The Emergence of Task Complexity and 1/f scaling: A study of Motor Coordination

M.Sc. Thesis

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When people perform repeated goal-directed movements, consecutive movement durations and trajectories inevitably vary. This motor variability is traditionally conceived as noise that can be dealt with by discarding it, thereby relying upon the assumption of uncorrelated trial-by-trial variability. In this thesis motor variability is taken as sensitive to the complexity inherent to task production and is shown to yield important information about cognitive processing. Evidence is provided that movement variability is not a random phenomenon, but rather shows a coherent temporal structure, referred to as 1/f scaling. This effect is unexpected from the traditional paradigms in the behavioral sciences. Furthermore, we show this temporal structure to be contextually constrained. The scaling relation appears more clearly as participants become trained in a hard motor task, as performance improves. Because of the learning effect, the interaction between task and participant is modified while the task remains constant. Instead of task-dependent properties, the context of task production yields an indication for how difficult a task actually is to a person embedded in a context. 1/f scaling constitutes a gauge in this respect. Also, co-occurring channels of 1/f scaling are observed. Apart from movement time series, 1/f scaling is observed in axial pen pressure and pen tilt. On these streams the training manipulation had little effect. These results support the idea that 1/f scaling is ubiquitous throughout the cognitive system, and suggest that it plays a fundamental role in the coordination of cognitive function [Van Orden, Holden & Turvey, 2003].

Human behavior inevitably varies, this is partly what makes human behavior such a complex topic of study. People behave differently at different moments in time and in different contexts. Studying a machine is easier in this respect. On each repetition, it performs a task in exactly the same way. A machine can easily be disassembled into its constituent parts, from which the machine's functional organization can be deduced. In contrast, people interact with and adapt to an environment that poses contextual constraints. Traditional paradigms in the behavioral sciences often deal with the complexity of the cognitive system in ways similar to the reduction of a machine to its component effects. A complex system, irrespective of it being human or non-human, is not decomposable into its constituents and its function is not embedded in its parts. This has been suggested to also hold for cognitive systems (Haken, 2006; Kelso, 1995; Kugler & Turvey, 1987; Van Orden, Pennington & Stone 2001, Van Orden, Holden & Turvey, 2003). From this approach the main issue is concerned with behavioral patterns that focus on the relations among things rather than on its parts. With respect to human performance this implies that task performance inevitably changes over time and never stands outside of context.

The present study aims to provide more insight into the acquisition of coordination in a simple motor task after training. It is argued that especially the variability of human behavior over time and context yields a richness of information about such elementary cognitive processes. Over time, repeated movements turn out not to be characterized by random noise arising from independent information processing components but rather by a coherent structure emerging from multiple interactions of phenomena across time scales. Over contexts, these coordination dynamics appear to take different forms. The phenomenon of coordination dynamics emerging with practice can be investigated using tools of nonlinear dynamical systems theory.

Variability over time

The occurrence of variability over time is a natural property of human movement that poses an intriguing problem to the study of motor control. It has been recognized for a long time that repeated movements always differ, and as such that variability is an inherent part of the motor system. If participants are instructed to end a movement at a particular time and space, movement trajectories typically vary (Bernstein, 1967), and both their durations and end-points deviate from specified targets (Woodworth, 1899). The mind and body will together create unique kinematics for each repeated movement. This is expressed by the fact that trial-by-trial variability demonstrates complicated patterns of behavior in even the simplest movements (Gilden, Thornton & Mallon, 1995; Hausdorff, Purdon, Peng, Ladin, Wei & Goldberger, 1996; Kelso, 1995). Motor variability is considered a basic and informative feature driving the motor control system (Kelso, 1995; Slifkin & Newell, 1998; Turvey & Schmidt, 1991). In this view, increases in variability are proposed not to characterize impoverished performance as has traditionally been assumed. Variability might as well serve as a 'trigger' for a change of the way in which movements are organized. In this approach variability plays a crucial role in human performance and enables for flexibility in human behavior. This perspective, however, is at odds with mainstream psychological science that focuses on group means and central tendencies at fixed points in time. In dynamical systems approaches the information that is discarded by focusing exclusively on means instead of on the dynamical patterns that accompany these means becomes a topic of inquiry, variability is conceived of as crucial for learning and coordination.

