenhaus, 1998; Spivey, Fitneva, Tabor, & Ajmani, 2002a; Spivey & Tanenhaus, 1998; Tanenhaus, Spivey-Knowlton, & Hanna, 2000). Normalized recurrence simulates the temporal dynamics of the competition that emerges when multiple information sources weigh in on alternative interpretations of a stimulus array. Like the probabilistic activations of idealized population codes (see Fig. 3), the architecture simply generates a probability distribution over possible categories in order to track their evolution over time (usually corresponding to hundreds of milliseconds of real-time cognitive processing).[1] Figure 5 shows the diagram of a very simple normalized recurrence architecture used to approximate the changing patterns of activation during the categorization of different animals into their respective classes (fish, mammal, bird, and reptile). As the normalized recurrence competition algorithm works, these five feature vectors (framed circles) are normalized to sum to 1 and are then combined at the integration layer (framed ovals), replacing its previous activation pattern. In this simulation, there are no differential weights for the five feature vectors; they simply sum together at the integration vector. The integration layer then divides each of its nodes' activation by the vector's sum activation, thus making the integration vector simply an average of the five feature vectors. Cumulative feedback is then sent by adding to each feature node the product of itself and its corresponding integration node. The next time step begins

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[1] The distributed population codes of the network are simplified as localist nodes for features and classes, as in our first example. However, this competition algorithm does not address what the localist representations are made of, nor how they developed. Despite these idealizations, the architecture allows for rather sophisticated modeling of temporal processes of interpretation and categorization.

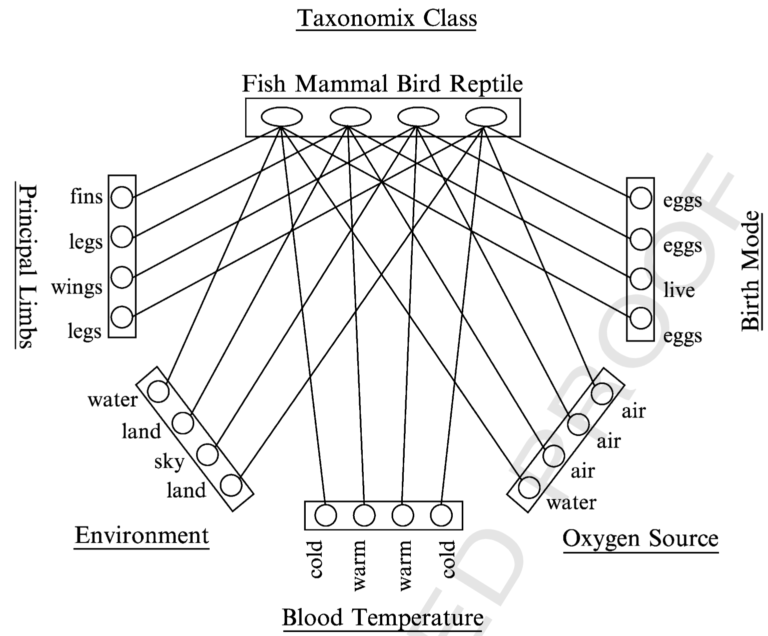

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Fig. 5. Schematic diagram of a normalized recurrence simulation of the temporal dynamics of categorization. The repeated node labels in some of the feature vectors (circles) are necessary because each integration node (ovals) must have its own unique feature node. This allows the feature vectors to function as probability distributions in their support for the appropriate taxonomic class. For example, after the initial feature vector normalization step, the birth mode vector for a live-birth animal would pass 1.0 activation to the Mammal node and 0 activation to the other taxonomic class nodes, whereas for an egg-laying animal the birth mode vector would send .333 activation to the Fish, Bird, and Reptile nodes, and 0 activation to the Mammal node.

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with the feature nodes normalizing themselves again (diving each node by the vector's sum), and the integration, normalization, and feedback take place again. These four calculations are computed within each time step, and the network continues until a criterion activation (often .95) is reached by an integration node. The cyclic recurrent flow of activation between the integration vector and the feature vectors allows strong and selective biases within certain feature vectors to coerce weak and uncertain biases in others, until the system gradually settles into a stable state.

This localist attractor network (inspired significantly by McClelland and Rumelhart's (1981). Interactive Activation model, and Anderson, Silverstein, Ritz, and Jones's (1977) Brain-State-in-a-Box model; see also Grainger & Jacobs, 1998; Zemel & Mozer, 2001) easily categorizes animals that are typical exemplars of their taxonomic class, such as "toucan," "goldfish," and "cat" (see Fig. 6). However, with animals that are unusual members of their class, the network undergoes a long, drawn-out competition due to the animal's partial match with multiple taxonomic classes.[2] The gradual activation curves are similar to those produced by Lamberts' (2000) information accumulation model, and the overall typicality effects coincide with theories of graded category structure (e.g., Rosch & Mervis, 1975; Smith, Shoben, & Rips, 1974). Note how, in Fig. 6, the simulations for "seal," "whale," "penguin," "turtle" and "platypus" exhibit slow rises to criterion for the correct classification, and even then their asymptotes are substantially below 1.0. In the end, the model concludes that a whale is .6 a mammal and .4 a fish. And, in fact, during its first few time steps of processing, the model briefly conceives of a whale as slightly more a fish than a mammal. A similar crossing of curves is seen with a turtle.

This simulation serves as a simple existence proof of how graded temporal dynamics can be realized in a system of neural population codes. Admittedly, even if the model's predictions were to fit human data perfectly, we would not contend that the mechanism matches the brain's own. But could these curves really be anything at all like what a human mind does when it categorizes animals? During the early moments of settling on a categorization for an animal, do people simultaneously partially consider multiple categories? And do those partially active representations compete over time in order for a cognitive trajectory to settle into eliciting a unique motor output?

Using the method of eye tracking, Nederhouser and Spivey (2004) conducted a pilot experiment that supports this speculation. Although, as described, comparing speeded instinctive responses to slow contemplative responses (e.g., Lin & Murphy, 1997) is a good start for measuring this kind of time course question, a semicontinuous measure may be more revealing by demonstrating accruing activation that supports different interpretations. Because eye movements occur about 2–3 times per and are largely unaffected by deliberative strategies, they can provide a stream of multiple honest "proto-actions" over the course of the few seconds required to produce a single overt verbal or manual action.

In the pilot study, the eye movements of 17 participants were recorded while they categorized small plastic toy animals (about 2″ × 3″) into either of

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[2] In fact, in this rather small and oversimplified simulation, since the Principal Limbs and Environment feature vectors for "bat" uniquely support the "bird" category, and only the Birth Mode feature vector uniquely supports the mammal category, there actually winds up being more overall support for incorrectly categorizing a bat as a bird (asymptote at .8) than as a mammal (asymptote at .2). Expansion of the model to include more features, more classes, and perhaps differential weights for the feature vectors, would be necessary to eradicate errors like this.

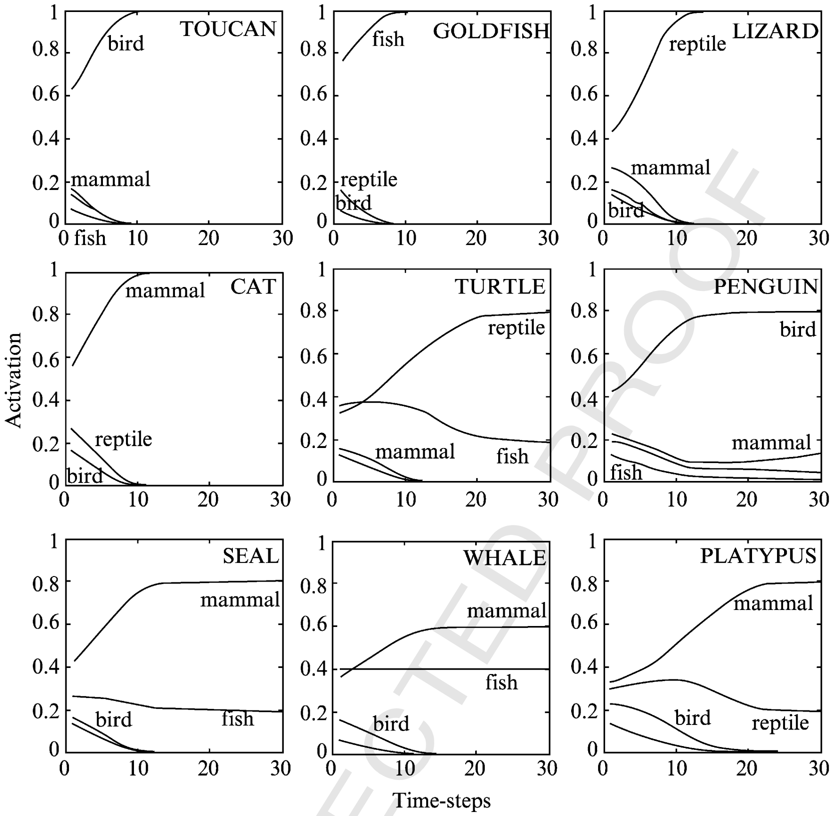

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Fig. 6. Activation curves from the simulation of the temporal dynamics of catregorization. Feature nodes that received 1.0 activation at start, for the five input vectors, were the following: CAT (legs, land, warm, air, live), SEAL (fins, water, warm, air, live), WHALE (fins, water, warm, air, live), TOUCAN (wings, sky, warm, air, eggs), DUCK (wings–legs, water–land–sky, warm, air, eggs), PENGUIN (wings, land–water, warm, air, eggs), LIZARD (legs, land, cold, air, eggs), GOLDFISH (fins, water, cold, water, eggs), EEL (all limbs, water, cold, water, eggs), TURTLE (legs, water, cold, air, eggs), WATERSNAKE (all limbs, land–water, cold, air, eggs), and PLATYPUS (legs, land–water, warm, air, eggs).

two bins. Participants were first shown a set of animals (half from one taxonomic class, half from another), and then were presented each animal one at a time. It was observed that animals that are atypical members of their taxonomic classes, like turtles, penguins, seals, and whales, took longer to categorize than more typical animals (cf. Glass & Meany, 1978; Rips, Shoben, & Smith, 1973), and they also elicited quite a bit of vacillation in eye movements between the two category bins. When participants categorized an atypical member of a category, they often fixated both bins multiple times before settling on the correct bin and dropping the animal into it. Crucially, when one looks again at the records of eye position over time, one can plot fixation curves based on the proportion of fixations at each time slice (Fig. 6), that resemble somewhat the activation curves from the network simulations (Fig. 7). The curves in Fig. 6 show, for each 33-ms time slice, the proportion of trials in which the subjects were fixating the correct category bin or the incorrect category bin, following their first saccade away from the toy animal that was placed in front of them. Note how, in the case of penguins, seals, and whales, some subjects continued to fixate the incorrect bin for the full 2 s shown; in some cases, they even placed the whale in the fish bin.

