

The Embodiment of Time Estimation

Ramon D. Castillo^{1,2}, Guy Van Orden¹, and Heidi Kloos¹

¹ Center for Cognition, Action and Perception (CAP); University of Cincinnati, OH, USA

{guy.van.orden, heidi.kloos}@uc.edu

castilrn@mail.uc.edu

<http://www.uc.edu/cap/>

² Facultad de Psicología; Universidad de Talca, Talca, Chile

<http://www.otalca.cl/>

Abstract. In this essay, we explain time estimation on the basis of principles of self-organization. Timing behavior can be seen as an outcome of the coupling and coordination across physiological events, overt behavior, and task demands. Such coupling reveals itself in scaling relations known as fractal patterns. The self-organization hypothesis posits a coherent relation between frequency and amplitude of change, as a single coordinated unity, that possess fractal features. Empirical data lend support of this hypothesis, initiating a discussion on how fractal properties of time estimation can be altered by the interplay of voluntary and involuntary control of behavior.

Keywords: Time Estimation, Pink noise, Fractal Time, Self-Organized Criticality, Involuntary and Voluntary Control.

1 Introduction

Timing is a central feature of behavior, whether the behavior pertains to physiological events such as brain activity, heartbeat, or breathing; overt motor behavior such as walking or dancing; or cognitive behaviors such reading, speaking, interacting socially, or participating in a laboratory task. In all these examples, the body finds a proper rhythm with surprising ease to ensure adaptive functioning (cf. for social coordination) [1-3]. What makes it possible that the activities of the body are so precisely orchestrated over time?

The question of timing has traditionally motivated a search for internal clocks – rhythmic structures of some sort that could supply timing information to human physiology and behavior. This approach to the many different timing concerns of the mind and body proposes a hierarchy of clock times ranging from circadian time, one day to the next, to the rapidly changing millisecond timescales of speech, movement coordination, and brain activity. Each timescale has been thought to be represented by its own clock network of brain structures, distributed across the brain [4-5].

The hypothesis of internal clocks has some drawbacks however. For example, the results of neuroimaging studies have failed to converge on a set of distinct timing networks that could correspond to the hierarchy of internal clocks. Instead, it appears as though the same brain networks are reused in a multitude of unrelated functions – rather than being dedicated in a modular fashion to timing functions (or to any other

mental functions, for that matter). Consequently, Anderson [6] has called for alternative hypotheses to make sense of neural reuse, which appears to be the basis for all cognitive functions.

In this essay, we describe such an alternative – one that is based on the idea of self-organization. Self-organization of a system's behavior takes place without a central executive authority or isolated causal timing structures. Instead local interactions among the components of a system yield the global pattern of the system's behavior. Examples of such self-organization come from a variety of domains in human behavior, including motor coordination [7], decision making [8], and brain activation [9]. For example, evidence from EEG studies suggests that the brain self-organizes global patterns of activity on the fly — even coming up with different functional organizations to suite the requirements of specific contexts [7, 10-13]. Similarly, networks of motor neurons and inter-neurons that produce rhythmic timing functions, so-called central pattern generators, were found to self-organize into context-dependent structures [14-16]. Previously inhibitory connections are reused as excitatory connections, new neurons that were not part of the network previously can be incorporated, or separate networks become fused into a new central pattern generator with changed timing pattern [17]. The inherent flexibility of the network structure originates in temporary synergies among the elements of the network that assemble to meet the demands of the immediate context [18-20].

Our goal in this essay is to explain behavioral phenomena of time estimation on the basis of these principles of self-organization. In doing so, we look at one particular task, one in which the participant first listens to a metronome beat marking the passing of repeatedly identical time intervals. The task is then to reproduce the duration of the time interval between metronome beats, repeatedly, after the metronome is turned off. This is a classic time-estimation task (cf. [5]) that has been used in several variations. For example, sometimes the participant controls the pace of responding, pressing a response key as each estimated interval passes. And sometimes a prompt appears (marking the beginning of the interval) and the participant responds when the estimated interval passes, after which another prompt will appear, and so on. What do data obtained from these kinds of tasks reveal about the kinds of processes that could give rise to time estimation?

