

Readiness-to-hand, extended cognition, and multifractality

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Abstract

A recent set of experiments of ours supported the notion of a transition in experience from readiness-to-hand to unreadiness-to-hand proposed by phenomenological philosopher Martin Heidegger. They were also an experimental demonstration of an extended cognitive system. We generated and then temporarily disrupted an interaction- dominant system that spans a human participant, a computer mouse, and a task performed on the computer screen. Our claim that this system was interaction dominant was based on the detection of $1/f$ noise at the hand-tool interface. The inference from the presence of $1/f$ noise to the presence of an interaction-dominant system is occasionally disputed. Increasing evidence suggests that inference from multifractality to interaction dominance is more certain than $1/f$ -like scaling alone. In this paper, we reanalyze the data using the wavelet transform modulus maxima method, showing that the human-mouse system displays multifractality. This reinforces our claims that the system is interaction dominant.

Keywords: perception; Heidegger; extended cognition; tool- use.

Introduction

Background

Heidegger's relevance to research in AI has been long demonstrated conceptually (Dreyfus, 1979), however, little to none has been done to incorporate his notions into empirical studies. In a former set of published experiments (see Dotov, Nie, & Chemero, 2010 for necessary details), we provided evidence for the transition in experience of tools from readiness-to-hand to unreadiness-to-hand as proposed by Heidegger's phenomenological analysis of the modes of being of tools.

When you are smoothly coping with a hammer that is ready-to-hand, the ready-to-hand hammer recedes in your experience, and your focus is on the task you are completing. A key point here is that from Heidegger's

perspective there is no need to presuppose that the place of the bones and tissues of your hand in your experience while working on a manual task is in any sense privileged relative to the place of the other tools making the task space. Your experience of the hammer is no different than the experience of the hand with which you are wielding it. This has inspired the hypothesis of extended cognition, i.e., the claim that cognitive systems sometimes extend beyond the biological body (van Gelder, 1995; Clark, 2008). Hammers and other tools that are ready-to-hand are literally part of the cognitive system. When a tool malfunctions, however, and becomes unready-to-hand, it becomes the object of concern; it is no longer part of the extended cognitive system, rather it is the thing that that the cognitive system is concerned with.

To demonstrate Heidegger's proposed transition and an extended cognitive system *is to show* that a human participant and a tool together comprised an interaction-dominant system. An interaction-dominant system (IDS) is a softly assembled system in which any part can take or lose the role of a functional unit of the system, depending upon the richness of physical coupling. Interaction-dominant dynamics can be contrasted with component-dominant dynamics more characteristic of traditional cognitive architectures (van Orden, Holden, and Turvey, 2003; Holden, van Orden, and Turvey, 2009).

In component-dominant dynamics, behavior is the product of a rigidly delineated architecture of modules, each with pre-determined functions; in interaction-dominant dynamics, on the other hand, coordinated processes alter one another's dynamics, with complex interactions extending to the body's periphery and, sometimes, beyond. Simply put, when, as part of an experiment, a participant is repeating a word, a portion of her bodily and neural resources, along with environmental support structures,

assemble themselves into a “word-naming device”. Since such IDS exhibit variability described as $1/f^\beta$ noise, its presence in an inventory of cognitive tasks is evidence that cognition is the product of a system softly assembled by virtue of interaction-dominant dynamics. Device assembly as the product of interactions within and across the temporal and spatial scales of elemental activity can account for the $1/f^\beta$ character of behavioral data. Meanwhile, assembly by virtue of rigid components with predetermined roles and fixed communication channels cannot easily explain $1/f^\beta$ noise. Thus we can take the presence of a $1/f^\beta$ long memory process at the interface between body and tool as indicative of a smoothly operating system spanning both body and tool.

Related Work

The current paper is an extension of our previous work where we generated a system that spans a human participant, a computer mouse, and a task performed on the computer screen. In Dotov, Nie, & Chemero, 2010, we perturbed the functioning of the mouse temporarily during performance of the experimental task in order to induce the frustrated, unready-to-hand mode of experiencing tools. Our claims to have generated a genuinely extended cognitive system and to have demonstrated Heidegger's transition in the laboratory setting were supported by analysis of the scaling properties of the noisy time series.