This comparison of pilot simulation and pilot data provides a glimpse into the beginning stages of how we might better understand the temporal dynamics of real-time categorization. The demonstration is intended to illustrate how one can begin to visualize the fuzzy and graded representations that change over time during categorization, both in a localist attractor network and in a semicontinuous record of cognitive processing. And perhaps some of the more static, formal approaches to concepts and categorization might have trouble accommodating such evidence that, during a categorization event, the mind spends so much of its time in graded, rather than discrete, mental states.

The important point to be made here is that these very specific locations in state-space that seem to have easily labeled identities, these pure mental states of "I see Ken" or "I see a mammal" can only be approximated by the actual neural system for which this state-space is an abstracted mathematical description. That is not to say those pure mental states are irrelevant or nonexistent. They do exist, as possible locations in the neural system's state-space. The neural population codes get sufficiently activated (i.e., the system approaches close enough to a frequently visited and identifiable attractor basin) to convince one phenomenologically that these pure mental states have been perfectly instantiated. We would argue instead that they have an infinitesimally small likelihood of ever happening.

With these simple examples to help guide our path, we now discuss language and vision, and the rather impressive support each brings to this perspective that cognition inherently consists of continuity.

III. Continuity in Language Processing

Here we consider language comprehension in real time as a particularly evocative example of continuous sensory input producing continuous cognitive processing—in spite of our clumsy metalinguistic introspection that we perceive one word and then silence and then another word. We argue that

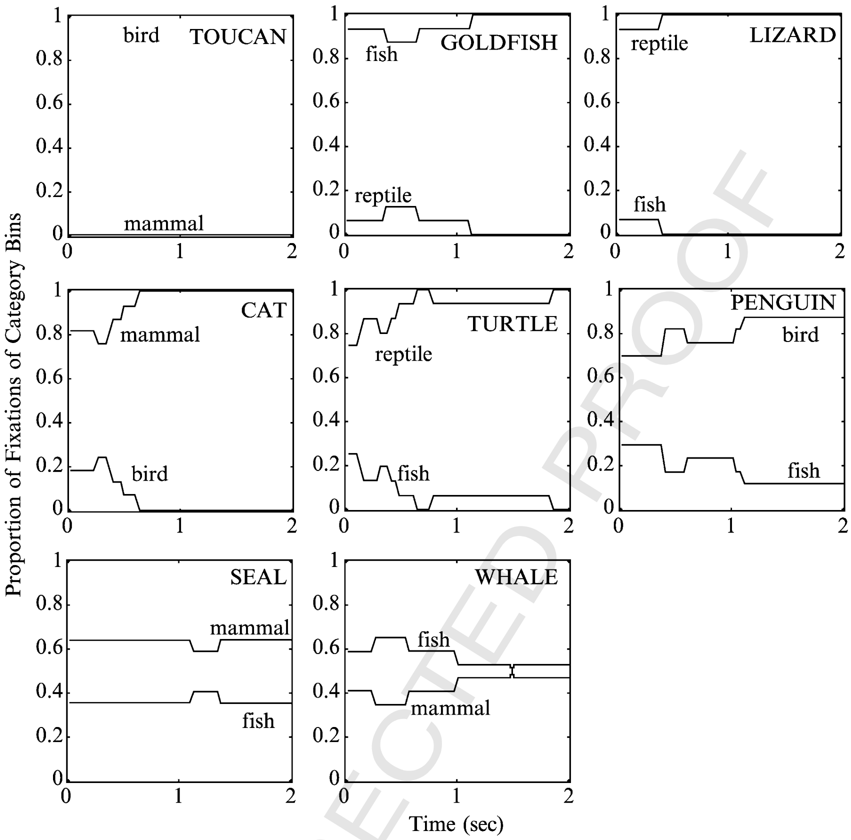

Fig. 7. Eye-fixation curves from Nederhouser and Spivey (2004). Animals that are atypical examples of their taxonomic class elicited considerable vacillation in eye movements during the early moments of categorization.

this process, at its various levels of complexity, is driven by graded and partially active information. We present these processes at increasing time scales, beginning with speech perception (hundredths of seconds), word recognition (tenths of seconds), and concluding with sentence processing (seconds). Despite these different time scales, each exhibits the continuity of mind.

A. Speech Perception

Humans are wont to carve up their world into seemingly very discrete categories. These categories are often imposed even within variation among the things being categorized. Categorical perception describes the general tendency to cut a fine line along a gradient of variation; any inputs that fall to the left or right of this line will be part of one or the other category. Despite its name, ‘‘categorical’’ perception of speech sounds can be made consistent with more temporally dynamic approaches to categorization (e.g., Anderson et al., 1977; Dailey, Cottrell, Padget, & Adolphs, 2002; Lamberts, 2000; Pisoni & Tash, 1974; Tuller, Case, Ding & Kelso, 1994; see also Cree, McRae, & McNorgan, 1999). Indeed, the previous sections would suggest that categorical speech perception does not just consist in graded patterns of neural activation, but might exhibit such gradation in behavior when we use continuous-time measures to investigate its finer temporal structure (rather than simply observe explicit identification of a speech sound).

In pursuit of this, McMurray and Spivey (1999) tracked participants’ eye movements while they performed the standard categorical identification task. This task involves categorizing different versions of ‘‘pah’’ and ‘‘bah’’ sounds, lying along the voice-onset time (VOT) dimension that distinguishes them, by clicking /ba/ and /pa/ icons on a computer screen. Thus, in addition to recording the participants’ explicit choice, there was also a semicontinuous record of how the eyes tended toward one or the other response icon during categorization. With ‘‘pah’’ or ‘‘bah’’ sounds near their categorical boundary, eye movements clearly exhibited conspicuous vacillation between the /ba/ and /pa/ icons. Figure 8 shows two typical eye-fixation-over-time plots during the speech categorization process for a clear ‘‘pah’’ stimulus (panel A) and for a sound that was near the category boundary but was nonetheless identified (by mouse click) as /pa/ 95% of the time (panel B). The eye position records depicted here came only from trials in which the /pa/ icon was indeed clicked at the end of the trial. Despite the identification outcome being identical in this subset of trials (all categorized as /pa/), the pattern of eye movements reveals substantially more time spent fixating the / ba/ icon (dashed area in panel B) when the speech stimulus was near the VOT category boundary; thus indicating a clear effect of perceptual gradations in speech sounds.

In fact, these temporary phonemic ambiguities, as tested with VOT continua and eye movement records, exhibit their effects not just in phoneme identification tasks but also in spoken word recognition tasks (McMurray, Tanenhaus, & Aslin, 2002; McMurray, Tanenhaus, Aslin, & Spivey, 2003). For example, within-category variation of VOT does not affect the final outcome of recognizing *bear* versus *pear*; however, it does affect the eye movement records of participants looking at and clicking the corresponding images on the computer screen (McMurray et al., 2002). A particularly compelling way to visualize these eye movement data for the phoneme identification task is to convert them into identification functions for early, intermediate, and late periods of time during the identification process.

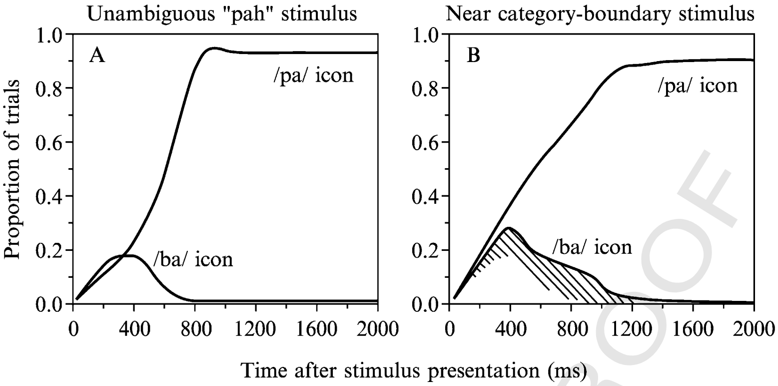

Fig. 8. Proportion of trials in which participants were fixating the /ba/ or the /pa/ icons, time slice by time slice, after hearing an unmistakable "pah" from the VOT continuum (panel A) and after hearing a speech sound near the category boundary (panel B). The hatched region in the panel B indicates the degree to which within-category variation (in contrast to panel A) affected eye movements to the competitor icon /ba/, even for just those trials that were identified as /pa/ (adapted from McMurray et al., 2003).

Figure 9 shows an example of the proportion of time the eyes spent fixating the /pa/ icon as a function of VOT. The later period of the identification process (1201–1500 ms) reveals an eye movement identification function that looks just like the typical discrete categorical identification function produced by button press responses. However, the earlier periods of the identification process (i.e., 0–300 ms, 301–600 ms, and even 601–900 ms) look significantly more probabilistic and are graded in a way that reveals some sensitivity to the continuous variation in VOT.

As done in the previous exploration of categorization, it can be illuminating to simulate the graded temporal dynamics of "categorical" speech perception with a localist attractor network. This practice helps to visualize the continuous changes taking place in the patterns of activation corresponding to competing "graded category" states. Figure 10 illustrates the architecture of a normalized recurrence simulation that integrates a speech vector (that pits "bah"-like sounds against "pah"-like sounds) and a visual vector (that compares fixation probabilities to a /ba/ icon, a /pa/ icon, and the central fixation dot). The speech vector is given a pattern of input corresponding to a speech sound somewhere along the VOT continuum. For example, a rather unambiguous "pah" sound might get a starting activation of (.1 0 .9) for those three nodes, whereas a borderline "bah" sound might get (.6 0 .4). The visual vector always starts at (.33 .33 .33), treating each visual object as equally worthy of attracting an eye movement.

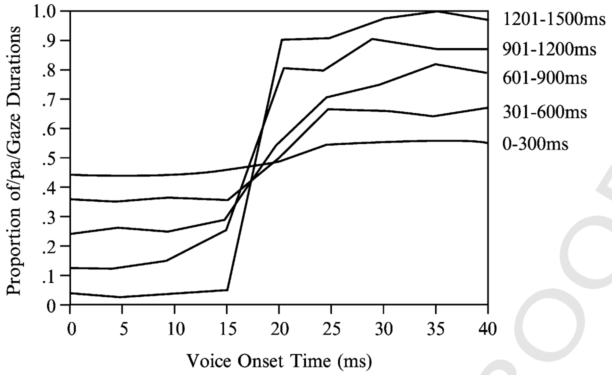

Fig. 9. When proportion of eye movements to /ba/ and /pa/ are treated like an identification response across the stimuli of the VOT continuum, the later periods of time after presentation (1201–1500 ms) exhibit the typical step-function of categorical perception, but the early periods of time (301–600 ms) exhibit a substantially more graded transition between ‘‘ba’’-like states and ‘‘pa’’-like states (adapted from McMurray & Spivey, 1999).

