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The Fractal Structure of Extended Communicative Performance

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Abstract

How does the mind sustain lengthy, continuous performances? Cognitive processes are continuous, dynamic and adaptive. However, until recently, we didn't have the methodological tools to study these features. In this study, we use Detrended Fluctuation Analysis (DFA) and a sliding window, to analyze the change in the fractal structure of body movement during the delivery of an academic lecture. We show that fractal structure varies widely during performance but also reveals a strong attraction towards 1/f noise. Our analysis also uncover a general inverted U pattern in the fractal organization of the performance: speakers exhibit relatively low exponents (i.e., less structure) at the beginning of their talk, that then increase as they get into their performance, and then decrease again as they finish their narration. This trajectory mirrors the familiar idea of academic lectures as performances in which we set up an argument, develop that argument, and conclude that argument.

Keywords: 1/f noise; fractal exponents; video analysis; communication; dynamic systems.

Introduction

Human cognition happens as a continuous stream from the moment we wake up to the moment we go to sleep. Our cognitive system goes from one activity to the next, engaging series of functions at multiple timescales, intertwined in interactions with the body and world, as a performance ever unfolding over time. The continuous and embedded nature of cognition makes it difficult to parse and isolate functions for study, so experimentalists typically use trials containing brief tasks separated by short breaks (Spivey, 2008). These snapshots of performance afford experimental control, and averaging over trials yields general patterns in how cognitive systems perform these isolated tasks.

One of the many properties and principles to come out of this rich tradition of experimental research is that cognitive performances are exquisitely context-dependent (Van Orden, Holden & Turvey, 2003; Kello, Brown, et al., 2010). Despite these robust findings, the focused nature of experimental research leads one to ask how these findings may apply in natural continuous performances, beyond the laboratory and often under more complex and less controlled contexts (cf. Kingstone, Smilek, & Eastwood, 2008). The way in which the cognitive system sustains its performance over time in complex tasks is a fundamental question in our field. The way the mind dynamically adapts to changing goals and environments, the way it structures itself to perform tasks as varied as solving the tower of Hanoi or cooking a delicious meal—all have been on cognitive science's "to-do list" from the beginnings of the discipline (Simon, 1962, 1992). In this paper, we present an analysis of the unfolding dynamics of a complex cognitive activity. Indeed, it is one that readers of this paper are probably quite familiar with: giving an academic talk.

Talks are dynamic on many levels (Abrahams, 2016), but in terms of physical activity, they involve systematic variations in the amplitude and rate of speech, gestures, and other movements that accompany the delivery of the message (Alviar, Dale, & Galati, under revision). Talks are also multimodal. They involve the use of verbal and non-verbal elements (Abraham, 2016), as well as the use of technology and objects in the environment for the creation and transmission of meaning (Pozer-Ardenghi & Roth, 2010). Talks involve covariation between modalities that suggests the existence of system-like patterns in the way speakers coordinate different signals during lecturing (Alviar et al., under revision). Lastly, the delivery of a speech when giving a talk exhibits hierarchical temporal structure that differs from the structure found in other communicative activities like conversations. At the same time, the same type of nested structure, seems to be common to the act of delivering a monologue presentation, irrespective of its topic or language (Kello et al., 2017).

There are a variety of methods that could be used to capture nested structures in talks and other cognitive performances (see Riley & Van Orden, 2005). Fractal methods stand out in that they gauge nested structures explicitly in terms of quantifiable fractal exponents. Fractals describe the correlation and self-similarity of behavior at different spatial or temporal scales. That is, they describe the relationship between the patterns of variation observed at larger and smaller scales of analysis (Van Orden et al., 2003). Indeed, Van Orden and colleagues (2003, 2011) have argued that fractal structure can reveal smooth coordinated behavior in a system; in other words, when its many parts are working together to sustain complex and time-extended behaviors.