Previously our major focus was on detecting long-range correlation as indexed by the Hurst exponent, $.5 < H < 1$, a characteristic of processes exhibiting $1/f$ -like scaling. We hypothesized $1/f$ -like noise for a fluidly functioning tool (indexing readiness-to-hand) and white noise when the tool was being perturbed. Our logic can be represented schematically using Figure 1. Here, the bond was established such that $1/f$ noise is what the scientist observes in any part of the extended participant-tool system while Heidegger's concepts describe the participant's experience of the situation. Importantly, the burden of determining what is “in” and what is “outside” the system falls not on the intuitive identification of the system's border with its skin but on quantifying the richness of interaction among all sections taking part in the task space.

Additionally, we used a second “probe” to get a hint of the participants’ cognitive reorganization during the task. By having participants count backwards by three in the range of three-digit numbers while using the mouse we could detect any significant shift of attention between the two tasks; we expected that such shifts would coincide with

the perturbation, thus supporting the hypothesis that at this point a new object of attention had emerged.

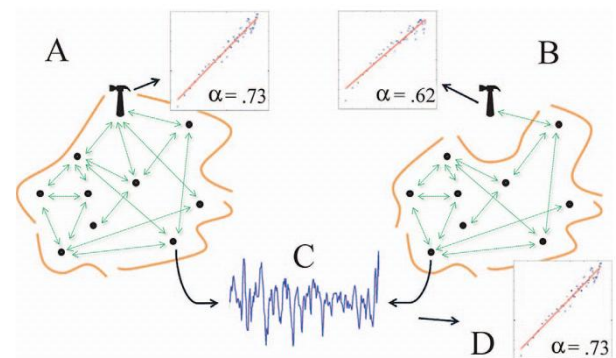


Figure 1: A schematic of a cognitive device, delineated using a border line, assembled by virtue of interaction-dominant dynamics that accordingly results in $1/f$ -like noise (C-D). In one case (A) the properly functioning tool possesses the same richness of interaction as all other parts of the fluidly assembled system and is therefore experienced as ready-to-hand, while in the other case (B) some kind of perturbation “impedes the flow”, impairing the richness of interactions and thereby causing the tool to be experienced as unready-to-hand.

As expected, along with the expected shift in attentional resources during perturbation (i.e., slower counting) we found long-range correlation in the hand-tool movements with both proper mouse and the perturbed mouse, but the scaling coefficient decreased significantly towards the white noise level during the perturbation (see Figure 2). We interpreted the two observed modes as readiness-to-hand and its impoverished version, unreadiness-to-hand. We took ourselves, therefore, as having demonstrated Heidegger's transition and as having induced a softly assembled, extended cognitive system.

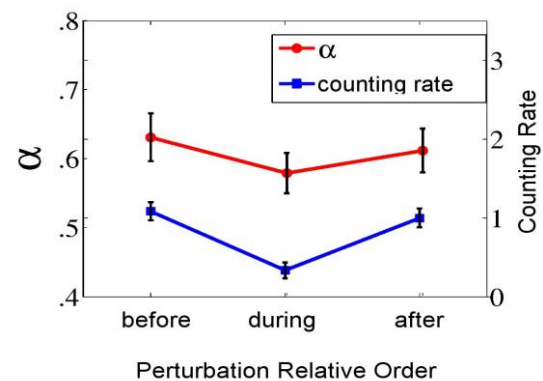


Figure 2: Averaged scaling exponents from Experiment 1 along with counting rates from Experiment 2.

Current Work

However, recent research has shown that $1/f$ -like noise can result from a component-dominant system, so $1/f$ -like noise is not sufficient to indicate that a system is interaction dominant (Thornton & Gilden, 2005; Torre & Wagenmakers, 2009). On the other hand, recent research has also shown that multifractality is more sufficient as an indicator that a system is interaction dominant (Ihlen & Vereijken, 2010). It has been shown that a single scaling exponent is insufficient to characterize behaviors of some noisy processes (Mandelbrot, 1986; Ivanova & Ausloos, 1999; Ivanov, Amaral, Goldberger, Havlin, Rosenblum, Struzik, & Stanley, 1999). For example, in the context of self-regulated biological signals, healthy heart-beat was shown to exhibit multifractal temporal scaling and the span of Hurst exponent reduced during perturbation-like periods such as congestive heart failure (Ivanov et al., 1999) and certain medicated interferences with normal heart-beat regulation (Amaral, Ivanov, Aoyagi, Hidaka, Tomono, Goldberger, Stanley, & Yamamoto, 2001).

In this paper, we subjected the data from our previous work (Dotov, Nie, & Chemero, 2010) to a necessary and more rigorous reanalysis using wavelet transform modulus maxima method. We attempted to show that the human-mouse system displays multifractal scaling indexed by a spectrum of local Hurst exponents, and, so, is based on interaction-dominant dynamics in a stronger sense.