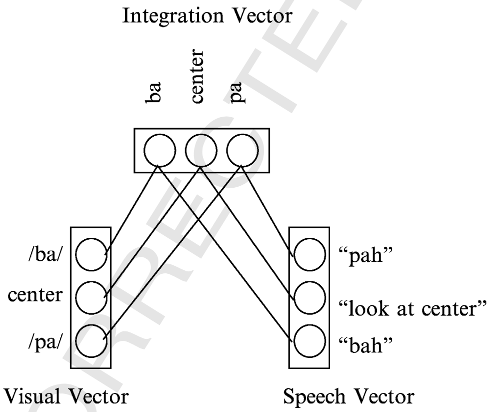

Fig. 10. A simple normalized recurrence localist attractor simulation of speech input from a VOT continuum and visual input from a set of response icons. See text for details.

As in the previous section, these two vectors simply sum at the integration layer, which then normalizes itself and sends feedback to the feature vectors.

In this simulation, we can sample the proportion of fixations from the visual vector, and thus watch the simulated eye movement patterns move away from fixating the central dot and toward one or the other response icon. Figure 11 shows the activation curves over time for the /pa/ visual node and the /ba/ visual node. Panel A plots these curves for a rather clear ‘‘pah’’ speech input (.2 0 .8), and panel B plots these curves for a ‘‘pah’’ speech input that is near the category boundary (.4 0 .6). These activation curves from the visual vector mimic the proportion of fixations at each time slice (Fig. 8) in the results of McMurray and Spivey (1999); and McMurray et al. (2002, 2003).

When this simulation is run for all 11 speech tokens along the VOT continuum, it is possible to calculate the proportion of time the model spends ‘‘fixating’’ the /pa/ icon versus the /ba/ icon, and thus plot a categorical identification function. Crucially, this can be done for early periods of time during the network’s settling process, as well as for intermediate and late periods of time—just as was done in Fig. 9. The resulting graph is shown in Fig. 12.

In both the normalized recurrence and human cases, the identification function starts out rather unbiased and gradually approaches the classic step-function profile by continuously increasing one-half of the curve and decreasing the other half of the curve over time. Thus, if the identification function is to be interpreted as a kind of signature of the internal pattern of activation favoring the perception of ‘‘bah’’ or ‘‘pah,’’ then this signature at those early moments in time looks decidedly more continuous than the legendary step function that motivated the aphorism, ‘‘speech is special’’ (cf. Liberman, 1982).

AU:6

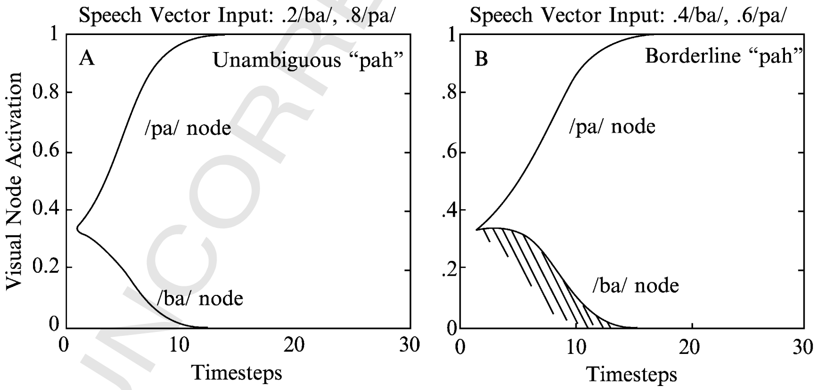

Fig. 11. Activation over time of the /ba/ and /pa/ visual nodes after an unmistakable ‘‘pah’’ (panel A) and after a speech sound near the category boundary (panel B). The hatched region in panel B shows portion of /ba/ node activation over and above that in panel A. (Compare to Fig. 8.)

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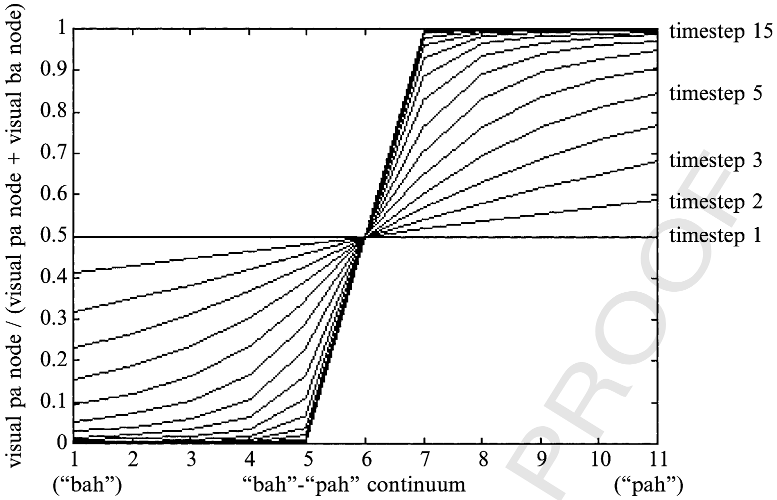

Fig. 12. Relative proportion of the /ba/ and /pa/ visual node activations (excluding "center" node) across different stimulus gradations between "ba" and "pa" at different cycles of competition in normalized recurrence.

B. Spoken Word Recognition

Even those readers wary of the continuity of mind must admit that the speech signal for word recognition is continuous. Individual phonemes do not occur discretely, as categorical perception described might suggest; instead, individual sounds, so to speak, smoothly blend into each other in natural speech. Speech is indeed quite exemplary of Gibson's continuous "flowing array of stimulus energy."

In a classic set of experiments, Marslen-Wilson and colleagues demonstrated that, to a first approximation, complete recognition of a word occurs shortly after the auditory input uniquely specifies a lexical candidate (for review, see Marslen-Wilson, 1987). For words of many syllables, this can occur prior to the end of the word. For example, the word *elephant* would be recognized shortly after the sound /f/. Prior to that, the auditory input would be consistent with the beginnings of several words, including *elephant, elegant, eloquent* and *elevator*. Thus, recognition of a spoken word is strongly influenced by the words to which it is phonetically similar, especially those words that share initial phonemes. Marslen-Wilson referred to the set of lexical candidates that is activated in the same phonetic environment as a "cohort."

Evidence from several experimental paradigms indicates that these candidates are partially activated as a word is being processed (not unlike the partial activations over time for the mental states in Fig. 4). For example, cross-modal lexical priming experiments demonstrate that semantic information associated with cohort members is temporarily activated as a word unfolds (Zwitserlood, 1989). The prior context of the utterance and subsequent input provide evidence that is used to evaluate the competing alternatives. While current models differ in how they account for these data, nearly all models incorporate the idea that the time it takes to recognize a word depends on a set of potential lexical candidates (see Cutler, 1995, for a review).

Providing concrete evidence for the activation of multiple alternative lexical items during recognition of a spoken word, Spivey-Knowlton, Sedivy, Eberhard, and Tanenhaus (1994) reported cohort effects in eye movement patterns by having subjects follow instructions to manipulate real objects. Participants sat in front of a table containing a central fixation cross and various objects around it (e.g., a fork, a mug, a candle). In some trials, objects whose names had similar initial phonemes were present on the table, available for manipulation (e.g., a bag of candy and a candle). For this "cohort competitor present" condition, Fig. 13 shows the proportion of trials, at each time slice, in which the participants' eyes were fixating each of the various objects. The probability of looking at the cohort object, (e.g., the candy, when instructed to "Pick up the candle"), rose just as quickly as

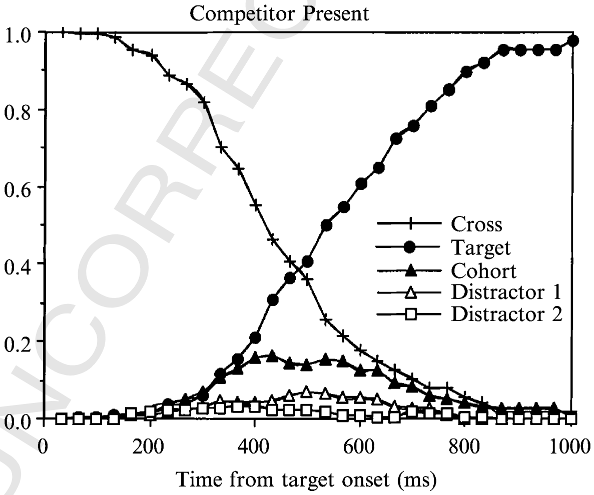

Fig. 13. Proportion of fixations of various objects across time as the target word unfolds (e.g., about 300 ms for the word *candle*). Note the conspicuous rise of eye movements to the cohort competitor object (filled triangles; from Spivey-Knowlton & Allopenna, 1997).

the probability of looking at the target object, for a period of about 200 ms around the tail end of the spoken word. And even when the two curves diverge, the proportion of fixations of the cohort object still persists for a few hundred milliseconds. This salience of the cohort object conspicuously attracting eye movements is indicative of the competing lexical representation being partially active during, and perhaps shortly after, delivery of the spoken word.

Headband-mounted eye-tracking studies like this have demonstrated this real-time lexical competition using computer-displayed objects (Allopenna, Magnuson, & Tanenhaus, 1998), using artificial lexicons (Magnuson, Tanenhaus, Aslin, & Dahan, 2003), with young children (Fernald, Swingley, & Pinto, 2001), and even across two languages in bilingual participants (Marian & Spivey, 2003; Spivey & Marian, 1999).

Marslen-Wilson's (1987) cohort theory naturally predicts findings like these, and McClelland and Elman's (1986) TRACE model can quantitatively simulate them. In the TRACE model of word recognition, activation is passed forward and backward between a layer of phonetic feature nodes, a layer of phoneme nodes, and a layer of word nodes. As the network receives phonetic feature activation corresponding to early speech information, it gradually settles toward a state of exhibiting activation for only the words that are consistent with the current speech input. In this way, TRACE can explicitly implement the cohort effect described in the Marslen-Wilson's cohort theory. In fact, by integrating TRACE with the normalized recurrence architecture previously described, to impose the visual constraints on which objects and lexical items accrue significant activation, quite accurate predictions about eye movement dynamics can be made (Spivey, in preparation).

The TRACE network also makes a prediction that diverges from Marslen-Wilson's cohort theory. Since TRACE has only positive connections *between* layers (and only inhibitory connections *within* layers), it does not prevent, and will in fact induce, the activation of lexical items that rhyme with the word being spoken. Therefore, TRACE predicts that when instructed to ''Pick up the candle,'' a person should conspicuously fixate a handle in the display, whereas the standard version of the cohort theory would not predict this. Indeed, TRACE's prediction holds true. Listeners will briefly look at an object whose name rhymes with the spoken word more so than unrelated control objects (Allopenna et al., 1998). Allopenna et al., showed that the activations of the lexical nodes in TRACE (once scaled by an exponential and normalized) closely mimic the probability-of-fixation functions from these eye-tracking experiments (compare Figs. 13 & 14).