Recent work has looked to the *variation* in fractal exponents to further examine how they reflect cognitive processes. Anastas, Stephen, and Dixon (2012) used fractal exponents to study executive control and rule discovery in a categorization task. The authors applied Detrended Fluctuation Analysis (DFA) as they slid a window over time series of measurements taken from the participants' hand

movements while sorting cards into groups. Participants that had to infer the sorting rule exhibited a series of fractal exponents that followed an inverted U pattern: The fractal exponent increased as the participants explored candidates for the sorting rule and decreased again as they constrained their behavior to comply with the inferred sorting condition. Similarly, in an earlier study of mathematical discovery, Stephen, Dixon, and Isenhower (2009) found that the entropy (i.e., disorder) on hand movement variation increased right before a new representation of a mathematical problem was achieved. From these examples, it seems like changes in scaling exponents are a common feature of cognitive performance and foretell qualitative changes in the organization of the cognitive system.

The studies by Stephen and colleagues demonstrate how time series of fractal exponents can shed light on the dynamics of cognitive processes over timescales on the order of minutes. To date, most studies of fractal structure in behavior and cognition have analyzed relatively short performances coming from experimentally collected data.

In the present study, we use time series of fractal exponents to examine the dynamics of a longer, more natural cognitive performance: academic lectures. Curiously, this complex behavior is a widely documented one, often recorded under relatively stable camera positions and reasonable audio-video quality. It is also easily accessible, with many available online, including our own seminar series from University of California, Merced. By using automatically extracted body-motion time series, we can obtain precisely the type of time series that allow the study of fractal dynamics. Our goal was to examine whether there are common patterns of change in fractal exponents over the course of a continuous cognitive performance, akin to the U-shaped pattern found by Anastas et al. (2012). In other words, an academic talk may show this kind of shift towards more fractal organization as speakers transition into their performance. Then, as a talk wraps up, that structure may dissipate as a speaker completes the complex performance. If so, then fractal dynamics can usefully describe cognitive processes that are organized to sustain longer and complex natural performances over time.

Method

Video Recordings

We reanalyzed data from a previous study (Alviar et al., under revision) that contains information on the variation of different communication modalities during the course of an academic lecture. The dataset contains repeated measurements of 30 speakers who participated in the Mind, Technology and Society seminar series at UC Merced. Because prior work from Stephen and others has shown that body motion can reveal interesting fractal structure in the lab, and reflect relevant cognitive processes involved in communication (Paxton & Dale, 2013), we used a similar measure here. As detailed below, we used an automatic optic-flow analysis over videos of academic talks to obtain the body movement of these speakers. There are 30 talks in the dataset (22 men), with an average duration of 56.45 minutes (SD = 10.21 min). The video recordings of the talks do not include the Q&A portion of the seminar. The selected talks were of sufficient video and audio quality to be suitable for automated analysis (for detailed information on inclusion criteria, see Alviar et al., under revision). The analyzed videos are publicly available in Vimeo[1] and YouTube[2].

Procedures

Body Movement Data We downloaded the videos from YouTube and Vimeo in the best possible quality using the iSkySoft Video Downloader (i.e., 1080p for YouTube videos, and 360p for Vimeo videos), and then converted them to AVI format using the Any Video Converter. The Optical Flow Analyzer (Barbosa et al., 2008) was then used to obtain the mean pixel change between frames of the video for an area of interest demarcating the speaker's position in the video during most of the lecture (see Figure 1). The speaker's area of interest was set up to included as much of the space in which the speaker was present during the video recording as possible, while also avoiding any overlap with the other moving parts of the video (i.e., the slides). In most videos, at least a part of the speaker was always present within the speaker area. However, in some cases, the speaker did step out of the defined area of interest. During these occasional brief periods the movement data was lost.

The Flow Analyzer compares the current frame of the video with the previous one, and tracks the direction and the magnitude of the displacement of each pixel within the defined area of interest. Then, it computes the sum of each of the pixel vectors and returns a vector reflecting the overall pixel change within the selected area. As the camera was kept fixed in the same position during the entire recording, the

Figure 1: Screenshot of the Optical Flow Analyzer showing the placement of the speaker's area of interest (green square at the bottom left).