Method

Participants (N=6 in Experiment 1) were told that the experiment was to investigate their motor control behaviors by way of their performance on two simultaneous tasks – one cognitive and one involving hand coordination with a visual stimulus. They played a video game that asked them to use a computer mouse to steer a target object to a designated area on the screen while verbally counting numbers backwards by three. To ensure participants' capability of taking effective control over the target while counting at the same time, the experimenter demonstrated doing both tasks and allowed them to practice with no mouse perturbation. Once sufficient practice trials were guaranteed six experimental trials followed.

The computer game was designed so that its mechanics resembles pole-balancing on the finger (Treffner & Kelso, 1999) where the mouse pointer acted as the point of contact between finger and pole while the target object acted as the projection of the center of mass of the pole onto the plane of the open hand. The participant was seated at a desk with the computer mouse and monitor. The virtual pole-balancing

game was played on a PC running a custom MATLAB (Mathworks, Natick, MA) script, see Figure 3. The green circle stands for the mouse pointer and is thus controlled directly by the participant and the blue circle responds to the green one based on the mapping, $\mathbf{t}_{n+1} = \mathbf{t}_n + a(\mathbf{t}_n - \mathbf{p}_{n+1}) + b\boldsymbol{\eta}$, where \mathbf{p} , \mathbf{t} are vectors of the computer screen Cartesian coordinates for the pointer and target objects, respectively, and b are experimenter-assigned parameters determined during pilot trials, and the vector $\boldsymbol{\eta}$ is a noise term taken from a pseudo-random uniform distribution. For each frame the locations of the circles are calculated and then plotted on the screen every 30 milliseconds. Approximately thirty seconds into each trial, a perturbation in the mapping between mouse movement and the pointer visible on the monitor was induced in order to trigger the transition into unreadiness-to-hand. Accordingly, the properly functioning computer mouse and pointer played the role of Heidegger's ready-to-hand tool.

Experiment 2 (N=13) shared the same design with Experiment 1 except that instead of capturing motion-data by using an optical infrared system in a different lab we audio-taped the counting task to obtain their counting rate.

Wavelet transform modulus maxima (WTMM)

A recent method of finding the distribution of the generalized Hurst exponents of a singularly-behaving signal uses wavelet transforms to locally analyze fluctuations of a certain scale and remove unwanted trends that can result in spurious results (Muzy, Bacry, & Arneodo, 1993). A singularity is a discontinuity in the trajectory that makes it impossible to be modeled locally using Taylor-expanded polynomials with integer exponents and instead requires fractional exponents. Identifying and quantifying these singularities in a times series stands for a great deal of the work accomplished in fractal analysis.

The first part of the method consists of sliding a selected wavelet function across the original series and convolving the two. This is a technique commonly used in signal-processing as a form of a band-pass filter. We follow the convention of using a derivative of the Gaussian function as a kernel. The third derivative, as used in our case, is capable of removing polynomial trends of up to a second order.

The time-scale decomposition of a signal is computed by time-shifting and amplitude-rescaling by a factor a the kernel wavelet. Convolution with a wavelet of a particular amplitude effectively results in reducing the fluctuations of the original time series to ones at a scale proportional to the scaling of the wavelet. Finally, the modulus of the maxima of the transform shows the location and strength of the

singularities in the series and, thus, a partition function $Z(a)$ of the singularities for scale a is derived (Muzy et al., 1993).

The wavelet decomposition of a signal can be represented visually by plotting the transformed signal in time versus the scale of the kernel, see Figure 4. These plots will reveal the singularities at a particular scale and for self-affine signal these singularities will form a hierarchal structure of connected lines while $Z(a)$ will scale as a power-law with respect to a .

The method described so far leaves us with a single scaling parameter. In order to check for multifractality, we need to “bias” the analysis towards fluctuations of a smaller or larger scale. This is performed using the moment q . Accordingly, we calculate $Z_q(a)$ using the q th powers of the local maxima in the wavelet transform and then we arrive at a spectrum of scaling exponents $\tau(q)$, $Z_q(a) \sim a^{\tau(q)}$. Negative values of q will stress the scaling of small fluctuations whereas positive q will stress large fluctuations (Ivanov et al., 1999) and when it is equal to two one can directly calculate the Hurst exponent H given by DFA, the analysis used in the previous study (Oświ ę cimka, Kwapi ę n, & Drożdż, 2006). For a certain class of systems it has been proven that the singularity spectrum $h(q)$, the main target of the analysis, is simply the derivative $\tau'(q)$ and, consequently, a linear relation in the plot of the fractal spectrum $\tau(q)$ versus q (see Figure 5a) reveals a constant $h(q)$ or monofractal behavior of the signal, whereas decelerating $\tau(q)$ leads to a decreasing $h(q)$ (see Figure 5b) and is the result of multifractal behavior (Muzy et al., 1993).

