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The Pervasiveness of 1/f Scaling in Speech Reflects the Metastable Basis of Cognition

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Abstract

Human neural and behavioral activities have been reported to exhibit fractal dynamics known as *1/f noise*, which is more aptly named *1/f scaling*. Some argue that 1/f scaling is a general and pervasive property of the dynamical substrate from which cognitive functions are formed. Others argue that it is an idiosyncratic property of domain-specific processes. An experiment was conducted to investigate whether 1/f scaling pervades the intrinsic fluctuations of a spoken word. Ten participants each repeated the word *bucket* over 1,000 times, and fluctuations in acoustic measurements across repetitions generally followed the 1/f scaling relation, including numerous parallel yet distinct series of 1/f fluctuations. On the basis of work showing that 1/f scaling is a universal earmark of metastability, it is proposed that the observed pervasiveness of 1/f fluctuations in speech reflects the fact that cognitive functions are formed as metastable patterns of activity in brain, body, and environment.

Keywords: 1/f noise; Scaling; Metastability; Criticality; Speech; Intrinsic fluctuations

1. Introduction

Cognitive functions are expressed as spatiotemporal patterns of activity in the nervous system and in behavior. These patterns connect with and extend out to their surroundings as a result of widespread interactions between brain, body, and environment (Chiel & Beer, 1997; Clark, 1997). In this light, the embodied, situated nature of cognition is founded on the ability of such expansive patterns to organize in space and time (Kello, Anderson, Holden, & Van Orden, 2007; Van Orden, Holden, & Turvey, 2003). Of course, these patterns must also adaptively and flexibly reorganize as organism and environment change in relation to each

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other. Thus in viewing cognition as situated pattern formation, a fundamental fact is revealed that parallels the well-known stability–plasticity dilemma (Carpenter & Grossberg, 1987): Patterns of cognitive activity must be able to organize, but also reorganize as new patterns in response to changes in conditions, e.g., changes in the environment, task demands, and so on.

How do interactions within and between brain, body, and environment enable the organization and reorganization of cognitive activities? This question may at first seem too broad to be approachable because interactions will differ in their specifics depending on the cognitive domain and other factors; such differences may appear to entail different theories and, therefore, different answers to the question. But domains notwithstanding, one may formulate and test general principles of brain–body–environment interaction that help to develop theories of cognition as situated pattern formation. In the present study we draw from statistical physics to formulate one such principle hypothesized to support the organization and reorganization of cognitive patterns. We then present an experiment that uses speech to test and ultimately support the hypothesized principle, which we and others have formulated in terms of *metastability* (Bressler & Kelso, 2001; Kello et al., 2007).

Metastability has been used by different research communities for different purposes, but we use the term to identify systems for which numerous patterns of activity co-exist as latent potentials. The probability of any particular pattern organizing into existence is a function of variables both internal and external to the system. A system becomes more flexible, and more metastable, as its capacity to concurrently hold many distinct latent patterns increases. This capacity is essential to the adaptability of cognitive systems, and biological systems in general, because it allows them to respond to changing conditions, i.e., by organizing different patterns of activity. From this perspective, systems become more adaptive as the probability distribution over potential patterns is shaped to maximize their expected fitness.

Particularly clear examples in this regard are patterns of fight or flight behaviors that must co-exist as latent potentials ready to organize in response to ecological competitors or foes (Cannon, 1932). These behavioral patterns must also be ready to reorganize in response to changing conditions, as when an organism becomes trapped and must convert flight behavior into submissive, or fight, behavior. A more cognitive example is provided by speech, in which many different articulations must co-exist as latent spatiotemporal patterns ready to organize as needed in the course of speaking (Fowler & Saltzman, 1993). Articulatory patterns span multiple time scales, from the millisecond dynamics of phonemic features to jaw movements that span multisyllabic words and phrases. These patterns must organize and reorganize as speakers transition from one phoneme, word, and phrase to the next. Although metastability has not yet been applied to theories or models of language and cognition, it has been applied toward understanding patterns of movement and neural activity (Bressler & Kelso, 2001; Kelso, 1994).

In statistical physics, metastability is known as a property of physical systems near their *critical points*, and the fluctuations of such systems are known to follow a *1/f scaling* relation (Bak, Tang, & Wiesenfeld, 1987; Usher, Stemmler, & Olami, 1995). Systems poised near their critical points are jittery, analogous to balancing on a tightrope, and the resulting fluctuations can be analyzed in terms of their frequency components (same as spectral analysis of sound or light). Critical point fluctuations are characterized by an inverse relationship between spectral power (amplitude) and frequency, $S(f) \approx 1/f^{\alpha}$, where $\alpha \approx 1$ (see Fig. 1; see also Bak,