[1] https://vimeo.com/user8418321
[2] www.youtube.com/channel/UCRcuWjRqxZ2RHvEdZGAliWw/videos?shelf_id=0&view=0&sort=dd

pixel displacement in the area enclosing the speaker serves as a measure of the speaker's movement. A time series of the amount of movement at each frame of the video (25 frames/s) was obtained for each one of the 30 speakers. During extraction of these data, we also validated this automated measure with human observers (Alviar et al., under review), showing that the algorithm identifies the presence or absence of body movement in agreement with human judges with about 93% accuracy**.**

Detrended Fluctuation Analysis (DFA) DFA (Peng et al., 1995) is a fractal method that quantifies the statistical self-similarity of the variability of a signal across different time scales. It allows detection of long-range correlations in a signal, which indicate long memory processes of a system. This is achieved by fitting polynomials of different orders (usually first-order) to an integrated time series that has been divided up into non-overlapping bins of different sizes (increasing by powers of two). The relationship between bin size and mean variability of the residuals for each bin size determines the scaling exponent that describes the behavior of the time series. Specifically, the slope of the line that better fits the relation between logged variability and logged bin size, is the Hurst exponent (i.e., the scaling exponent). Ihlen (2012) and Kelty-Stephen et al. (2013) provide good tutorials discussing the mathematical details behind this technique.

DFA is a highly sensitive analysis to the influence of outliers in a time series. For this reason, before running DFA on each signal, we logged transformed each time series to obtain normally distributed measurements, and to also diminish the influence of the outliers on the analysis. To track the change of the fractal exponent over time, we slid a window across the time series and performed DFA in segments of 2048 data points (81.92 s) at a time. We were interested in having a time series of 512 Hurst exponents after the windowed analysis. This, combined with the differences in the length for each of the selected talks, resulted in variable step sizes for each speaker. The resulting step sizes ranged from 93 to 232 data points (*M*=159.43; *SD*=29.76). This created variable overlap between windows as well, with a maximum overlap of 95.45% and a minimum of 88.67% (*M*=92.21%; *SD*=1.4%). A variable overlap was preferred over a variable length in the resulting time series, as this made it easier to align and compare relative times during talks, such being a quarter way, halfway, and three-quarters through a talk.

The window size, and the scales of interest were chosen following Ihlen's (2012) recommendations to get a stable estimate of the Hurst exponents. We had non-overlapping scales of analysis that increased in powers of two, and we used first order polynomial detrending. We performed the DFA analysis using MATLAB, and the time series of fractal exponents was saved for each speaker. Two speakers were removed from further analysis because of missing values on their resulting time series of Hurst exponents.

Surrogate Time Series We created a surrogate version of each time series by shuffling the order of their data points. The surrogates act as a baseline condition in which the temporal dependency of the observed time series is removed. This acts as a control condition that allows us to show that the structure unveiled by the analysis emerges from the temporal dependency of the data and not from possible confounding variables (Ihlen & Vereijken, 2010). We ran the DFA analysis on the surrogate time series using the same parameters that were described before.

Data Analysis

All the analysis on this paper were done over the resulting time series of Hurst exponents for both the observed data set and the shuffled one. We first collected descriptive measures of the variation of Hurst exponents for both datasets. Then, to find general trends in the variation of the scaling exponent across speakers, we scaled the individual time series and modeled their patterns of change by fitting polynomials up to the fifth order to each one of them. We treated the resulting beta coefficients as descriptive measures of the individual trends of variation. We aggregated these coefficients and performed one sample *t*-tests to see if the mean beta coefficients were significantly different from 0 and, therefore