A final measure that is needed is $D(h_i)$, the fractal dimension of the set of zero-dimensional objects that are the indexes of the original time series where one finds singularities characterized by h_i . In the limit where the original time series consists only of singularities of kind h , their indexes form a continuous line, a one-dimensional object and, hence, $D(h)$ will be equal to unity. Here we can derive $D(h)$ theoretically from the wavelet (multi)fractal spectrum $\tau(q)$ using the Legendre transform, $D(h) = qh(q) - \tau(q)$.

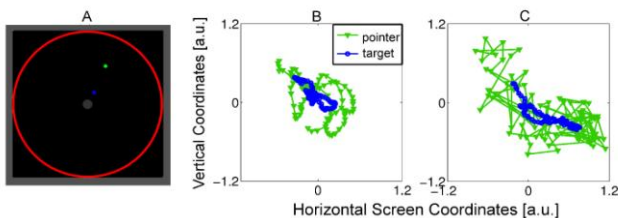


Figure 3: The visual playground environment. A single frame (a) captured during the course of a trial is shown and

visible inside it are the pen, the grey center, and blue and green circles for the target and pointer objects, respectively. Representative pointer and target object trajectories on the screen from three-second excerpts with a normally behaving (b) and impaired (c) mouse are portrayed.

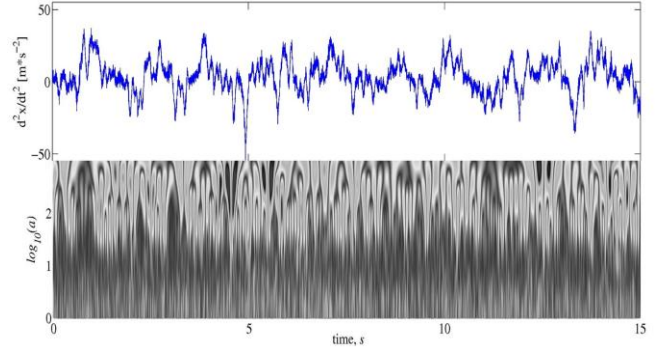


Figure 4: Using a representative 15-second section of a trial. The raw acceleration data is shown (a) along with its time-scale wavelet decomposition (b).

As a dependent measure in the current study we could use equivalently the nonlinearity of $\tau(q)$ or the range of $h(q)$. We use the latter since it is of theoretical interest generally and has also been used previously to address similar questions as ours (Amaral et al., 2001; Struzik, Hayano, Sakata, Kwak, & Yamamoto, 2004).

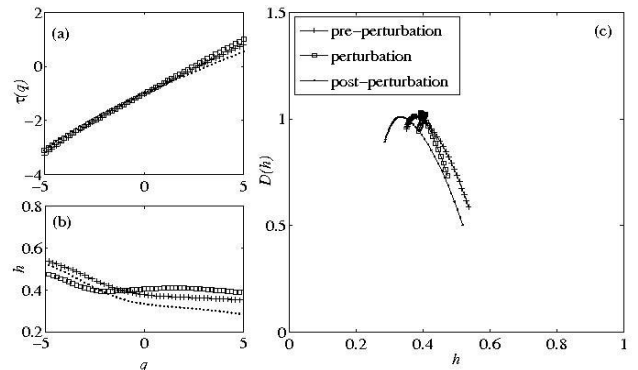


Figure 5: For a representative trial the relevant functions found from the three sections before, during, and after perturbation are plotted: (a) the wavelet multifractal spectrum as a function of moment q , (b) the corresponding singularity exponents h as a function of moment q , and (c) the fractal dimension of the singularity spectrum.