The phenomena that are revealed in time estimation data are generic patterns of local changes that emerge across successive time-estimation trials [8, 21-24]. Figure 1 illustrates how such patterns are visualized in a spectral plot (following the prescriptions for spectral analysis of Holden, [25]): The raw data (a series of successive time estimates; shown at the top right of the figure) are decomposed by a Fourier transformation into sine waves (illustrated by examples on the left side of the Fig. 1). Slow changes in the data series are simulated by the low-frequency sine waves and fast changes are simulated by high-frequency waves. Similarly, large changes are simulated by high-amplitude sine waves, and small changes are simulated by low-amplitude sine waves. The ordered pairs of frequency and power (amplitude squared) for each of the obtained sine waves are then plotted on log/log scales (shown at the bottom right of the Fig. 1). The remarkable phenomenon is that the paired amplitudes and frequencies of the simulated changes turn out to be proportional, aligning themselves together along a regression line, also known as scaling relation.

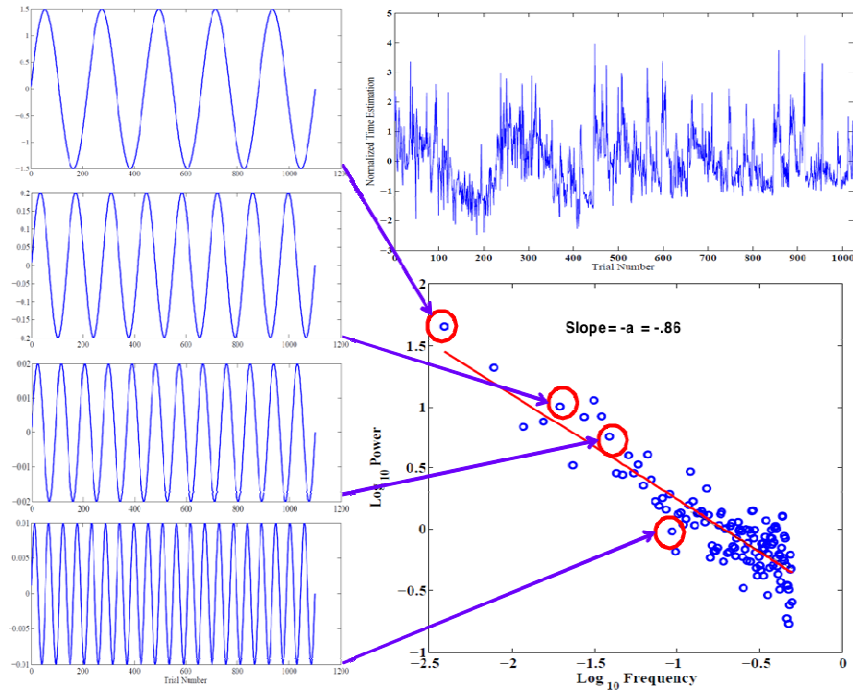


Fig. 1. One person's time estimation data (top right), decomposed into sign waves of a particular amplitude and frequency (examples of which are shown on the left). Each sign wave is plotted as a function of its amplitude (power) and frequency, in log-log coordinates, yielding a spectral plot (bottom right). The slope of the regression line reflects the scaling exponent α .

1.1 Fractal Variation in Time Estimation

Why does the lawful scaling relation between frequency and size of variation appear in time estimation? Some scientists entertain a hypothesis that the scaling relation is a universal feature of human performance [8, 23, 26-28]. If so, then it either is a spurious feature of behavior revealing little or nothing about the essential nature of human behavior. Or else, the scaling relation is a deeply rooted phenomenon that may reveal of the essential nature of human behavior. The latter possibility is assumed by proponents of a self-organization hypothesis, which views the universal scaling relation as a fractal pattern across time, a scaling relation that is sometimes called fractal time.

Fractal patterns are self-similar structures that exhibit the same statistical features at all scales of observation. They are simulated using iterative functions, such that the state of a system at one point in time serves as input to the state of the system at the next point in time. The function connecting one state to the next reflects the coupling among the component processes, which is accomplished in positive and negative feedback loops among the processes. This allows processes to cooperate as well as compete to determine the next state of the system.

The scaling relation illustrated in Fig. 1, aligning amplitude (power) and frequency of change, is a common identifier of fractal structure. Fractal structure suggests a coherence across scales, which in turn implies a coupling among the processes of the mind, brain, and body, across all the scales of the mind, brain, and body. Coupling allows continuous updating of each process by every other process, ensuring that each process informs the dynamics of every other process. Appropriately conceived, it provides a basis for the alignment of frequency and amplitude of change in the scaling relation [26, 28-30].