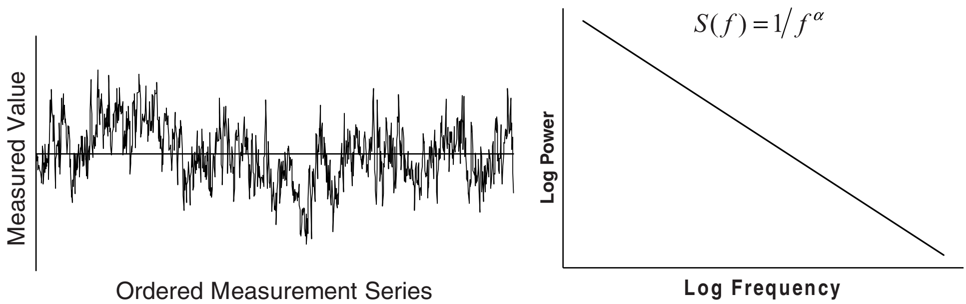

Fig. 1. Idealized 1/f fluctuations. *Note:* An example time series of fluctuations is shown that follows an idealized 1/f scaling relation (left). Large, low-frequency changes spanning many measurements can be seen, and nested within them are smaller, higher frequency undulations spanning fewer measurements. Fourier analysis can be used to compute the power spectrum of a time series (right). When plotted in log–log coordinates, 1/f spectra are linear with a slope of –1, i.e., $\log S(f) = -\alpha \log f$, where exponent $\alpha = 1$ in $1/f^{\alpha}$.

1996; Sornette, 2004). These fluctuations are most clearly observed in a system's *intrinsic fluctuations* (Gilden, 2001; Kello et al., 2007; Van Orden et al., 2003).

Intrinsic fluctuations are simply changes in activity that originate from the system being measured when it is minimally affected by external perturbations. Intrinsic fluctuations in behavioral activity can be measured by eliciting the same behavioral act repeatedly under constant measurement conditions. Gilden, Thornton, and Mallon (1995) provided a very clear example when they instructed participants to estimate from memory the same temporal interval (e.g., one second), or the same spatial interval (one inch), over and over again, without feedback. Because the stimuli and measurement conditions did not change across estimates, the resulting fluctuations can be viewed as intrinsic to behavior; that is, one would expect their temporal structures to fall in the same universal class regardless of the stimulus or response being repeated.

Gilden et al. (1995) found that fluctuations in interval estimates followed a 1/f scaling relation, and similar findings have been reported in a number of other behavioral studies, including mental rotation and translation (Gilden, 1997), visual search (Aks, Zelinsky, & Sprott, 2002), simple classifications (Kelly, Heathcote, Heath, & Longstaff, 2001), lexical decision (Gilden, 1997), word naming (Van Orden et al., 2003), color and shape discrimination (Gilden, 2001), and self-esteem ratings (Delignieres, Fortes, & Ninot, 2004). All of these protocols were (sometimes inadvertently) well-suited for eliciting intrinsic fluctuations because the same task was performed repeatedly with relatively small changes in stimuli and responses from one trial to the next.

1/f scaling has also been found in intrinsic fluctuations of neural activity, such as current flow through neuronal ion channels (Banerjee, Verma, Manna, & Ghosh, 2006), rate of neurotransmitter secretion (Lowen, Cash, Poo, & Teich, 1997), interspike intervals between action potentials (Bhattacharya, Edwards, Mamelak, & Schuman, 2005), fluctuations in local field potentials (Leopold, Murayama, & Logothetis, 2003), amplitude levels within EEG and MEG frequency bands (Linkenkaer-Hansen, Nikouline, Palva, & Ilmoniemi, 2001), fluctuations in interchannel EEG synchronization (Gong, Nikolaev, & van Leeuwen, 2003; Stam

& de Bruin, 2004), and voxel activations in functional magnetic resonance imaging (fMRI; Thurner, Windischberger, Moser, Walla, & Barth, 2003; Zarahn, Aguirre, & Desposito, 1997). Again, all of these protocols were well-suited for observing intrinsic fluctuations.

Results to date indicate that 1/f scaling is associated with intrinsic fluctuations across a wide range of behavioral and neural expressions of cognitive activity, further supporting the metastability hypothesis. Nevertheless, it is possible that each observation has its own domain-specific account, and many such accounts have been offered. For neural 1/f fluctuations, they include gating processes for ion channels (Siwy & Fulinski, 2002), calcium flow for neurotransmitter secretion (Lowen et al., 1997), threshold resetting for neuronal spiking (Davidsen & Schuster, 2002), the filtering properties of brain tissue for local field potentials (Leopold et al., 2003), and cardiorespiratory pulsation for fMRI data (Bullmore et al., 2001). For behavioral 1/f fluctuations, they include combinations of ongoing, independent processes of brain and body (Ding, Chen, & Kelso, 2002; Pressing & Jolley-Rogers, 1997), and quirks of specific processes such as attention or cognitive control (Wagenmakers, Farrell, & Ratcliff, 2004).

The metastability hypothesis is different from domain-specific accounts in that metastability predicts a *pervasive* quality to 1/f scaling, whereas domain-specific accounts do not. This pervasiveness comes from the fact that critical phenomena result from the way system components interact with each other, not any particular system component or process. Moreover, the components can be cells, brain areas, body parts, or entire organisms, because metastability is hypothesized to hold across scales of analysis. Thus potentially many distinct series of 1/f fluctuations should be observable across different measures of intrinsic fluctuation taken from systems near their critical points. By contrast, domain-specific accounts posit that 1/f fluctuations come from isolable, oftentimes singular, sources. For instance, Wagenmakers et al. (2004) proposed a simple model whereby shifts in strategy or attention might generate 1/f fluctuations. In this case, only one or possibly two distinct series of 1/f fluctuations should be observed for any given series of behaviors.