Results and Discussion

The average spread of the fractal spectrum $h_{\max} - h_{\min}$ was higher for the section before the perturbation ($M=.236$, $SD=.013$) than for the one containing the perturbation ($M=.202$, $SD=.008$) or the one following it ($M=.199$, $SD=.007$). Our expectation based on the literature reviewed

here was that in the case where the experiment had induced an interaction-dominant system that included the mouse, the perturbation would result in a narrowing of the multifractal spectrum. This effect was supported. Furthermore, it lasted well into the remaining of the trial, something we did not predict, see Figure 6. This could be explained by the taxing nature of the perturbation. Many participants reported that the two tasks made for a rather taxing exercise, and in some discarded trials participants were so absorbed by the pole-balancing task and its perturbation that they completely interrupted counting and forgot to resume after the perturbation disappeared. Notice that the average counting rate for a six-second block containing the perturbation is close to zero (Figure 2).

A two-way Repeated Measures ANOVA was performed with perturbation and trial number as factors. The main effect of perturbation was significant, $F(2, 10) = 4.22, p < .05, \eta^2 = .45$, while the effect of trial was not significant, $F(5, 25) = .73, p = .60$. Therefore the possible interpretation of the observed effect in terms of a function of time and variables such as fatigue and learning was not supported. The interaction between the two factors was not significant either, $F(10, 50) = .54, p = .86$.

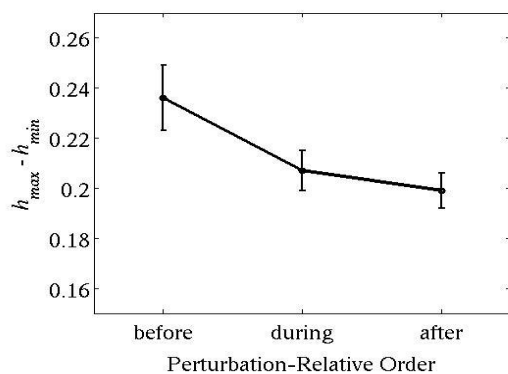


Figure 6: Averages of the multifractal spectrum range scores ($h_{\max} - h_{\text{mean}}$) as a function of perturbation-relative order.

Error bars are standard errors.

Multifractal analysis was adopted to better distinguish between genuinely interaction-dominant systems and other models that generate $1/f$ scaling; it also allowed behavior on longer and larger scales that has an anti-persistent character into the analysis. Liebovitch and Yang (1997) pointed out that the characteristic cross-over scaling behavior of fractal signals recorded from continuous biological motion is a somewhat trivial feature of the experimental paradigm. The significant mass of the body segments necessarily leads to positive correlations over short intervals while the physical

constraints on the range of motion leads to negative correlations at longer scales. In our results, the presence of both positive and negative correlations in the signal is not surprising given the frequently observed anti-persistent character of biological limb motion at longer time scales (Liebovitch & Yang, 1997), and the fact that here we use a longer analysis window of 15 seconds. At the same time, however, we cannot not reject the possibility that as in other paradigms there are meaningful sources of scaling exponents of the movement data in addition to such features. The multifractal formalism is thus useful in our study because it can reveal all exponents without presupposing which scale of behavior is the relevant one and allows the behavior to be viewed in its full complexity.

We wish to stress that the multifractal spectrum taken as a whole supports the idea of an interaction-dominant system and is hard to explain by alternative models. For this reason it is more interesting to focus on it and changes induced by perturbation rather than try to explain specific values of H or identify the source of scaling for each and every part of the parameter range. In this vein, our results support our general hypothesis of an interaction-based coupling between tool and user that leads them to becoming an interaction-dominant system that operates smoothly before the perturbation of the coupling and continues to function, albeit less fluidly, during and after the perturbation.

Interestingly, according to the monofractal DFA analysis H reverted relatively quickly to its pre-perturbation level whereas a lasting effect of perturbation can only be seen in the multifractal range of h_i exponents. This pattern resembles the aforementioned data regarding heart beat dynamics in that only a multifractal analysis is subtle enough to detect some cardiac conditions (Ivanov et al., 1999; Amaral et al., 2001).

The results of the wavelet transform modulus maxima analysis showing that the behavior at the hand-mouse interface displays not just $1/f$ scaling, but also multifractality. This finding reinforces our interpretation of the results from Dotov et al. (2010). The present, more definitive, analysis confirms that the human-mouse system is interaction-dominant. This confirms our claims that the human-tool system is, for the duration of the trial, a single cognitive system, providing direct, empirical support for the hypothesis of extended cognition. The analysis also confirms the demonstration of Heidegger's proposed transition from ready-to-hand to unready-to-hand. While the participant is smoothly engaged in playing the video game, the mouse is part of the system engaged in the task and is experienced as ready-to-hand. The perturbation disrupts the

activity of this interaction-dominant system, causing the participant to experience the mouse as unready-to-hand.

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