Applied to time estimation (as well as the observed timing of physiology and behavior), timing intervals of timing behavior can be seen as the outcomes of the coupling and coordination of the body. The self-organization of coordination itself is the paramount activity. Time estimation is simply a product of that activity, not the other way around. This view allows us to dispense with the anti-realist assumption that space and time constitute fundamental dimensions of human embodiment or phenomenology. Instead embodied time is a performance, physiological and behavioral events are primary, while their timing reflects the coordination across the sequential orders of events (cf., [31, 32]).

Of course, one could be skeptical of the self-organization hypothesis. The scaling relation might be an idiosyncratic feature of behavior; or it might be a simple aggregate of ordinary mechanisms that happen to change on different timescales. Alternatively, the scaling relation might be equated with one or more specific mechanisms, elicited by the particular task environment, in line with the conventional idea of distinct mental functions [33-36]. For example, the high-frequency range of the spectral plot might reflect a motor component, while the low-frequency range might reflect a conceivably cognitive timing-function underlying time estimates. Finally, the scaling relation could reflect a spectrum of distinct internal clock frequencies that accidentally align their amplitudes [37].

These contrasting viewpoints differ from our viewpoint in terms of their predictions about the coherence of the apparent scaling relation. They predict that the scaling relation comprises an independent process or is composed of independent processes. Thus the right kind of manipulation could possibly dissect a scaling relation into distinct components, with different frequencies and amplitudes of change. The self-organization hypothesis, on the other hand, predicts a coherent relation between frequency and amplitude of change, which means that it will change in unity, as a rigid line that changes in slope. Holden and collaborators tested this prediction by injecting random white noise into the experimental protocol of time estimation and manipulating its amplitude [38]. Findings show that the injected low-amplitude noise changed the slope of a spectral plot toward whiter noise, but without splitting the spectral plot along lines of frequency or amplitude. Similarly, the injected high-amplitude noise changed the slope toward whiter noise (much more than before), but again without splitting the spectral plot. In both cases, spectral slopes changed equivalently across the spectrum of amplitudes, as a coherent relation between frequency and amplitude (cf. [39-40]). These findings undermine the idea of causally independent processes within the scaling relation. Instead they suggest that timing behavior results from the coupling and coordination of all the components of body and mind [26, 41].

1.2 The Meaning of Spectral Slopes

So far we have ignored an important aspect of spectral plots: the slope of the regression line between the amplitude, $S(f)$, and frequency of change, f . The negative slope of the regression line, indicated as $-\alpha$, is used to estimate a scaling exponent α , such that: $S(f) = 1/f^\alpha = f^{-\alpha}$. In the data set shown in Fig. 1, the obtained scaling exponent is $\alpha \approx 0.86$, a value close to $\alpha = 1.0$. This value (and values near to $\alpha = 1.0$) is explicitly predicted by a core feature of the self-organization: self-organized criticality [28]. The value $\alpha = 1.0$ represents the ideal scaling relation of fractal time, predicted to appear near criticality [42, 43]. So-called critical states are tipping points at which complex systems spontaneously reorganize, consistent with the neural reuse hypothesis and observed spontaneous reorganization of the central nervous system [7]. Indeed, skilled motor performance will converge on the scaling relation of $\alpha = 1$ over extended or developmental time (e.g., for Fitts task performance: [44]; for walking: [45]).

Time estimation data often reveal near pristine examples of fractal time [26]. Likewise, time estimation performance appears to converge on the scaling relation $\alpha = 1$ across development [46]. The task was identical to the generic time-estimation task: after the metronome was switched off, children between 4 and 12 years of age pressed a button repeatedly to indicate when the designated time interval had passed. Data were subjected to analyses like that portrayed in Fig. 1, yielding a reliable developmental trend. Younger children produced patterns more like overly random white noise, while older children and adults produced patterns more like fractal time with $\alpha = 1$. Younger children might lack capacities to sufficiently control the degrees of freedom afforded by the unusual task. With development, they might better coordinate their bodies with an idiosyncratic task, and they might better sustain the intentions that follow from experimental instructions.