Kello et al. (2007) tested the pervasiveness of 1/f fluctuations in the intrinsic fluctuations of key-press responses. They examined not only series of reaction times but also key-contact durations (i.e., the brief time a key is held down for a typical key-press) in a number of two-alternative forced-choice experiments. In each experiment, the authors found two distinct and separately perturbable streams of 1/f fluctuations in these two parallel measurement series. Extant domain-specific accounts predict only one source of 1/f scaling, and hence only one source of 1/f fluctuations in key-press responses. Metastability predicts pervasive 1/f scaling, which naturally accommodates findings of parallel yet distinct series of intrinsic fluctuations.

Nonetheless, Kello et al. (2007) acknowledged that domain-specific accounts might still be formulated *ad hoc*. Although it does not appear plausible to assign attentional versus strategic shifts to reaction times versus key-contact durations, one might instead propose that 1/f fluctuations come from decision-making processes in reaction times, and motor processes in key-contact durations. The authors argued against this kind of domain-specific account, but it is difficult to rule out all such accounts on the basis of only two parallel series of intrinsic fluctuations.

Here we provide a more stark contrast between the metastability hypothesis and its domain-specific alternatives. We conducted an experiment in which intrinsic fluctuations were elicited in repetitions of the spoken word *bucket*, rather than key-press responses. The word “bucket” was used because its acoustic syllables could be automatically separated and each spectrally analyzed to yield many parallel intensity estimates across a wide range of acoustic frequencies. Intensities fluctuated across repetitions, and the individual series of intensity fluctuations were analyzed for 1/f scaling. Also, mutually orthogonal series were extracted from the multivariate data in order to test for many parallel yet linearly independent 1/f fluctuations.

If 1/f scaling pervades intrinsic fluctuations as predicted by the metastability hypothesis, then all fluctuation series should follow the 1/f scaling relation, including as many linearly independent series as allowed by the articulatory and acoustic properties of “bucket”. By contrast, domain-specific accounts posit isolable, individual sources of 1/f scaling (e.g., the combination of factors, attention, strategic control, motor timing, etc.). Therefore a linearly distinct source must be posited for each parallel yet linearly independent series of 1/f fluctuations. The viability of domain-specific accounts diminishes as the number of distinct series of 1/f fluctuations increases. Such ad hoc accounts lose explanatory power because a new source must be posited arbitrarily for each new series of 1/f fluctuations.

2. Experiment

2.1. Method

2.1.1. Participants

Five male and five female undergraduate students 18 to 27 years of age participated in the experiment for course credit. All reported having normal hearing from birth.

2.1.2. Apparatus and procedure

Utterances were transduced by a head-worn cardiod microphone in a quiet room, and digitally recorded at 44 kHz using the Logic Pro audio software on an Apple computer. Using earbud headphones, participants were presented with an audio tone every 1,200 msec, and they were instructed to pronounce the word bucket in a normal speaking voice each time the tone was presented. After a short practice session, a block of 1,150 utterances was recorded for each speaker.

2.1.3. Data preparation

Each recording was visually inspected for noise artifacts that would interfere with acoustic analyses, and these artifacts were removed along with the affected word utterances. Of the remaining utterances, the initial ones were discarded so that 1,024 remained for further analysis. Initial utterances were discarded to minimize any possible start-up effects, and the number of utterances needed to be a power of two for the upcoming spectral analyses. A total of 1,024 utterances was chosen in order to cover three orders of magnitude, which is a rule of thumb needed for reliably estimating a 1/f scaling relation.

After normalization of audio levels across speakers, each series of word utterances was segmented into two series of syllable signals, one for “buck” and one for “ket.” Syllable signals were segmented using the automated segmentation tool (with default parameters)