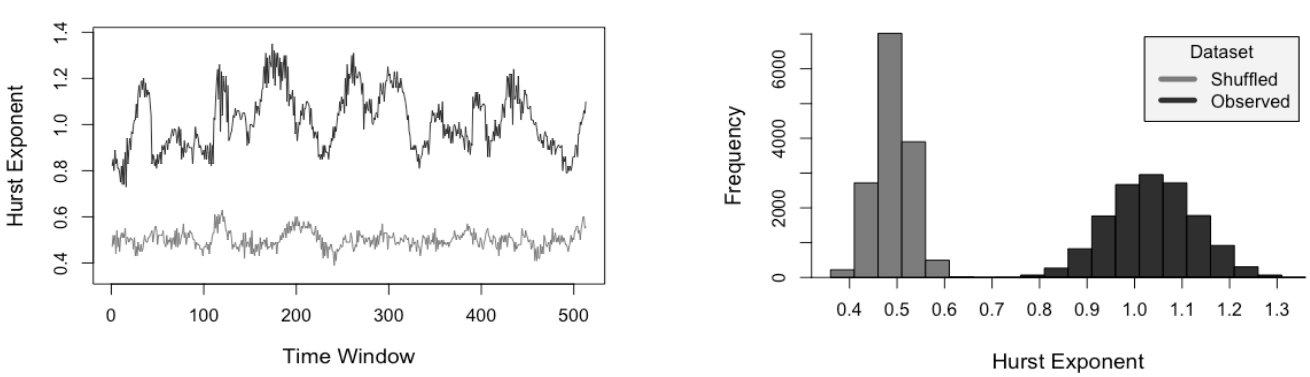

Figure 2: Example of an observed and surrogate time series for one speaker (left) and histograms showing the distributions of fractal exponents for the shuffled and the observed datasets. The surrogates are presented in lighter gray.

indicated common trends across speakers. In this way, for example, if most speakers exhibit a linear increase on their scaling exponents over time, the positive betas describing the increasing slope of the linear trend, will add up to a value significantly greater than zero.

Results

Figure 2 presents an example of a time series of Hurst exponents for one speaker and its surrogate (on the left), and the histograms summarizing the distribution of Hurst exponents across speakers for the observed and the surrogate dataset (on the right). Two significant things can be observed here: First, there is quite a lot of variation in the scaling exponents that better describe the scaling relations in performance over time. The Hurst exponents for the observed dataset vary widely, fluctuating in a range from 0.71 to 1.36 (*SD*=0.091). They also vary more than the Hurst exponents describing the scaling relations in the shuffled time series. The fractal exponents of the surrogate dataset fluctuate in a range from 0.37 to 0.65 (*SD*=0.038). Second, the scaling exponents are radically different for the observed and the shuffled time series. Fluctuation in the scaling relationships for the observed cognitive performance are centered around a mean Hurst exponent of 1.042. This indicates a variation of performance distributed strongly around the scaling exponents that indicate the existence of *1/f noise* (i.e., H~1). By their part, fluctuations in scaling exponents for the shuffled dataset are centered around a mean Hurst exponent of 0.496. In this case, variation is distributed strongly around scaling exponents that indicate the existence of uncorrelation, or what is the same, white noise *scaling* relationships (i.e., H~0.5).

As mentioned in the Data Analysis section, we performed growth curve analysis and one sample t-tests to identify regularities in the fluctuation patterns of the fractal exponents across speakers. These analyses revealed that only a negative quadratic trend systematically described the variation patterns across speakers, producing a mean beta coefficient that was significantly different from zero (Mean ß = -2.42, t = -3.36, p = .002). This suggests that the fractal exponents increase towards the middle of the performance and then decrease again as the talk comes to an end. The average variation across speakers illustrating this trend is depicted in Figure 3 (left). The quadratic polynomial is super imposed for reference.

The application of growth curve analysis and one sample t-tests to the surrogate dataset failed to show significance of any of the polynomial trends. The right panel of Figure 3, shows the average variation across the surrogate time series. The lack of patterns in the surrogate data, suggests that the quadratic trend in the observed data is a function of changes in the fractal scaling of the cognitive system during the delivery of a lecture, as opposed to other mathematical or methodological artifacts.