Despite findings of fractal time, note that the scaling relation of $\alpha = 1$ is not equally present in every time estimation performance (or, for that matter, in other task performances that reveal scaling relations). Different task conditions can change the pattern of variation across time estimation data, usually to become more like a random pattern of white noise. For example, the fractal parameter of the scaling relation is close to zero when the metronome is left on during testing trials – but not when or when participants tap in a syncopated rhythm, between the beats of a metronome [47]. Similarly, the fractal parameter is close to zero when participants are provided with feedback on every time-estimation trial [48]. What does the change in spectral slope reveal about the system that gives rise to the observed performance?

Figure 2 shows idealized data patterns and spectral plots that define the range of scaling relations discovered using different tasks and task conditions. The range runs from random white noise with $\alpha = 0$ to brown noise with $\alpha = 2$ at least or higher. We argue that the range of scaling relations can often be understood as a trade-off between voluntary and involuntary control [49]. To explain, we discuss the nature of control in more detail below (see also [28, 50]).

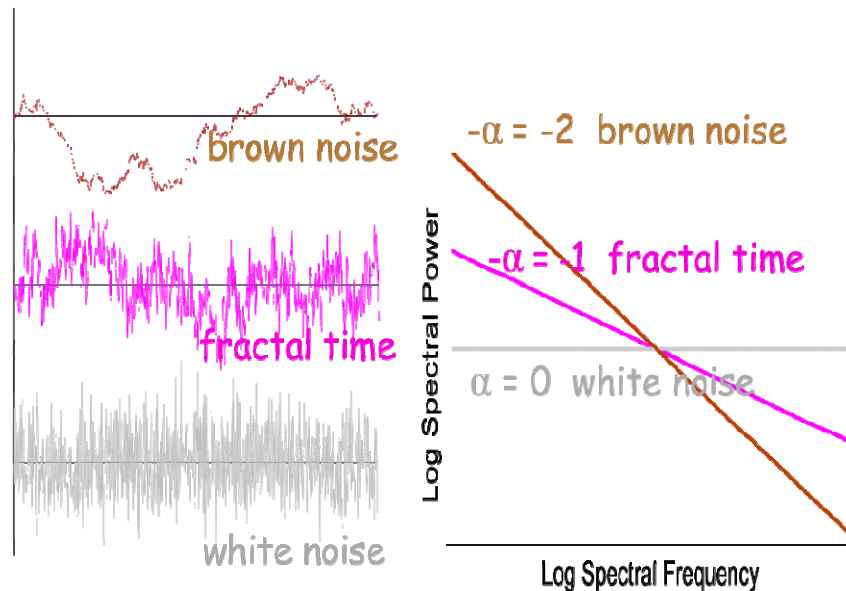


Fig. 2. Idealized data patterns of variation spanned by development, training, and manipulation of tasks and task demands (see text). Different task conditions change the pattern of variation across time estimation data to become more or less like a random pattern of white noise with $\alpha = 0$ or the pattern of fractal time with $\alpha = 1$ [28, 38]. Conditions of rigid or exaggerated control can change the variation in data to resemble brown noise with $\alpha = 2$ (for a review [49]).

1.3 The Nature of Control

The starting point is our assumption that behavior is a self-organization of dynamical structures across all scales. The dynamical structures in the behaviors of organs, for example, combine in the coordination of organ systems, which in turn combine in the coordination of the behaving organism. One advantage of this view point is that the dynamics of the behavior of physiological systems – as well as the behavior of the entire organism – share common principles and the same theoretical language [51]. Control in all cases originates in sources of constraint that limit degrees of freedom (cf., [52]). Successful task performance therefore requires that a participant can exploit the controllable degrees of freedom that a task environment affords.

There are two broad sources of constraint that shape a particular task performance: involuntary control and voluntary control. Voluntary control pertains to a person's will, purpose, or intention; while involuntary control refers to all the other sources of control — including control in the task environment, embodied control, and an organism's capabilities and skills that concern successful task performance [53-54]. An increase in voluntary control relative to involuntary control is predicted to move the variation in performance data away from white noise and toward overly regular brown noise. And an increase in involuntary control relative to voluntary control is predicted to move variation in the direction of overly random white noise [50, 55]. Formula (1) reflects this relationship between voluntary and involuntary control as a ratio.

$$\text{Variation in Human Performance} : \frac{\text{Over Random}}{\text{Over Regular}} = \frac{\text{Involuntary Control}}{\text{Voluntary Control}}. \quad (1)$$