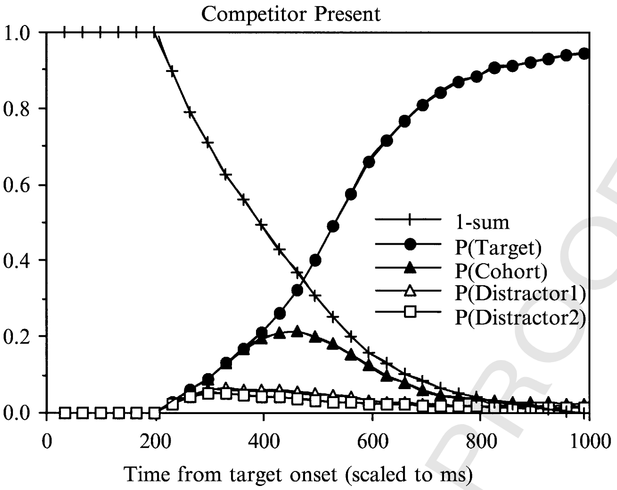

Fig. 14. Activations of the lexical nodes in McClelland and Elman's (1986) TRACE model of speech processing, scaled by an exponent and normalized (from Spivey-Knowlton & Allopenna, 1997). (Compare to Fig. 13.)

C. SENTENCE PROCESSING

In the 1970s, a "clausal processing theory" emerged in psycholinguistics, arguing that most of the syntactic and semantic processing of a sentence took place at the ends of its clauses rather than continuously throughout the sentence (e.g., Bever & Hurtig, 1975). The impetus for this theory largely derived from two sources. One was to maintain some level of consonance between psycholinguistic investigation and linguistic theories that incorporated a unique syntactic level of processing. The second, interestingly, was largely induced by Marslen-Wilson's famous shadowing experiments (Marslen-Wilson, 1973). In these experiments, participants verbally followed a spoken passage played to them and tried to repeat it out loud as quickly as possible. This close speech-shadowing task revealed that mistakes made by participants were largely grammatically and semantically appropriate amidst their previous and subsequent repetition. This suggested that syntax and semantics are in fact being processed together continuously during sentence processing. Clausal processing theory aimed to counter these results and bring psycholinguistics closer to contemporary syntactic theories in linguistics.

Subsequent theories of sentence processing often urged the continuous nature of syntactic and semantic computations on linguistic input, but assailed the interactive aspect of Marslen-Wilson's (1973; Tyler & Marslen-Wilson, 1977) framework. Frazier and Fodor (1978) proposed a set of syntactic structuring heuristics for real-time sentence processing that offered an account of certain errors and hence misunderstandings in parsing a sentence. Frazier and colleagues argued that a syntactic parsing module in the mind automatically attaches each new incoming word in such a way that minimizes the number of branches in a syntactic tree structure. With sentences like that in (1), taken from Bever (1970), which contain temporary syntactic ambiguities, the particular tree-structuring format that Frazier employed posited fewer branching nodes if the verb ''raced'' was integrated as part of the sentence's main verb rather than as a relative clause describing ''horse.'' This ''minimal attachment'' hypothesis predicted that a reader or listener will build the syntactic structure consistent with the horse doing the racing (rather than being raced by someone), and this would essentially lead comprehension ''down a garden path'' that will not work with the subsequent words. The result is that by the end of the sentence, the verb *fell* has nowhere to attach and thus cannot easily be grammatically integrated into the sentence.

(1) The horse raced past the barn fell.

Throughout the 1980s, Frazier and colleagues recorded eye movements during reading tasks and concluded that sentence processing did not involve real-time interaction between syntax and meaning because semantic and discourse context did not appear to prevent the all-important syntactic heuristics from generating garden path effects (e.g., Ferreira & Clifton, 1986; Rayner, Carlson, & Frazier, 1983). In addition, in opposition to clausal processing theory, they argued that sentence processing involved continuous flow of information (or at least word-by-word incremental flow) because the effects of the syntactic heuristics are detectable in the eye movement data (as increases in reading times) the moment the reader fixates the critical word disambiguating the sentence, regardless of where any clauses begin or end (Frazier, 1998; Frazier & Clifton, 1989; Frazier & Rayner, 1982). This work constituted more than a decade of research characterizing comprehension as an incremental word-by-word (not clause-by-clause) process in which syntax alone was processed in an early stage of the system, and then semantics and other contextual constraints were consulted in a later stage of the system, in the event of anomalies like garden path effects.

There remains ongoing debate about the interactive nature of sentence processing. To illustrate, consider sentence (2) (from Tanenhaus & Trueswell, 1995). It has exactly the same structure as (1) but does not induce a garden path effect.

(2) The land mine buried in the sand exploded.

If syntax were sovereign in this situation, it should be equally difficult to process sentences (1) and (2). The semantic constraints imposed by the lexical items in (2), ‘‘landmine’’ and ‘‘buried,’’ seem to steer the reader away from the garden path, implicating a more interactive perspective on sentence processing. MacDonald, Pearlmutter, and Seidenberg (1994) argued that examples like these illustrate that structural biases during parsing emerge out of the interaction of both syntactic and semantic constraints. They report extensive experimental evidence in support of this perspective. The theoretical upshot from MacDonald et al. was to propose that multiple constraints are marshaled in the service of sentence processing. These constraints (lexical, semantic, pragmatic) act simultaneously to influence online interpretation of sentences. Indeed, when these various factors are controlled for their relative contribution, the accumulating evidence overwhelmingly supports an interactive perspective on sentence processing AU:7 (e.g., Altmann, Garnham & Dennis, 1992; Altmann & Steedman, 1988; Farrar & Kawamoto, 1993; Pearlmutter & MacDonald, 1995; McRae et al., 1998; Spivey & Tanenhuas, 1998; Spivey-Knowlton & Sedivy, 1995; Trueswell & Kim, 1998; Trueswell, Tanenhaus, & Garnsey, 1994; van Berkum, Brown, & Hagoort, 1999).[3]

One way of demonstrating the power of these contextual effects is through the semicontinuous record of eye movements during spoken sentence comprehension. For example, when presented with a real 3-D display containing an apple on a towel, another towel, and an empty box, and then instructed to ‘‘Put the apple on the towel in the box,’’ participants often look briefly at the irrelevant lone towel near the end of the spoken instruction before returning their gaze to the apple, grasping it, and then placing it inside the box (Spivey, Tanenhaus, Eberhard, & Sedivy, 2002b; Tanenhaus, Spivey-Knowlton, Eberhard, & Sedivy, 1995). (With unambiguous control sentences, such as ‘‘Put the apple that’s on the towel in the box,’’ they almost never look at the irrelevant lone towel). In this case, the syntax is ambiguous as to whether the prepositional phrase *on the towel* is attached to the verb *put* (as a movement destination) or to the noun *apple* (as a modifier). Given the actions afforded by the display, the latter syntactic structure is the correct one. However, people tend to have a bias toward interpreting an ambiguous prepositional phrase as attached to the verb (Rayner, Carlson, & Frazier, 1983), at least

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[3] In fact, at this point in the literature, the debate has largely shifted to determining how the AU:8 AU:9 syntactic alternatives of an ambiguity, supported by their various constraints, are adjudicated; with some researchers advocating a temporally dynamic competition process (e.g., McRae et al., 1998; Spivey & Tanenhaus, 1998; Spivey, Fitneva, Tabor & Ajmani, 2002a; Stevenson, 1994; Tabor & Tanenhaus, 1999; Tanenhaus et al., 2002) and others describing an immediate winner-take-all framework (e.g., Jurafsky, 1996; van Gompel, Pickering, & Traxler, 2001).

when it is an action verb like *put* (cf. Spivey-Knowlton & Sedivy, 1995). Thus, the brief fixation of the irrelevant lone towel indicates a temporary partially activated incorrect parse of the sentence. To demonstrate the influence of visual context on this syntactic ambiguity resolution process, the display was slightly altered to include a second apple (resting on a napkin). In this case, the visual copresence (in Herb Clark's, 1992, words) of the two potential referents for the phrase *the apple* should encourage the listener to interpret the ambiguous prepositional phrase *on the towel* as a modifier (in order to determine which apple is being referred to) rather than as a movement destination (cf. Altmann & Steedman, 1988; Crain & Steedman, 1985; Spivey & Tanenhaus, 1998). And, indeed, with this display, participants rarely fixated the irrelevant lone towel, indicating that visual context had exerted an immediate influence on the incremental syntactic parsing of the spoken sentence (Spivey et al., 2002b; Tanenhaus et al., 1995; see also Knoeferle, Crocker, Scheepers, & Pickering, 2003).

The current state of affairs in the field of sentence processing is at a consensus with regard to the continuity of information flow and has been gradually approaching consensus with regard to the rapid integration of syntax, semantics, and pragmatic context. Just as the processing of speech sounds, at the scale of tens of milliseconds, appears to be characterized by multiple partially active phonemic representations competing over time (McMurray et al., 2002, 2003), and the comprehension of spoken words, at the scale of hundreds of milliseconds, appears to be characterized by multiple partially active lexical representations competing over time (Allopenna et al., 1998; Marslen-Wilson, 1987; McClelland & Elman, 1986), so does the resolution of syntactic ambiguity, at the scale of seconds, appear to be characterized by multiple partially active syntactic representations competing over time (MacDonald et al., 1994; Spivey & Tanenhaus, 1998; Stevenson, 1994; Tabor & Tanenhaus, 1999).

IV. Continuity in Visual Perception

As speech enters the sensory system through time, it is perhaps an obvious case where continuous temporal dynamics would be prominent in the resulting perceptual-cognitive processing. Visual input, however, is often delivered to the sensory system in an instantaneous fashion (in the laboratory, at least). Does the internal processing of an instantaneously presented visual stimulus exhibit any interesting temporal dynamics? In this section, we describe a number of findings and demonstrations of continuous accrual of activation during visual processing.