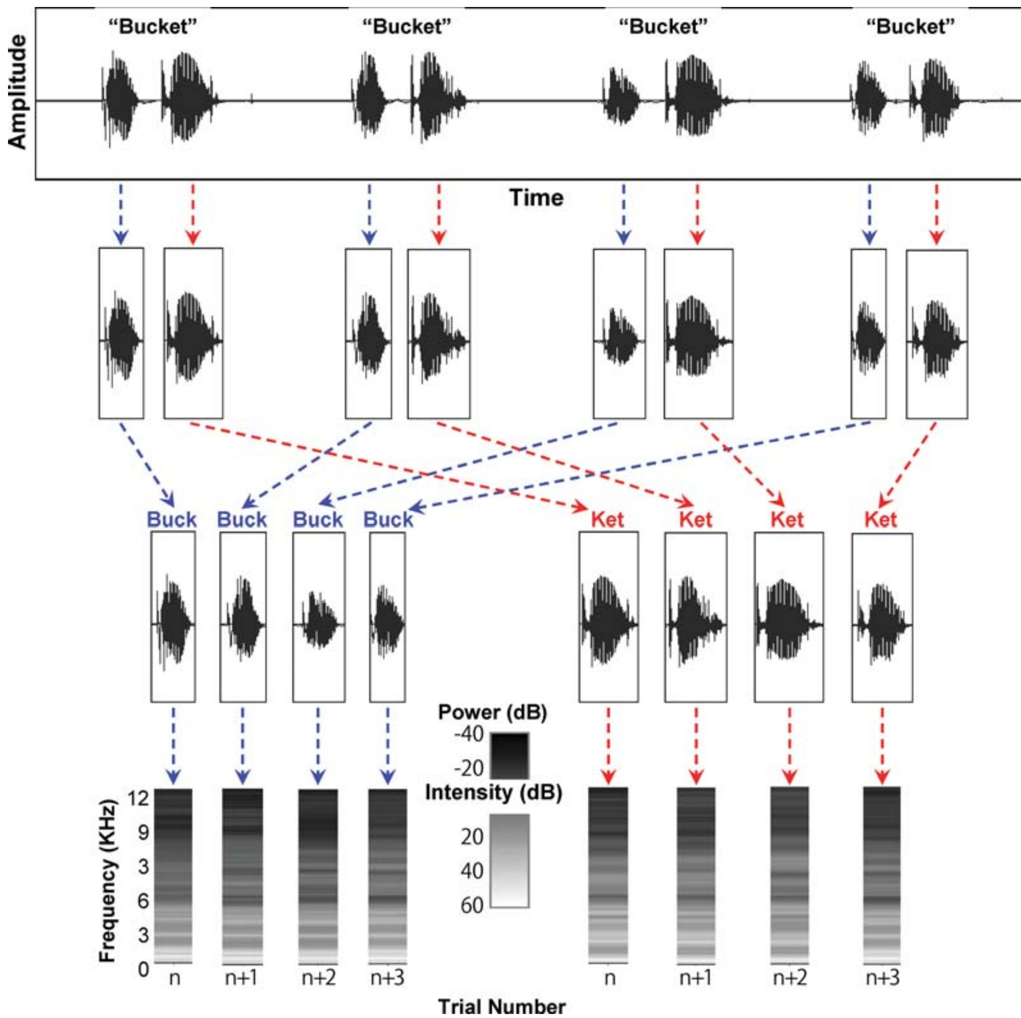

Fig. 2. Sample acoustics and analysis diagram. *Note:* At the top is plotted the acoustic waveform of four consecutive utterances of *bucket* for 1 participant. Acoustic energy thresholds were used to automatically segment the syllables (upper middle), and one series of "buck" syllables and one series of "ket" syllables was extracted for each speaker (lower middle). A long-term average spectrum was computed for each syllable waveform (bottom) resulting in 45 intensity estimates with frequency bands 300 Hz wide and center frequencies from 150 Hz to 13,350 Hz.

that is part of Logic Pro. Then, using the Praat speech analysis software (Boersma & Weenink, 2000), a long-term average spectrum was computed for each syllable signal using 300 Hz frequency bands with center frequencies evenly spaced from 150 Hz to 13,350 Hz (see Fig. 2). The result was 45 intensity estimates per syllable, 90 intensity measurements per spoken word, and 90 measurement series per speaker (see Fig. 3). Bin width was chosen to be just large enough to integrate over harmonics in the acoustic signal that create unwanted variations in measurements across frequencies. The upper frequency cutoff was chosen by inspection to be near the point at which the speech signal fell below noise.

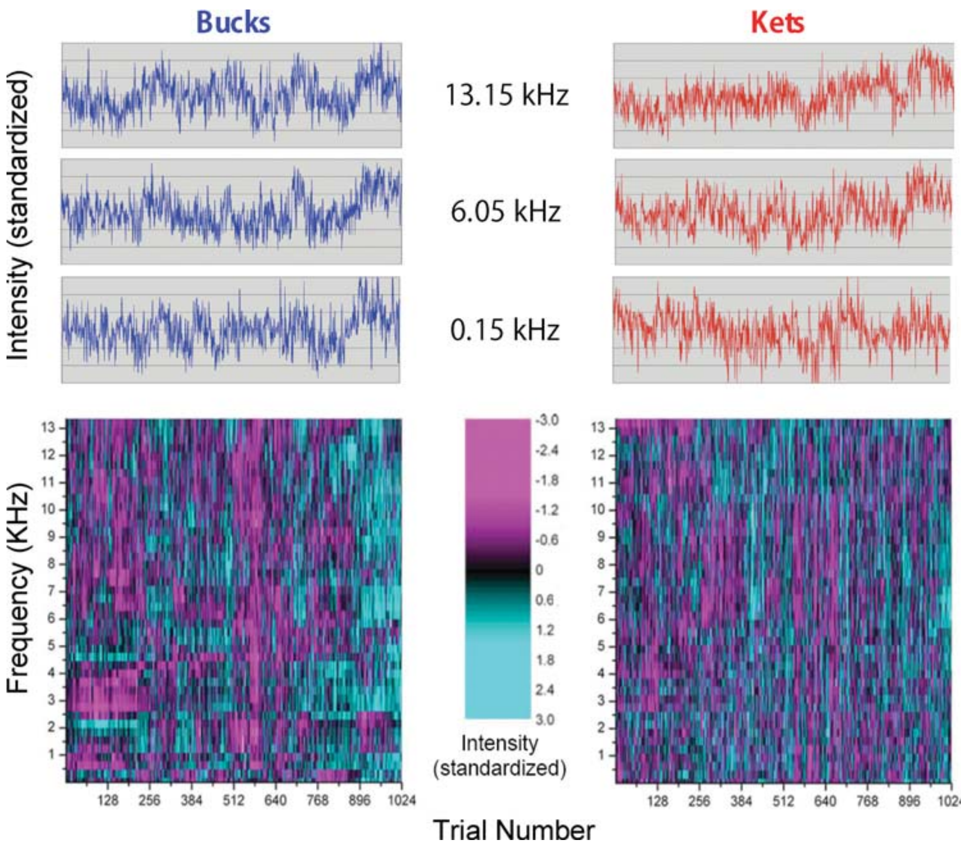

Fig. 3. Sample series of intensity measurements. *Note:* At the top are plotted three example fluctuation series of intensity estimates at three different frequencies, for each syllable and for the same participant as in Fig. 2. To visualize this participant's full pattern of fluctuations, all 45 intensity series for each syllable are plotted as two spectrograms. Intensity is coded using a magenta–black–cyan color scale, and the trial series is on the *x* axis. The spectrograms show that intensity fluctuations were temporally non-random and yet non-identical across frequencies. Spectrograms for other participants are part of the online supplemental materials, as are randomized trial series that serve as baseline comparisons. All participants showed qualitatively similar patterns of intricate structure across the intensity series.