Discussion and Conclusions

In this study, we aimed to explore the dynamic nature of a long, continuous cognitive performance by analyzing variation in the fractal structure of movement during academic lectures. The fractal analysis revealed scaling exponents that indicated a strong attraction of the performing cognitive system towards 1/f noise. The distribution of exponents found here replicates the distribution found by Kello et al. (2008) in the analysis of the intrinsic fluctuations of speech energy when a given word is spoken repeatedly for an extended period of time. The distribution of exponents

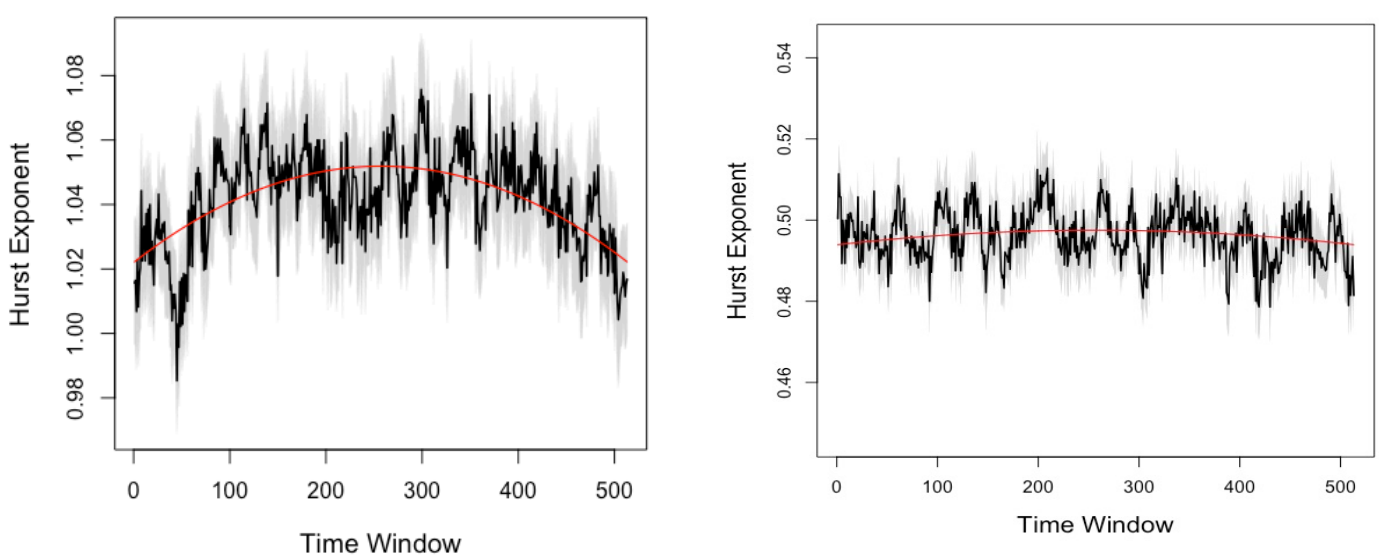

Figure 3: Overall patters of variation of the fractal exponents over time for both the observed (left) and the surrogate data set (right). The quadratic polynomials are superimposed for reference. The light gray shading shows the *SE* of the mean.

around 1/f noise also aligns with previous studies of cognitive measures like reaction times (Van Orden et al., 2003), conversational speech interactions (Abney, Kello, & Warlaumont, 2015), card sorting (Anastas et al., 2012), aiming (Wijnants et al., 2009), and even self-esteem measures (Delignières, Fortes, & Ninot, 2004). This attraction towards pink noise has been argued to be characteristic of self-organized, soft-assembled, interaction-dominant systems, whose behavior emerges from the interaction of simple units (Van Orden et al., 2003). It is thought to indicate states of self-organized criticality that favor both stability and adaptation and facilitate information transmission across the system (Van Orden, et al., 2011). Within this framework, it makes sense for the trajectory of fractal exponents of the performing cognitive systems analyzed here, to constantly hover around 1/f noise. This attraction towards pink noise, would allow the cognitive system enough stability to sustain performance, and enough flexibility to restructure and adapt to the changing demands of that performance over time.