A. Object and Face Recognition

As vision is a modality in which we share much in common with nonhuman primates, it has been studied in-depth with neurophysiologically invasive real-time measures that, indeed, quite richly illustrate the temporal dynamics of the resulting perceptual-cognitive processing. Vision research is replete with examples of temporal continuity in real-time perception. The gradual settling (or pattern completion) of a neuronal population code, over the course of hundreds of milliseconds, is a common way to think about how the visual system recognizes objects and faces. Compelling visualizations of the continuous manner in which sensory input gradually produces a percept can easily be found in visual neuroscience. For example, Rolls and Tovee (1995) recorded from multiple neurons in the inferotemporal cortex of the macaque monkey and found that it takes a few hundred milliseconds for the right population of cells to achieve their appropriate firing rates for fully identifying a fixated object or face. The cumulative information (in bits) provided by an inferotemporal neuron in the service of recognizing a face or object accrues continuously (though nonlinearly) over the course of about 350 ms (see Fig. 15). About 80 ms after the presentation of the visual stimulus, these cells begin firing, and during the first 70 ms of firing, about 50% of the total information to be encoded is already accumulated. Thus, very quickly, the inferotemporal network is able to project itself into the correct "neighborhood" in its state-space. (This allows some coarse gistlike visual discriminations to actually be made with 100 ms or less of stimulus presentation time; e.g., Potter, 1976, 1993; Van Rullen & Thorpe, 2001.) However, over the next 200 ms or so, the process of object or face recognition is still in progress, during which the remaining 50% of the information to be represented by the distributed population code is gradually accumulated.

Perrett, Oram, and Ashbridge (1998) report further patterns of gradual accumulation of neuronal evidence for face recognition. When an object or face is partly rotated away from a canonical or frontal view, recognition or matching will generally take longer as a function of how far it is rotated (e.g., Cooper & Shepard, 1973; Jolicoeur, 1985; Shepard & Metzler, 1971; see also Georgopoulos, Lurito, Petrides, Schwartz, & Massey, 1989). Perrett et al. (1998) describe recordings from cells in the monkey temporal cortex during viewing of frontal, three-fourth profile, profile, and one-fourth profile schematic faces. When the accumulated action potentials are plotted over time, these curves rise at different rates as a function of how canonical the face orientation is. Figure 16 depicts the continuous nonlinear rise in accumulated neuronal spikes over the course of several hundred milliseconds as recognition takes place. As these curves plot accumulated spikes, rather than

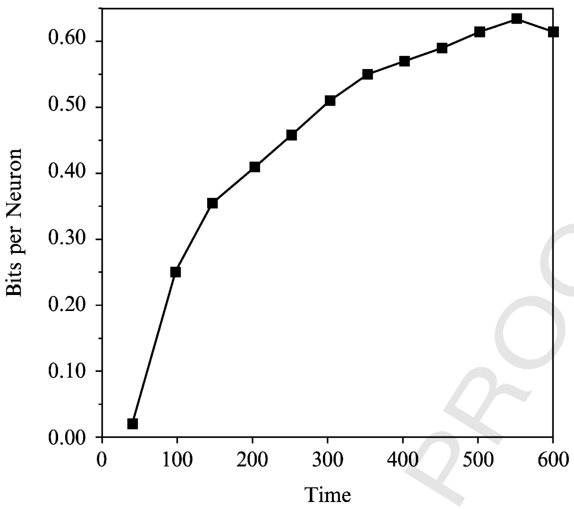

Fig. 15. Average cumulative information accrued over milliseconds by inferotemporal cells representing objects and faces (adapted from Rolls & Tovee, 1995).

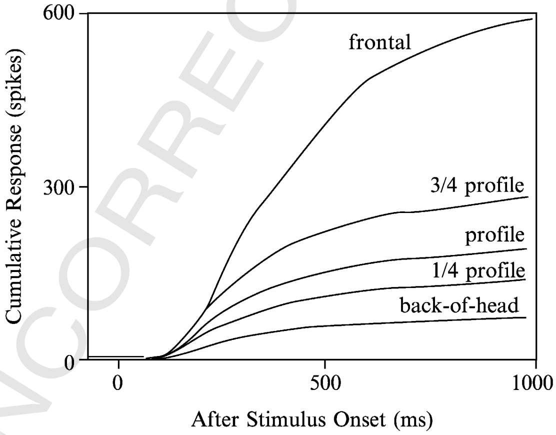

Fig. 16. The accumulation over time of neuronal spikes (over and above the baseline spike rate) from cells responding to faces at various rotations around the vertical axis (adapted from Perrett et al., 1998).

information-theoretic bits per neuron, they asymptote somewhat later in time than the curve in Fig. 15. Note again how these curves reach their half height relatively early on, yet still spend several hundred milliseconds gradually approaching their respective asymptotes (except for the back-of-head view, which asymptotes rather low within a few hundred milliseconds).

A few (or even several) hundred milliseconds for a population code to be "in transit" on the way toward achieving its potentially stable asymptotic state might initially seem like a rather small amount of time to get excited about. Are these transition periods perhaps just interesting curiosities, while the important observation is that a stable state is eventually reached, and is it *that* on which discrete mental computations might be performed? We think not. It is our hypothesis that in more complex visual (as well as auditory, somatosensory, etc.) environments, the proportion of time spent in these unstable regions of state-space—that is, in the process of traveling toward an attractor basin, but not in one yet—is actually much greater than the proportion of time spent in relatively stable regions of state-space.

This gradual accrual of the information comprising a population code (Figs. 15 and 16) has powerful consequences for how we conceptualize what the brain is doing when we go about our business of naturally perceiving the world around us. Consider how your eyes move around a complex scene like the one in front of you right now. Your eyes rest, with the two foveas fixating a particular location in the visual field, for about 300–400 ms on average (cf. Rayner, 1998). They then make a fast, ballistic, jump (lasting a few dozen milliseconds or so) away from that location to fixate another location in the visual field. After resting there for another 300–400 ms, they jump yet again to another location. Each new fixation brings a new word, object, or object part into the high-resolution view of your foveas for little more than one-third of a second. Now, if it takes almost half a second for the appropriate population code to get fully settled in recognizing a fixated object (Figs. 15 & 16), but your eyes normally move to a new object every one-third of a second, how can the brain possibly achieve a genuinely stable asymptotic state (or temporally discrete representation) for any object recognition event?

B. VISUAL SEARCH

The same kind of gradual accumulation of perceptual evidence can be observed when multiple objects are competing for attention during visual search. The field of visual search has generally been driven by two opposing treatments of attention. The serial-processing perspective holds that the observer allocates attentional resources wholly and discretely to individual objects, one at a time (e.g., Treisman, 1988; Treisman & Gelade, 1980). The parallel-processing perspective holds that attention is best characterized as comprised of partially active representations of objects simultaneously competing for probabilistic mappings onto motor output (e.g., Desimone & Duncan, 1995; Reynolds & Desimone, 2001).

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In a conjunction search task, the target object is defined by a conjunction of features, and reaction time increases linearly with the number of distractors, often in the range of 15–25 ms per item (Duncan & Humphreys, 1989; Treisman & Gelade, 1980; Wolfe, 1994). These linearly increasing reaction times as a function of set size were originally interpreted as evidence for serial processing of the objects in the display and contrasted with the near flat function of reaction time by set size observed with feature search displays, where a single feature is sufficient to identify the target object. It was argued that the early stages of the visual system process individual features independently and in parallel (Livingstone & Hubel, 1988), allowing the target object to ‘‘pop out’’ in the display if it is discriminable by a single feature, but requiring application of an attentional window to the individual objects, one at a time, if the target object is discriminable only by a conjunction of features (Treisman & Gelade, 1980).

However, several studies have discovered particular conjunctions of features that do not produce steeply sloped reaction-time functions by set size (McLeod, Driver & Crisp, 1988; Nakayama & Silverman, 1986; Theeuwes & Kooi, 1994). Moreover, it has been argued that steeply sloped reaction-time functions may not reflect serial processing of objects in the display, but rather noise in the human visual system (Eckstein, 1998; Palmer, Verghese, & Pavel, 2000; see also McElree & Carrasco, 1999). Overall, a wide range of studies have suggested that the distinction between putatively ‘‘serial’’ and ‘‘parallel’’ search functions is continuous rather than discrete and should be considered extremes on a continuum of search difficulty (Duncan & Humphreys, 1989; Nakayama & Joseph, 1998; Olds, Cowan, & Joliceur, 2000; Wolfe, 1998; see also Spivey, Tyler, Eberhard, & Tanenhaus, 2001).

Desimone and Duncan (1995; see also Reynolds & Desimone, 2001) describe a theory of ‘‘biased competition’’ in which multiple representations of objects are simultaneously partially active and compete for the privilege of driving motor output (e.g., pressing the ‘‘target present’’ button, reaching to grasp the attended object, or turning to shoot the computer-generated avatar of your opponent in a video game). Experimenter instructions, goal-oriented plans, and contextual constraints also provide some of the ‘‘bias’’ for this competition process.

The following normalized recurrence simulation serves as a kind of abstract implementation of a ‘‘biased competition’’ account of visual search (see Humphreys & Müller, 1993; Phaf, Van der Heijden, & Hudson, 1990, for somewhat similar models). In this simulation, one feature vector represents the likelihood of each object being the target based solely on it exhibiting the target property of *redness*, and the other feature vector represents the likelihood of each object being the target based solely on it exhibiting the target property of *verticalness*. The integration vector serves as a measure of each object's overall likelihood of being the target. Figure 17 shows a schematic diagram of this normalized recurrence network with input values corresponding to a target-present conjunction search for a red vertical bar with a set size of seven (i.e., one red vertical, three red nonverticals, and three nonred verticals).

Within each cycle of competition, the two feature vectors are normalized, then averaged at the integration layer,[4] and the integration vector then sends pointwise multiplicative cumulative feedback to those feature vectors. As cycles of competition continue, the integration node corresponding to the target object (exhibiting both redness and verticalness) increases in activation while the other nodes decrease in activation. Competition continues until an integration node exceeds a .95 activation criterion.

This normalized recurrence competition algorithm produces a nearly perfectly linear slope of settling time as a function of set size; $r^2 = .995$[5] (see Fig. 18). This basic result out of such a simple localist attractor network is noteworthy. One of the field's landmark findings that has traditionally been taken as evidence for a serial fixed-duration template-matching of each object one at a time, that is linear search functions, is exactly mimicked by a parallel competitive architecture where the only "capacity limitations" are that its representations share a probability density function.

Initially, it is not necessarily obvious why normalized recurrence should produce this linear increase in search time as a function of set size. As set size increases linearly, the initial activation of the target object's integration node decreases nonlinearly. In addition, as competition takes place within a given trial, that target integration node's activation value increases nonlinearly over time. In fact, this nonlinear increase over time exactly compensates for the nonlinear differences in starting activation across set size. For example, as shown in Fig. 19, competition increases the target integration node's activation with an asymmetric sigmoid function over time. Thus, although the initial activation values vary nonlinearly with set size (i.e., .415, .225, .155, .118, .095, for set sizes 4, 8, 12, 16, and 20), their nonlinear rise over

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[4] The Bayesian approach to this feedforward integration process would be to multiply these probabilities and then normalize them, but with binary feature vectors that would of course eliminate any temporal dynamics, as the target integration node would achieve 1.0 activation on the first time step.