2.2. Results

2.2.1. 1/f scaling analyses

In most observations of 1/f fluctuations, the 1/f scaling relation is often "whitened" in the higher frequencies (i.e., it is intact in the lower frequencies, where most of the 1/f variance is represented), but there is more power in the higher frequencies than expected if one extrapolates from the 1/f scaling relation in the lower frequencies. Whitening is at least partially explained by the fact that measurement errors (e.g., due to imprecision in equipment and protocol) are likely be independent from one measurement to the next. The resulting white noise, when added to 1/f fluctuations, will have its greatest effect on the highest frequencies because power is always least in the highest frequencies of 1/f fluctuations. Therefore, high-frequency whitening does not undermine a 1/f scaling conclusion, but it does complicate estimation of the $1/f^{\alpha}$ scaling exponent.

To account for high-frequency whitening, Thornton and Gilden (2005) developed a method for fitting a "fractional Brownian motion plus white noise" (fBmW) model to time series data averaged in the frequency domain (fractional Brownian motion corresponds to $1/f^{\alpha}$ scaling with variable α). The two free parameters are the 1/f scaling exponent (α) and the amplitude of white noise (β), and the model allows one to estimate α while accounting for whitening with β. The authors argued that the fBmW model provides a better account of intrinsic fluctuations in human behavioral data compared with short-range correlation models, which are often-cited alternatives to 1/f scaling (Farrell, Wagenmakers, & Ratcliff, 2006; Wagenmakers et al., 2004). Here, we use the fBmW model to estimate scaling exponents while taking into account measurement errors that add white noise to data.

In order to use the fBmW model, first a composite spectrum was computed for each individual series of 1,024 spectral intensities, for each participant and each syllable. Each composite spectrum consisted of eight power estimates divided among eight octave-sized frequency bins that spanned the full range of measurable frequencies given the number of data points. Thornton and Gilden's (2005) maximum likelihood method was used to find the best-fitting α and β parameters for each composite (the method was also used to fit short-range correlation models, but the fBmW model was found to be more likely overall given the data; see Appendix). The distributions of parameters are shown in Fig. 4, collapsed across participants and syllables.

Both distributions were approximately normal, and the scaling exponent distribution had a mean of 1.06, which is near ideal 1/f scaling ($\alpha = 1$). Also, scaling exponents fell well within the lower bound of ideal white noise ($\alpha = 0$) and the upper bound of ideal brown noise ($\alpha = 2$). White noise fluctuations are uncorrelated from one measured value to the next, and brown noise fluctuations are just the running sum (integration) of normalized white noise. 1/f scaling is categorically distinct from white and brown noises because only 1/f fluctuations

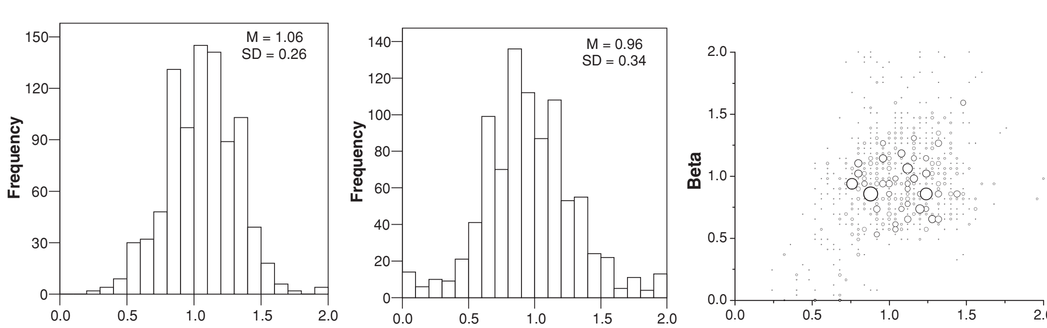

Fig. 4. Distributions of model parameter fits. *Note:* Thornton and Gilden's (2005) model was used to estimate the scaling exponent (α) and amplitude of white noise (β) that best characterized each composite spectrum. The resulting α and β frequency distributions are plotted, collapsed across acoustic frequencies, syllables, and participants. Their joint distribution is plotted with circle diameter representing frequency count.