In fact, although the resulting scaling exponents are centered around pink noise, they do vary quite widely across performance. This variation in scaling exponents is in line with findings coming from the literature exploring the multifractality of cognition (Ihlen & Vereijken, 2010). From this point of view, the multiplicity of fractal exponents necessary to describe a behavioral signal would reflect transitions of the system to new structures. The spectrum of exponents would vary widely to reflect scaling structures at both moments in which the system opens up to explore new patterns of organization, and in which it settles back down into new structural configurations that better adapt to the ever-changing demands of the environment (Stephen et al., 2009). In future investigations of these results, it would be interesting to go back to the specific of the presentations and explore if rapid changes in fractal exponents tend to happen in synchrony with changes in the environmental or task constrains. For example, it would be interesting to see if dips in the fractal exponent, like the one we see around the 50th time window (~5.3 minutes), correspond to dramatic changes in the topic, or the end of the most rehearsed part of the talk and the introduction of more complex or less established information for which the cognitive system needs to create new structures.

The analysis of variation across speakers revealed an inverted U-shaped pattern for the trajectory of fractal exponents over time. This pattern of Hurst exponents indicates that the system goes from a state of more randomness and less memory in its behavior, to a state of more rigidity and determination in which the small variations in behavior carry and reflect the history of the system more strongly at each time step. This suggests, at a dynamic level, the emergence of structures that constrain the behavior of the individual components of the system making the behavior of the system less variable and less flexible over time (Kloos & Van Orden, 2010). Towards the end of the performance, the system, finally returns to a less rigid, more adaptable state as the structures dissipate when finishing the task. In more simple words, speakers go from relatively less structured dynamics at the beginning of their talks, to more structured dynamics during the middle, and then back to less structured dynamics as their talks come to an end. This trend stands out in a nice parallel to the common organization of a talk: as we begin, we present our problem and set up for our performance, then, we get into a "groove" as we present our main argument, and then, we wrap up and finish by concluding with the last details of our narration. The cognitive performance of giving a lecture follows this same general trend of organization: setting up structure, maintaining structure, and coming out of structure. This pattern also mirrors the inverted U progression of scaling exponents found by Anastas et al. (2012) in their study of executive function, as well as the one found by Stephen et al. (2009) in their study of mathematical discovery. There are many substantial differences between the performances of card sorting versus giving a talk, most notably their lengths and degrees of heterogeneity, but all performances can be said to have a beginning, middle, and end. It makes sense that beginnings and endings may be symmetric like bookends, with the middle being different.

It is important to mention an unfortunate limitation of our study that is necessary to have in mind when interpreting the results presented here. Unintentionally, our sample includes a much higher number of men than women. This is probably a reflection of larger trends in science and academia (Ceci, Williams, & Thompson, 2011), and makes the results and analysis limited in their potential to be generalized to women's presentation styles. It is an open and interesting question if a more balanced sample would yield different conclusions. Future work should correct for the unintentional bias in our dataset.

As next steps from the present work, it would be interesting to test if this pattern shows up when measuring fractal change in the other modalities involved in communication. Would our speech be structured in a similar way than our body movement is? Would the informational flow during a talk as measured by the complexity of the language being used follow a similar trend? Also, as mentioned before, exploring specific aspects of the environment or the task during rapid changes of fractal scaling at the individual level, might be interesting to discover the types of changes that trigger reorganizations of the cognitive system during performance. As a third avenue for future exploration, obtaining information about the expertise of the presenter and collecting performance measures (e.g., learning outcomes of the audience, or overall interest or enjoyment of the presentation) and relating them to patterns of fractal variability might shed light on the organizational patterns that are behind successful presentations. Answering all of these questions might give us additional insights in the mechanisms that make sustained multimodal cognition possible.

Conclusions

In this paper, we show how fractal methods and dynamical systems accounts of the mind can be of service to study interesting questions about the continuity and organization of cognitive performance. We show that fluctuations of fractal scaling during continuous performance in a communicative task, although highly variable exhibit a heavy attraction towards 1/f noise. We also find that sustained performance during a talk shows a trajectory of fractal scaling that follows the traditional idea of a presentation as having a beginning or an introduction, a middle or main argument, and end or conclusion.

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