[5] Moreover, it is clearly not simply operating within a linear portion of an otherwise nonlinear function. All the way to a set size of 300, in steps of 10, the slope function produced by normalized recurrence is perfectly linear, $r^2 = 1.0$.

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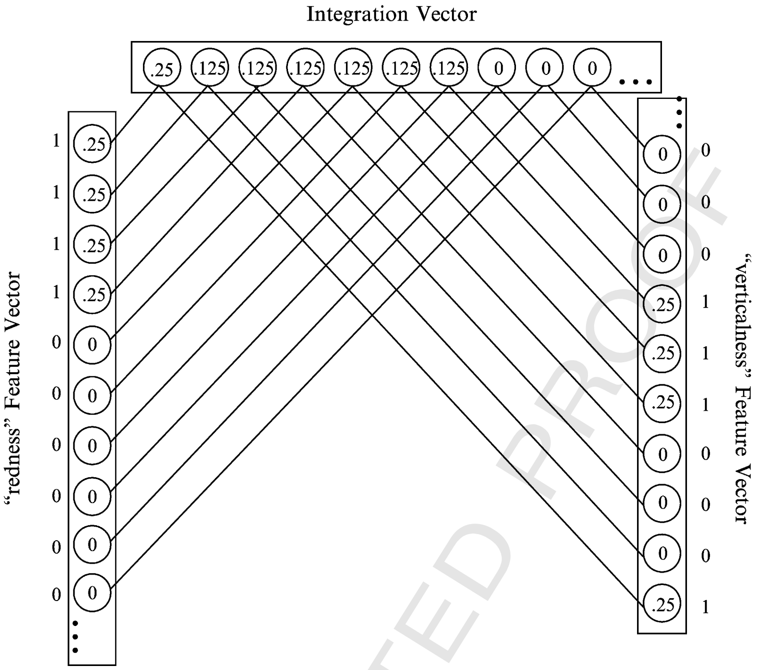

Fig. 17. Schematic diagram of a normalized recurrence simulation of visual conjunction search.

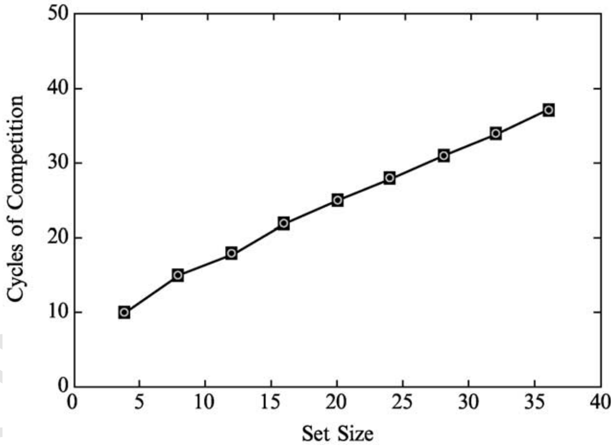

Fig. 18. Settling times for normalized recurrence during a conjunction search with different set sizes.

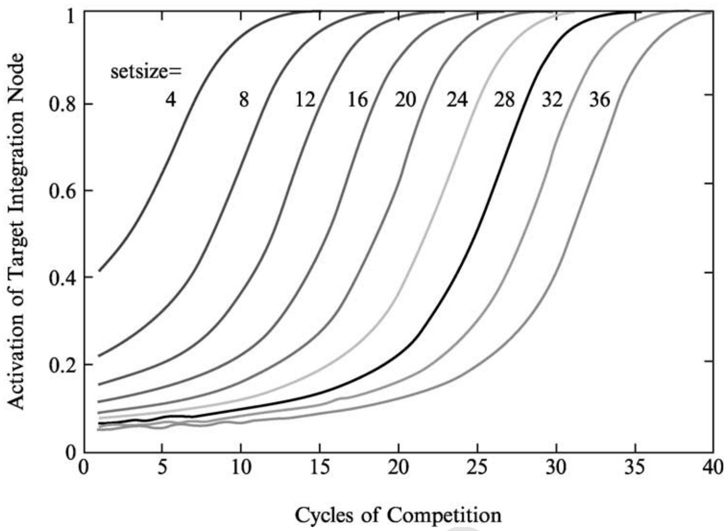

Fig. 19. In normalized recurrence, the winning node's activation rises with a sigmoid function, but this curve shifts linearly in time as set size increases.

time causes them to achieve a criterion of activation at approximately linear intervals in time (Spivey-Knowlton, 1996). In a sense, two nonlinearities make a linearity.

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A key observation from this little simulation is the fact that the representations of the various objects are all processed simultaneously, their activations updated in tandem. Despite this parallel processing of all object representations, the network produces linearly increasing settling times, as a function of set size, which were previously interpreted as evidence for serial processing. Thus, the simulation stands as an existence proof that linear functions can come out of a system in which multiple partially active representations are competing simultaneously, and an object's ''targethood'' gradually emerges over the course of hundreds of milliseconds during visual search.

C. Perceptual Decisions

Our final example of continuous temporal dynamics in visual processing comes from work by Gold and Shadlen (2000) examining decision processes in the frontal eye field (FEF) of the macaque. A common task in visual psychophysics involves presenting a display of quasi-randomly moving dots. As the experimenter increases the proportion of dots that move in a roughly consistent direction, the perception of a coherent direction of flow amidst the dots becomes more apparent (Britten, Shadlen, Newsome, & Movshon 1992). Gold and Shadlen presented such displays foveally to monkeys and trained them to indicate the perceived direction of dot flow, upon offset of the stimulus, by making an eye movement to one peripheral location or an opposite one. Then they found a region of FEF in which electrical microstimulation produced an involuntary saccade that was perpendicular to the two voluntary response saccades. On some of the direction-of-flow judgment trials, this region of FEF was microstimulated immediately after the moving dot display disappeared, that is, exactly when the monkey was supposed to produce a voluntary eye movement that would indicate his response regarding the perceived direction of flow of the dots.

Perhaps not surprisingly, the evoked involuntary saccade was executed first, and a corrective saccade typically redirected the eyes to the voluntarily chosen response location. However, the evoked saccade was not bereft of influence from the burgeoning perceptual decision. In fact, when the percentage of coherent motion was greater and (more importantly, for our argument) when viewing time was longer, more perceptual evidence apparently accrued to induce greater deviation of that initial involuntary saccade in the direction of the voluntary response.

Essentially, by incrementally increasing viewing time, the experimenters could observe the gradual increase in ‘‘strength’’ or ‘‘confidence’’ of the perceptual decision over time, as indicated by the degree to which that voluntary decision ‘‘leaked into’’ the execution of the FEF-microstimulated evoked saccade. Thus, the population of cells that—once some of them were microstimulated—produced the *evoked* saccade were already somewhere in the process of settling on a pattern of activation that would produce the *voluntary* response saccade. If the microstimulation took place early on in this decision process, rather little effect of the voluntary response would be apparent in the evoked saccade, but if the miscrostimulation took place later on in the decision process, a significant amount of the voluntary response would be apparent in the evoked saccade. These results suggest that decision processes themselves may be coextensive with the gradual settling of partially active and competing neural representations in motor areas of cortex (Gold & Shadlen, 2001; Schall, 2000; see also Georgopoulos, 1995). AU:13

Overall, this brief selection of observations in visual processing is consistent with a general view of perception, cognition, and action in which partially active mental representations compete over time until one (or in some cases an amalgam of more than one) wins the privilege to execute its associated motor output. Whether the visual system is recognizing a face, searching among a cluttered array for a ‘‘target’’ object, or deciding on what oculomotor signal to send to the eye muscles, the population code corresponding to the representation that will get to drive behavior (or even just constitute an internal monolog) spends a considerable amount of time approaching that status, and (in natural complex real-time interactive environments) rather little time enjoying it.

V. Continuity in Complexity

We have so far argued that our cognitive system consists of partially active and gradually emerging information, the ''states'' of which are more or less interpretable regions of the state-space in which a system lives. As described in many previous studies, this continuity ''resides'' in the neural substrate of the brain—vast arrays of networks blending into each other, sometimes moderately functionally specific (Zeki, 1993), and other times highly redundant across regions (Haxby et al., 2001). We would argue that continuity is itself a consequence of this inevitable complexity of the brain. Patterns of activity emerge gradually through local interaction of individual neurons, themselves composing more global connectivity. There is, therefore, organization within the system at varying time scales, from local neural influences to larger and larger organization, within regions and across them. Several theorists in the past 20 years have suggested that such a state of affairs admits of particular dynamics, regardless of the specific subject matter. For example, dynamic analyses of earthquakes (Bak & Tang, 1989), radioactive decay (Prestwich, Kenneth, & Pepper, 1986), and even traffic flow (Choi & Lee, 1995) suggest that complex systems of this kind exhibit certain global patterns (for an excellent review of this and related phenomena, see Ward, 2002).

If human cognition is indeed a complex dynamic system of the kind we are arguing, then similar patterns should be observable in this domain. In this section, we offer a review showing that behavior related to the previous sections, language and vision, also exhibits dynamic properties of complex systems.

A. Pink Noise

Among these properties, pink noise has perhaps invited the most investigation and speculation (Ward, 2002). Indeed, it is its apparent violation of a basic intuition about experimental procedures and inferential statistics that has likely engendered such interest (Gilden, 2001). According to this traditional intuition, pure experimental error should generate a random noise signal. When such a noisy signal is subjected to a fast-Fourier transform, it exhibits equal energy across its component frequencies (Press, Flannery,

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Teukolsky, & Vetterling, 1992). Pink noise, instead, is error or noise that is correlated with the frequency components contributing to it. The most common kind of model to describe correlated noise is that of colored noise:

$$Power(freq) \propto \frac{1}{freq^{\alpha}}$$

Pink noise is usually referred to as a pattern of noise whose power spectrum has a value of approximately 1 for α, also known as 1/f noise (see Fig. 20). Vast ranges of natural phenomena exhibit this kind of noise. Another form of colored noise, *brown noise*, is often illustrated using Brownian motion and is generated by a random walk process (i.e., a small random process that cumulatively adds or subtracts from a moving scalar time series). Brown noise has a power spectrum $1/f^2$. Pink noise is the most thoroughly investigated in psychological data and generally considered more interesting in other physical systems as well.