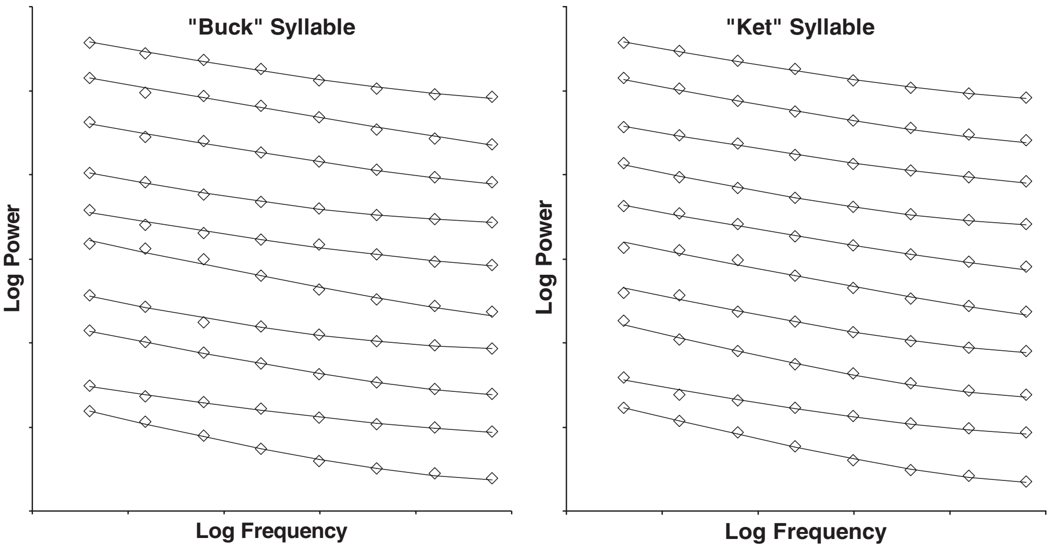

Fig. 5. Average composite spectra for each syllable and participant. *Note:* The 45 composite spectra for each syllable and each participant were averaged together, and each composite per syllable ("buck" left and "ket" right) and per participant (10 participants, top to bottom) is plotted in log–log coordinates (open diamonds). Participants' composite spectra are separated in each graph by log units for the sake of visibility. The fBmW model was fit to each plotted composite, and the resulting model spectra are shown by the solid lines.

exhibit *long-range correlations* (i.e., each measured value is, in the limit, a function of past measured values extending arbitrarily far in time; see Bak, 1996; Sornette, 2004).

The distribution of white noise amplitudes indicates that, as expected, the observed scaling relations were somewhat whitened in the higher frequencies. To better see this effect, composite spectra were averaged over all 45 measurement series per syllable per subject, and each of the 20 resulting averaged spectra is plotted as a function of frequency in Fig. 5. Every spectrum shows a negative linear trend in log–log coordinates (indicating a scaling relation) and for most of them, the slope of the trend is slightly shallower in the higher frequencies (this whitening appeared less than for typical reaction time data). The figure also shows that the fBmW model provided a close fit to each participant's averaged data.

2.2.2. Mutually orthogonal fluctuations

The model fits and resulting α and β parameters indicate that all intensity fluctuations for all participants tended to follow a whitened 1/f scaling relation. The lawfulness of this finding is striking when one considers that the individual time series were mostly different between syllables and acoustic frequencies. Differences can be seen, for instance, in spectrograms of one participant's data shown in Fig. 2 and in spectrograms for all the other participants reported in the online supplemental materials. One can see that fluctuations align in some regions of the acoustic space for a given syllable, but overall they differ between syllables and at sufficiently disparate acoustic frequencies. In terms of linear relations, this heterogeneity of fluctuation is depicted by correlation matrices, shown for one participant in Fig. 6 and in the