More formally, voluntary and involuntary control can be reframed with respect to the timescales of observation. Voluntary control brings temporary constraints into and out of existence as task performance requires. These constraints tighten or loosen the coupling between task and participant in vigilance, poise, mental set, anticipation, and so on. Such waxing and waning sources of voluntary control unfold more slowly than the trial kinematics of measured behavior. That is, constraints due to voluntary control change more slowly than the trial performances that are controlled. These sources of constraints, changing more slowly than the pace of measurement, amplify slow frequency variation in performance to resemble brown noise. In other words, voluntary control exaggerates over regular, slower oscillations supplying higher amplitude, more slowly changing variation to the data. High-amplitude slow changes are the basis for change in the direction of brown noise with $\alpha = 2$ in the spectral portrait.

Involuntary control, on the other hand, concerns all other sources of constraints apart from voluntary control. Changes in the difficulty of a task or task demands, the knowledge or skill of a participant, or across the participant's development are all changes in involuntary control. Involuntary sources of constraint may affect all timescales of constraint. Sources of involuntary control that change on timescales faster than (or as fast as) the measurement will perturb performance unsystematically, changing the pattern of variation to resemble white noise. In contrast, sources of voluntary control that change on slower time scales than the time scale of the measurement will change the pattern of variation to resemble brown noise.

Taken together, these predictions give a good account of the observed changes in time estimation data. For instance, consider the baseline to be the fractal time obtained when participants listen to the metronome beat until the metronome is turned off, and then produce the remembered time interval. An increase in involuntary control can be enacted by leaving the metronome on, eliminating the need to remember the time interval, and ceding this source of control to the task metronome. Indeed, leaving the metronome on, as an enhanced source of involuntary control, yields the expected change in variation toward overly random white noise [47]. Anecdotally, we have also observed skilled drummers who cede control to their automatic skill set, producing white noise in the metronome-off condition.

Now taking the metronome-on condition as a baseline, an increase in voluntary control can be necessitated by another change in the task instructions. Instead of instructions to produce intervals in synch with the metronome, the participant is instructed to produce syncopated intervals that begin and end between the beats of the metronome. Compared to the in-synch condition, the more difficult syncopated intervals require a concentrated voluntary effort to sustain accurate performance. The enhanced voluntary control moves the pattern of time estimate variation back away from a resemblance to white noise and $\alpha = 0$ toward brown noise with $\alpha = 2$ [47].

Finally, consider the change in control that comes from the presence or absence of trial feedback. Feedback perturbs time estimation data, trial to trial, resulting in an unsystematic source of perturbations with respect to the behavioral measures of tapping. In contrast, feedback is a source of slow changes with respect to more rapidly changing brain activity. Slowly changing constraints on brain dynamics originate in the voluntary use of feedback to constrain and improve an upcoming performance. In other words, it

is the relative timescales of the measurement that determines whether trial-to-trial feedback moves variation in data toward white noise or brown noise. Feedback in time estimation fits these predictions. When the measurement pertains to tapping, trial feedback is a source of involuntary control, which in turn perturbs the pattern of variation in the direction of white noise [48]. On the other hand, when the measurement pertains to rapidly changing brain dynamics, slow trial feedback moves the variation in measurements of brain dynamics in the direction of brown noise [56, 57].

2 Conclusions

Our goal was to address the issue of timing under the framework of self-organization. Under this framework, performance – in this case proper timing – does not require separate causal structures. No internal clock needs to be postulated to explain the intricate and apparently effortless timing performances that humans display. Self-organization postulates instead that higher-order structures arise from the interplay among a multitude of component processes that interact as a balance of competing and cooperating tendencies. Timing performance is a product of such an interaction.

Evidence for our claims comes from the persistent coherence between the ordered pairs of amplitude (power) and frequency of sine waves that simulate variation in performance. Whether the task involves tapping out a learned rhythm, or syncopated tapping between the beats of a metronome, spectral analyses reveal a characteristic pattern: Rather than arbitrary pairings of possible amplitudes and frequencies, systematic changes are apparent. A scaling relation changing in unity speaks to the interdependence of the component processes of the system. Whether a process changes on a faster or slower time scale, it is coordinated with other processes, which self-organize human performance in task specific and participant specific ways. Timing then is a result of such self-organization embodied in the interaction of processes at all the scales of the body and brain.

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