Gilden, Thornton, and Mallon (1995) sparked the recent spate of interest in pink noise in human brain and behavior. By the time these authors published their well-known results, others had already investigated pink noise in other areas (e.g., Voss and Clarke, 1975, offer a now famous

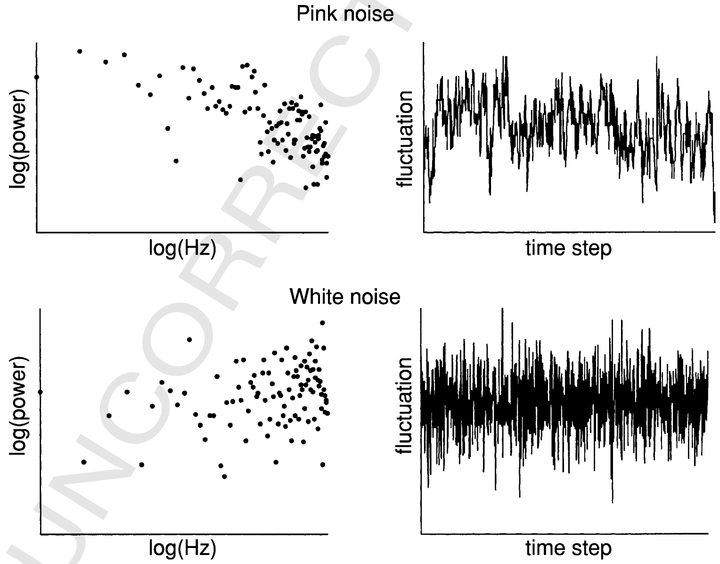

Fig. 20. Top row: the power spectrum (left panel) for pink noise (right panel) is correlated negatively with frequency. Bottom row: white noise has a power spectrum that is not correlated with frequency.

demonstration in musical structure and speech). Gilden et al.'s results demonstrate that certain human behaviors also exhibit this general property of complex systems. Their experiments primarily demonstrate that judgments, such as of time or space, have error in time that reveals a pink power spectrum. However, in an experiment involving reaction time to a simple discriminative stimulus, no such pink noise was found. The authors speculate that 1/f noise emerges as a consequence of mental judgments. Clayton and Frey (1997) soon after demonstrated that pink noise can emerge in reaction time measurements in experiments with a memory load. Three different response-time tasks were presented to subjects. In the easiest, subjects responded to a stimulus immediately. In another task of intermediate difficulty, they responded to the sameness of two subsequent stimuli; in the most difficult, subjects pressed a key if the stimulus was the same as presented two trials back in the experiment. All conditions produced colored noise in time series analyses of the reaction times, indicating that reaction times also display pink noise. In fact, the authors demonstrated that the harder the task, the more whitened the power spectrum becomes.

In an extensive series of experiments, Gilden (1997) demonstrated pink noise in a wide variety of decision tasks. In reaction times for both mental rotation and lexical decision, pink noise was observed in the time course of fluctuations from the mean. More recently, further evidence has surfaced that the visual system also reveals these patterns. Aks and Sprott (2003) revealed that perspective shifts in Necker cube interpretation exhibit pink noise effects. In an earlier paper, Aks, Zelinsky, and Sprott (2002) demonstrated that visual search performance shows both pink and brown noise. Variation in absolute eye position exhibits $1/f^2$ noise, resembling the random walk pattern of brown noise. However, variation in saccade amplitude generates a highly pink signal, indicating that long-term correlations emerge out of differences in eye position.

Several simple mathematical models can be devised to generate a pink signal (for a review, see Ward, 2002). Also, theories about coordinated time scales across brain regions have been offered (e.g., Chen, Ding, & Kelso, 1997; Ding, Chen, & Kelso, 2002; Gilden 2001; Gilden et al., 1995; Ward, 2002). Most recently, Van Orden, Holden, and Turvey (2003) lament the concoction of these relatively simplistic models, sometimes just to capture data from a few experiments. The authors offer experiments demonstrating that relatively automatic processes (e.g., word naming) can generate pink noise, despite the suggestion by some that this should not happen in such automatic processes (e.g., Gilden, 2001). Given their results and extensive theoretical discussion, Van Orden et al. suggest that pink noise ''is not the product of a particular component of the mind or body. It appears to illustrate something general about human behavior'' (p. 345). To Van Orden et al., pink noise may be a by-product of interaction-dominant dynamics, dynamics dependent upon the activity of large numbers of interactive components (see also Usher, Stemmler, & Olami, 1995). Indeed, this perspective is highly consonant with our own. As discussed, such neural complexity begetting 1/f noise would also be responsible for the temporal continuity of cognitive processes.

B. STOCHASTIC RESONANCE

Stochastic resonance is a phenomenon of nonlinear systems in which a weak periodic signal is amplified by ''optimal'' noise. As mentioned in the previous section, noise is generally considered troublesome from a traditional perspective, yet the discovery of stochastic resonance in the 1980's has resulted in entire conferences and textbooks on the topic, from statistical theory to applications (e.g., Ando & Graziani, 2000). The simplest way of picturing stochastic resonance, as it is traditionally introduced (Gammaitoni, Haenggi, Jung, & Marchesoni, 1998), is a bistable symmetric nonlinear system: a double-well potential. With the addition of noise, if past a certain threshold of average amplitude, the system will ''hop'' between the two states. Consider then subjecting this double-well potential to a weak sinusoidal, periodic signal that can bias or shift the probability distribution in the system wherein one potential becomes a favored absolute minimum for the system by having the hopping synchronize with the weak signal. The hopping will result in a stable state while this resonating of noise

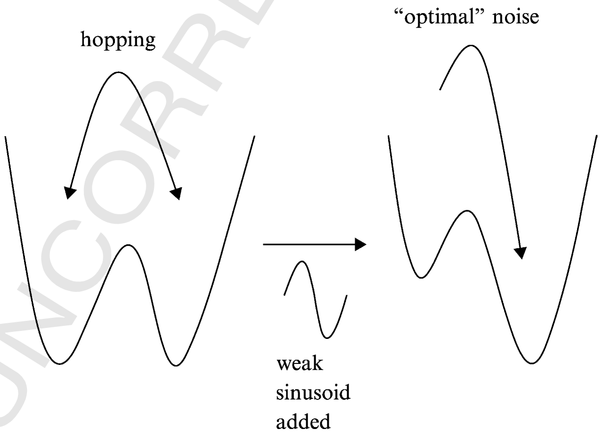

Fig. 21. When a weak sinusoid is added to an equibiased stochastic process, resonance can produce a significantly biased stochastic process.

and sinusoid occurs (see Fig. 21). Stochastic resonance was initially proposed as the explanation for the ice ages due to synchronization between the ‘‘weak signal’’ of climate change due to orbital situation of the earth, and a ‘‘Gaussian’’ noise signal from smaller-scale temperature fluctuations (Benzi, Sutera, & Vulpiani 1981; Nicolis, 1982). It was then experimentally demonstrated in simple devices, such as electronic logic gates and lasers.

Ward (2002) paints an interesting portrait of the relevance of stochastic resonance by describing the life of a crayfish. Its ‘‘watery world of a rippling brook’’ (p. 183) is terribly dangerous. The crayfish is preyed upon by other creatures, such as larger fish, that can quickly spring upon this species, if it were not for stochastic resonance in uniquely tuned hair cells on the crayfish. These cells can detect the specific frequency of the crayfish’s predators, helping the animal escape. It functions highly efficiently in its ‘‘watery world’’ due to the ambient noise in the watery environment and having that noise amplify the weak signal generated by an oncoming predator. Douglass, Wilkens, Pantazelou, and Moss (1993) demonstrated this experimentally in the crayfish by generating the relevant noise and weak predatory signal in an experimental chamber.

This is one of the simplest demonstrations of the potential biological benefit of cells that can take advantage of this statistical effect. It has also been demonstrated, for example, in the visual system of the cat. Noisy jitter induced by micro-ocular tremor may actually enhance visual acuity to a stimulus. By generating noise in a visual stimulus by producing motion jitter of different amplitudes, Hennig, Kerscher, Funke, and Woergoetter (2002) demonstrated that certain cells in cortical areas 17 and 18 of the cat increase responding to a moving oriented bar at intermediate levels of noise. Other animals may make use of stochastic resonance as well, including crickets, toads, and rats (see Ward, 2002, for a review).

In humans, Simonotto and colleagues (Simonotto, Riani, Seife, Roberts, Twitty, & Moss, 1997; Simonotto et al., 1999) have demonstrated the role of stochastic resonance in both human psychophysical and neuro-physiological recordings. Simonotto et al. (1997) exposed subjects to contrast gratings of variable spatial frequency under different noise conditions and asked them to report where their sensitivity to spatial frequency ceased. An intermediate amount of noise reduced perceptive threshold considerably lower than when the stimulus was noise-free. Simonotto et al. (1999) extended these results to the human brain through imaging. Results of fMRI demonstrated that visual regions of the brain contained more activity by volume under optimal noise conditions. These kinds of experiments have been extended to audition (Ward, Moss, Desai, & Rootman, 2001; Zeng, Fu, & Morse, 2000) and tactile stimulation (Richardson, Imhoff, Grigg, & Collins, 1998).

As with pink noise, very simple systems can also be devised to model stochastic resonance. For example, as mentioned, a simple double-well potential can exhibit it. Also, it can be modeled with a relatively simple threshold mechanism (Ward, 2002). However, much as we discussed in the context of pink noise, these simplistic models may belie the interactive complexity through which stochastic resonance emerges in the human brain. Though these simple models may serve as useful mathematical predictors, the means by which the human brain shows stochastic resonance may be considerably more complex. In a sophisticated neural model, Stemmler, Usher, and Neibur (1995) simulated lateral neural interaction in V1 that can benefit from internal noise. A large 20,000-node artificial neural network, consisting of half excitatory neurons and half inhibitory neurons, served to model receptive fields (with these receptive fields having varied sensitivities organized in a spatially distributed manner across the large network). Connections among these neurons served to model spatial excitatory and inhibitory input: Inhibitory inputs were sparsely distributed, coming from throughout the visual cortex, and excitatory input more closely packed. The model actually enhances a weak signal to a receptive field by having noise-induced input from inhibitory surround neurons. The model illustrates that patterns of stochastic resonance (among other patterns the model can fit, such as visual search pop-out), can emerge from the interaction of large numbers of small units.

C. RECURRENCE IN TIME

Recurrence quantification analysis (RQA) is a novel method of investigating the time course of complex systems (Webber & Zbilut, 1994; Zbilut & Webber, 1992). RQA permits its users to establish both global and local measures of regularity or even randomness in a system. RQA exemplifies the benefit of these dynamical analyses, showing how human brain and behavior are highly amenable to analysis of the global properties of very complex systems.