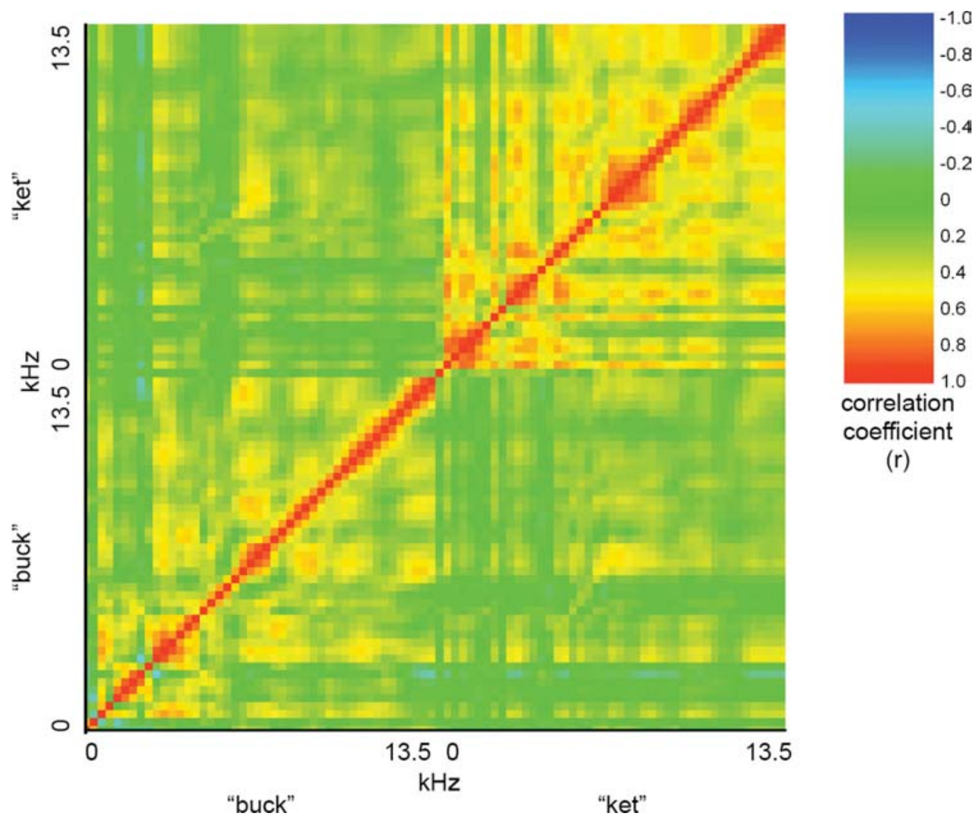

Fig. 6. Sample intensity correlation matrix. *Note:* The correlation matrix for one participant's set of 90 intensity fluctuation series is plotted, organized by syllable and by acoustic frequency within syllables. Fluctuations at nearby frequencies were strongly positively correlated (red squares along the diagonal), with certain frequency ranges showing greater concentrations of correlation than others (e.g., large red square about midway through the "ket" frequency range). Also, correlations were generally more positive within syllables than between them (i.e., more red in the bottom left and upper right quadrants).

supplemental materials for other participants. This heterogeneity suggests that 1/f fluctuations in speech do not have a single, linearly isolable source; instead, they appear to pervade the intrinsic fluctuations of speech.

To examine more explicitly the pervasiveness of 1/f scaling, we used principal components analysis (PCA) to determine the mutually orthogonal sources of 1/f fluctuation that can be extracted from each participant's multivariate data set. Each participant's set of 90 fluctuation series was subjected to PCA using the covariance method without rotation, and all 90 principal components were retained (i.e., 100% of the variance in each set). Each original set of fluctuations was projected onto its principal component basis to create 90 mutually orthogonal fluctuation series, each one aligned with one of the components and ordered from most to least variance accounted for. These fluctuations were then subjected to the same 1/f scaling analyses as described earlier, resulting in 90 pairs of α and β parameters per participant.

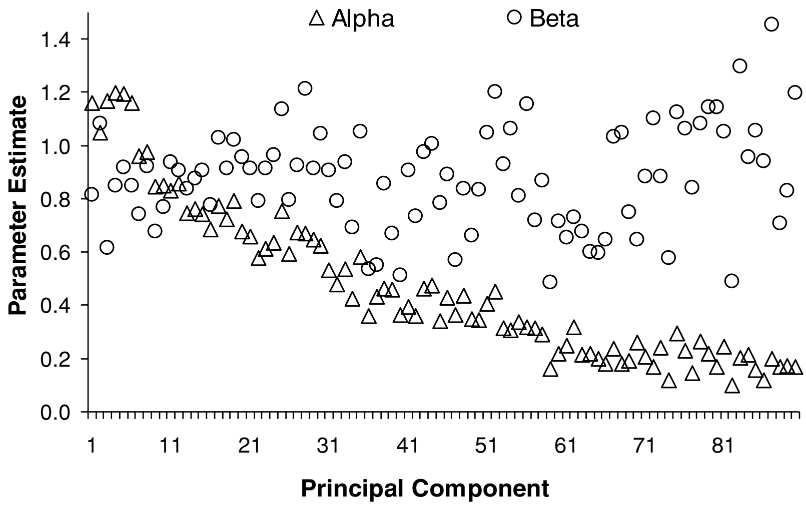

Fig. 7. fBmW model fits to mutually orthogonal fluctuations. *Note:* Mean α and β estimates for composite spectra plotted as a function of principle component, where each data point is averaged over participants. Principle components are ordered from most to least variance accounted for.

Parameter estimates for each principal component are plotted in Fig. 7, averaged over participants. The figure shows that the strongest components of the data also exhibited the most ideal expression of 1/f scaling (α closest to 1), and that α fell toward zero gradually as components decreased in significance (i.e., accounted for less and less variance; an exponential decay function provided a close fit to the trend: $\alpha = 1.111e^{-0.023x}$, where x is principal component rank, and $R^2 = 0.91$). Also, α was greater than 0.5 for the top 30 orthogonal fluctuation series, which on average accounted for 90% of each participant's data. $\alpha > 0.5$ has been reported as indicative of 1/f scaling in previous studies of human behavioral fluctuations). Thus we can conclude that the large majority of variance in "bucket" fluctuations followed a 1/f scaling relation. Moreover, if one assumes isolable sources of 1/f fluctuations, then about 30 such sources would need to be posited in order to explain this variance. β estimates were more variable and did not appear to change as a function of principal component, which is expected if fluctuations are whitened by random and independent sources of measurement error.

3. General discussion

We conclude from our results that 1/f scaling pervades the fine-grain, intrinsic fluctuations of a repeatedly spoken word. Pervasive 1/f scaling is predicted by the metastability hypothesis, which states that cognitive functions organize and reorganize as spatiotemporal patterns of activity spanning brain, body, and environment. Metastability is known to be a property associated with systems near critical points, and 1/f scaling is predicted to pervade the fluctuations of systems near their critical points (Usher et al., 1995; Zhang & Liang, 1987). The pervasiveness of 1/f scaling in speech stands as evidence against domain-specific accounts of 1/f scaling in human behavior, because one would need to arbitrarily posit many distinct sources of 1/f fluctuations that manage to express themselves individually in the repetitions of a spoken word.

The pervasiveness of 1/f scaling in speech activity is analogous to its pervasiveness in neural activity as expressed by intrinsic fluctuations in single-cell recordings and fMRI voxels (Bhattacharya et al., 2005; Thurner et al., 2003). Whether one measures behavioral or neural expressions of cognitive function, the key to eliciting 1/f fluctuations is to hold conditions as constant as possible from one measurement to the next. In fact, fluctuations in neural activity from one utterance of "bucket" to the next should also exhibit 1/f scaling, but these fluctuations are not likely to be directly expressed in measures of acoustic fluctuations. Acoustic variation is nonlinearly related to kinematics of the speech apparatus (Stevens, 1989), and kinematics are likely to be nonlinearly related to whatever neural activity is involved in their production. Thus 1/f scaling in speech and neural activity suggests that a general principle is at work across these levels, rather than a single source of 1/f fluctuation being reflected in both speech and neural activity. For instance, it is not that the cerebellum, or any other single isolated neural structure, is broadcasting a 1/f signal that is detectable in both neural and behavioral activities.

Despite the pervasiveness of 1/f scaling, one might argue that intrinsic fluctuations are too peculiar to support such general conclusions; after all, strictly repetitive behaviors are not typically found in the laboratory or in the wild. Nonetheless, 1/f fluctuations have so far been found in every task domain of cognitive science where intrinsic fluctuations have been measured, and intrinsic fluctuations can be measured from any neural or behavioral system. Thus, the same systems that produce intrinsic 1/f fluctuations also produce more natural acts of cognition. This fact leaves us with two related questions: (a) What principles are universal to neural and behavioral systems, at all scales, such that they produce 1/f fluctuations under conditions of intrinsic fluctuation; and (b) How do these principles inform theories of cognition in traditional domains such as perception, memory, attention, and language?

Metastability is our proposed answer to the first question, but more empirical and theoretical work is needed to investigate the kinds of systems that have metastability as a pervasive property, and the kinds of measurement conditions that elicit intrinsic fluctuations. As for the second question, we suggested how metastable patterns are responsive to changing conditions and may thus provide a foundation for theorizing about the flexible, situated nature of cognition (Van Orden, Kello, & Holden, in press). For instance, language is notorious for its flexibility and context dependencies that have thus far confounded traditional notions of representation and processing (Elman, 2005; Fowler & Saltzman, 1993). Metastability may play a foundational role in developing theories that accept the flexibility and contextuality of language as a first principle. Language processes would be simulated as metastable patterns of activity that organize and reorganize in response to changing conditions.

As a final note, the potential value of metastability for cognitive science was demonstrated by two recent neural network modeling studies. In one, Kwok and Smith (2005) built a model that solves combinatorial optimization problems like the famous traveling salesman problem. The model has a parameter that governs the strength of interaction among neural components. Network performance was found to be optimal near the point of criticality because the resulting metastable states enabled the model to most effectively search the problem space for globally optimal solutions. In the other study, Bertschinger and Natschlager (2004) examined the effect of criticality on the computational power of neural network models, where power is defined in terms of the complexity and diversity of the input/output mappings that can be processed (see also Langton, 1990; Packard, 1988). Their networks consisted of randomly connected thresholding neurons, and criticality was assessed as a balance of convergence (order) and divergence (chaos) in network dynamics. When trained as classifiers, the networks' ability to discriminate among classes was greatest at the critical point. It remains to be seen whether such models can be adopted to simulate human cognitive functions.

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Appendix

Thornton and Gilden (2005) developed a maximum likelihood method to test between two qualitatively different models of time series data, one being fractal long-range correlation models and the other being short-range correlation models. The authors used the fBmW model described in the Results section as the canonical long-range correlation model, i.e.,

$$O_{\mathrm{t}} = \mathrm{fractal}(\alpha)_{\mathrm{t}} + \mathrm{white}(\beta)_t|,$$

where O_{t} is the series value at time *t,* and fractal (α) and white (β) are functions that stochastically generate $1/\mathrm{f}^{\alpha}$ series and white noise series with amplitude β, respectively. They used the autoregressive moving-average (ARMA) model as the canonical short-range correlation model, i.e.,

$$O_{\mathrm{t}} = \phi O_{\mathrm{t}-1} + \varepsilon_t + \theta\varepsilon_{t-1}|,$$

where ϕ and θ are free parameters that govern the autoregressive and moving-average components, respectively, and ε is a source of white noise.

ARMA and fBmW models will generate statistically similar time series under certain parameterizations, although fluctuations of the former have a characteristic time scale, whereas fluctuations of the latter do not (for in-depth discussions, see Thornton & Gilden, 2005; Wagenmakers et al., 2004). Any given set of parameter values in either model will generate a distribution of fluctuations. From a predefined space of parameter values, the maximum likelihood method chooses the set that is most likely to generate fluctuations with the spectral characteristics of an observed fluctuation series. Thus, in a Bayesian sense it finds the best parameter fit for each model given the data, and the best fit overall.

The two-dimensional parameter space for each model consisted of 2,500 evenly spaced points. For the fBmW model, α and β each ranged between [0.0, 2.0]; and for the ARMA model, ϕ ranged between [0.1, 0.95]; θ ranged between [–0.9, 0.0]. Of 900 composite spectra (90 fluctuation series for each of the 10 participants), 748 (83%) were more likely to be generated by the fBmW model compared with the ARMA model (mean fBmW likelihood = 51.9, mean ARMA likelihood = 47.6; for method details, see Thornton & Gilden, 2005). Given the model fits shown in Fig. 5, we conclude that the fBmW model provides a very close account of the data that is superior to the ARMA model.