RQA is the quantification of a recurrence plot (RP), introduced by Eckmann, Kamphorst, and Ruelle (1987), and related to the correlation integral of dynamic systems mathematics (Takens, 1985). An RP is produced by measuring at regular intervals some scalar quantity generated by a system. For example, one might measure the temperature in a certain region or error generated by a neural network. *Any* scalar quantity in any kind of system will do, provided the measurements are at regular intervals. This time series is then embedded in multiple dimensions by overlaying the time series with temporally staggered versions of itself. Figure 22 illustrates this process. Roughly, the columns of this embedded time series have a time index

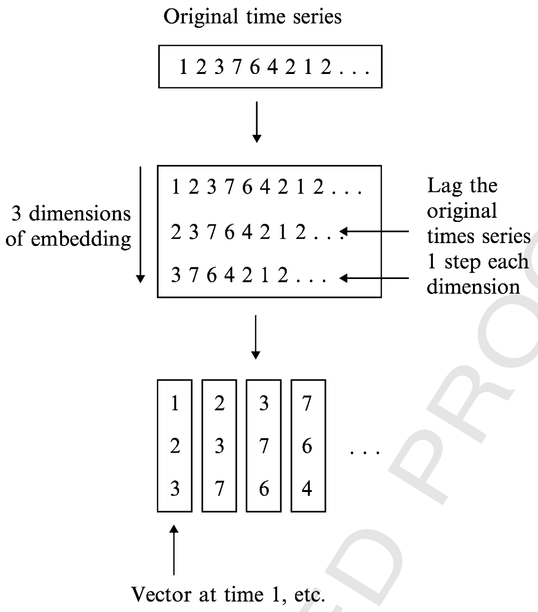

Fig. 22. An example of embedding a time series using, for example, three dimensions and a lag of 1. (See text for details.)

themselves and can be compared to column vectors of other time indices. When two such columns are compared, we can compute the distance between them. For any two vectors, at index *i* and *j*, say, we draw a point on the RP (*i, j*) if their distance satisfies a certain threshold. In this way, periodicities in the system result in undulating streaks of points in the RP (see Fig. 23). RQA directly quantifies the pattern of points on the RP (for a clear and concise introduction, see Riley, Balasubramaniam, & Turvey, 1999).

A particularly fruitful area in which RQA has been applied is the study of postural control. The studies of Riley, Balasubramaniam, and Turvey (1999) and Balasubramaniam, Riley, and Turvey (2000) primarily used RQA to study the variables controlling minor adjustments in our center of pressure (COP) during standstill (see also Riley & Clark, 2003). Riley et al. had subjects look at depth gratings while standing on a device that could monitor minor changes in their postural control (along the two axes of control, antero-posterior, [AP] and medio-lateral [ML]). Subjects performed trials in different conditions, including eyes—open versus closed, and looking straight-on versus looking to the right. The time series generated by recording postural control, generally regarded as nonstationary and fluctuating,

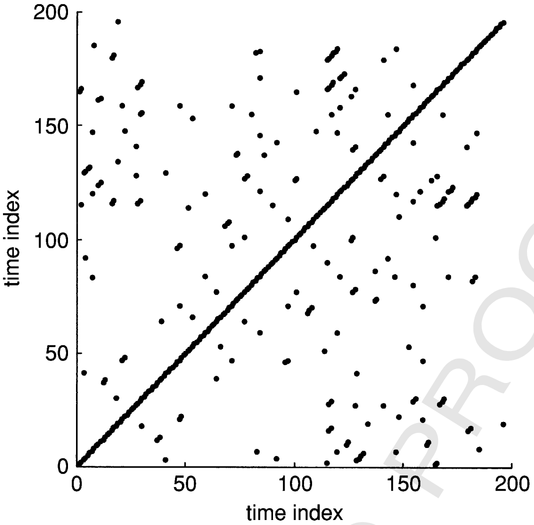

Fig. 23. In this very simple example of a recurrence plot, a series of sine values with some noise added was subjected to embedding. The diagonal is the line of identity, where $i = j$, and one can observe further diagonal structure emerging at other time indices, indicating some periodicity in the noisy sinusoidal time series.

permitted the authors to make the tentative observation that COP dynamics are more "complex" when the eyes are closed. Also, postural sway was not entirely random in that the RQA measure of determinism was fairly high for the various COP time series. However, nonstationarity obviously present in the RP analysis indicated that postural control may be a coupled dynamic between stochastic processes and more deterministic controlled processes (e.g., closing the eyes resulted in more deterministic, controlled patterns in the RP).

In an interesting pair of experiments, Balasubramaniam et al. (2000) used RQA to explore the conditions of fluctuation of COP in a precision task: maintaining a laser pointer on a target at a certain distance. Once again, measurements along the same two axes were compared. They used RQA to measure, for example, determinism, recurrence, entropy, and trend in the time series of these axes (these are values RQA generates from the RP; see Balasubramaniam et al., 2000). The authors demonstrated that the axis relevant to the task, such as the ML axis for holding the laser straight on (for accuracy), and the AP axis for across your body to the side toward the target, exhibited higher values of these measures, especially as task difficulty increased. The overall analyses indicate that there is a level of independence between these two sources of postural sway.

In a similar application, Shockley, Santana, and Fowler (2003) used RP and RQA to analyze postural shifts during conversational interaction. Participants engaged in discussion about cartoon images in different conditions, depending on whether they were conversing with each other or confederates outside the experimental area and whether they were facing each other or away from each other during interaction. The authors measured postural shifts by measuring changes in the location of the head and waist during conversation. Participants talking to each other, rather than a silent confederate, always exhibited more recurrence (a simple RQA measure) in a cross-recurrence plot of their postural sway (i.e., an RP generated by comparing two separate, embedded time series). Current related work is showing that cross-recurrence in eye movements of a speaker and a listener predicts accuracy on comprehension questions (Richardson & Dale, 2004) and that recurrence of linguistic forms in novel contexts characterizes the acquisition of various syntactic categories in children's language learning (Dale & Spivey, submitted). AU:15

Importantly, as related to our above discussion, the crucial aspect of RP and RQA is that they visualize processes that change in time, whether stationary or nonstationary, highly periodic or random. The fact that human behavior—such as visual–postural interaction, postural control during conversation, and eye movements during instruction and comprehension—is amenable to this analysis at least indirectly supports the perspective of continuity (see also Marwan & Meinke, 2004, for an application of RQA to event-related potentials). In summary, all the previous phenomena, especially when taken together, suggest that cognition is based in a complex system composed of interaction-dominant subcomponents blending at multiple time scales, thus generating continuity in behavioral outcomes. Indeed, all these properties of complexity substantiate our highlighted time scale (of hundreds of milliseconds), since both noise and recurrence seem implicated in real-time visual and linguistic processes.

VI. Conclusion

In this chapter, we have strolled briskly through a number of different examples of using continuous (or semicontinuous) measures of perceptual-cognitive processing to reveal various mental phenomena as composed of multiple partially active representations that compete over time. However, it can sometimes seem that whenever a mental process is shown to exhibit such continuous temporal dynamics (or to rely on distributed representations), then the process in question is relegated to "part of perception, not cognition," where analog processing is not surprising. In Sections I–V, we touched on evidence for, and simulations of, the temporal continuity of representational dynamics in categorization, speech perception, spoken word recognition, sentence processing, object and face recognition, visual attention, and perceptual decisions, as well as correlational cross-talk between rather different time scales of task performance. If all of these mental phenomena were to be expunged from the domain of cognition on the grounds that they do not rely on discrete temporally static symbolic representations, then scant little would remain in that vaunted realm—perhaps only problem solving and reasoning. (And, just to warn you, the movement has its eyes on those processes as well; cf. Townsend & Busemeyer, 1995).

Rather than imputing to cognitive processes the unrealistic property of functioning in a discretely symbolic way that real biological neural hardware is incapable of implementing, perhaps we can instead welcome a smooth merging of perception, cognition, and action as encouraged by Dewey (1986). Environmental stimulation continuously flows into perceptual areas of the brain, but since those areas receive some degree of feedback from more cognitive areas of the brain, they're really processing a combination of afferent sensory patterns of activation and reentrant cognitive patterns of activation. These blended patterns of activation cascade to ‘‘higher’’ areas of the brain where the relative concentrations of cognitive-like versus perceptual-like components in the patterns may shift toward the cognitive end. And soon, as these patterns of activation continuously travel toward motor areas of the brain, in preparation for influencing behavior, the distributed patterns begin to exhibit a significant degree of actionlike components as well. For example, action representations themselves may be predominantly defined in terms of their anticipated perceptual outcomes (cf. Prinz & Hommel, 2002, for an excellent collection of reviews). And don't forget Dewey and Gibson's reminder that relatively continuous motor output dramatically alters the patterns of continuous sensory stimulation, thus looping the entire system back onto itself. There simply does not appear to be, nor should there actually need to be, an internal stage in which the graded, distributed patterns of activation are converted into single unitary symbols with logical truth values. After all, they would only have to be reconverted right back into the graded, distributed patterns of activation that we know occur in the motor cortices (e.g., Georgopoulos, 1995).

Although it is comforting to think of cognition in terms of multiple different easily labeled interpretations of individuated stimuli having nonoverlapping symbolic descriptions (e.g., Dietrich & Markman, 2003; Fodor & Pylyshyn, 1988), the fact of the matter is that the brain spends most of its time in regions of state-space that do not allow discrete symbolic descriptions. Thus, rather than being the digital computational intermediary between analog perception and action, whose job is to collapse the probabilistic distributions into discrete symbols, cognition is perhaps just as analog and graded as the sensory and motor systems themselves. And the much awaited collapsing of those distributed multifarious representational patterns does not actually take place until motor movement is executed (and even then it sometimes comes out as an amalgam of two motor programs, e.g, Gold & Shadlen, 2001).

Finally, we should acknowledge that, in our effort to speak to the traditional cognitive psychologist, it is possible that we have focused too much on the dynamics of internal cognitive processing and not enough on the dynamics of larger systems such as that of a human coupled with its environment (e.g., A. Clark, 2003; Gibson, 1979; O'Regan & Nöe, 2001; Spivey, Richardson, & Fitneva, 2004; Turvey; & Carello, 1981) or multiple humans interacting with one another (e.g., Knoblich & Jordan, 2003; Schmidt, Carello, & Turvey, 1990; Sebanz, Knoblich & Prinz, 2003; Shockley, Santana, & Fowler, 2003). However, in describing and supporting the continuity of mind for an audience of cognitive psychologists, showing how internal perceptual-cognitive processing exhibits continuous change in the salience of multiple simultaneously active representations is perhaps the crucial first step in steering the field away from its digital computer metaphor for cognition. By first replacing the concept of discrete representations in the mind with multifarious patterns of neural activation that change continuously over time, we can set the stage for exploring a reconsideration of exactly how "representation-like" these continuous trajectories in state-space really are (regardless of whether we're talking about a neural state-space or an organism-environment state-space). In this way, we hope that the cognitive sciences can eventually find a responsible and coherent integration of the useful, lasting insights that came from cognitive psychology and from connectionism, and those that are coming from neuroscience, ecological psychology, and dynamic systems theory.

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