Variability over context

In behavioral research, typically only effects due to a certain task are inferred. The dynamics emerging from the multidimensional interaction between task and agent embedded in a history is generally not the topic of inquiry. This focus is mainly driven by the goal of observing reproducible data, accepting the cost of missing many particularities induced by the system of investigation. The underlying argument is that psychological constructs are motivated by "behavioral consistency over varying contexts" (Cronbach & Meel, 1955; Embretson, 2006, p. 50). Or, at least, context effects are attributed to secondary performance limitations that come and go with the task, rather than with a participant's primary competence. An important aspect of task performance, however, is the effect of overall context. (Cox & Smitsman, 2006; Kloos & Van Orden, 2007; Thelen & Smith, 1994; Van Orden et al., 2001; Van Orden et al., 2003). Context can be taken as the overall spatiotemporal constraints in task production. The context of task production, task complexity, is created by the interaction between task, participant and history, and incorporates how behavior changes over time and context. The central lesson from complex adaptive systems is that everything is ultimately connected to everything else. This interconnectedness is reflected in the intrinsic dynamics of the cognitive system.

Precision aiming

In this thesis, I will investigate task complexity by looking at precision-aiming movements. Precision aiming requires reaching for or heading at a specified set of targets back and forth. The focus of inquiry regarding precision aiming generally is the time required to reach for a specified target or a set of targets along with the imposed accuracy constraints. Throughout the years, several variants of the precision-aiming task have been used. Generally, a participant is instructed to move a pen device (or alternatively a mouse, trackball, or another device) at an optimal velocity while attending to the accuracy constraints of the task. In a discrete precision-aiming task, the instruction is to tap as fast and as accurately as possible between two targets. In this thesis, the focus will be on reciprocal or continuous aiming. Participants are asked to draw lines back and forth between two targets as fast and as accurately as possible. Fitts' law is, arguably, the most robust and most cited effort to model precision-aiming movements (but see also Mottet & Bootsma, 1999). A focus on the validity of the assumptions underlying Fitts' law will be informative with respect to how complex dynamical patterns of variation and their relation to task complexity generally become discarded in behavioral research.

Fitts' law

In precision aiming, Fitts' law predicts a linear relation between movement time and the ratio of target size and distance that separates the targets. Some examples of this robust relation include small and large movements, for younger and older people, under water and movements under a microscope (see e.g., Plamondon & Alimi, 1997; Smidt & Lee, 2005). This robustness has led researchers to apply Fitts' principles in kinematics, human factor research, and Human-Computer Interaction. Fitts' model provides information regarding how much time it takes to reach a certain target. He argued that the average time (Movement Time or MT) required to complete a pointing movement linearly relates to the difficulty of the task. Task difficulty can thus be expressed as an Index of Difficulty (ID) defined in terms of the amplitude and precision constraints imposed (see Formula 1), in terms of task-dependent properties.

$$MT = a + b\ (ID) \qquad (1)$$

ID can be more formally defined as $log_2\ (2D\ /\ W)$, with D representing the target distance, and W representing target width. The a and b values in the equation are constants, a denotes the intercept and b the slope of the regression line that shows the linear relation between Index of Difficulty and Movement Time. What Fitts tried to establish, is that a target-reaching movement should behave like an information-processing channel of limited capacity. This perspective to the study of perceptual-motor function has been built on the tenets of information theory (Shannon, 1948) and the traditional cognitivist approach to human cognition, which treat errors and variability as the product of signal, the motor command. The motor signal is transmitted through a channel of limited capacity, and as such it is contaminated by noise at some point in the information-processing stream (Bernstein, 1967; Fitts, 1954). Task difficulty (ID) in this framework denotes the number of 'bits of information' transmitted through the channel necessary for carrying out a constrained movement. In other words, this is the amount of information necessary to specify the target width relative to the distance to be covered. If the ID is divided by Movement Time, an Index of Performance (IP) in bits/sec is derived, that is, the channel's capacity. An alternative definition of the IP measure is 1/b. Fitts' central working hypothesis was that the information flow through the channel is constant, so the Index of Performance should be constant across the entire range of values for Index of Difficulty. This follows from the prediction of a linear relation between average Movement Time and Index of Difficulty. Derivations from an information-processing principle to the cognitive system, as in Fitts' law is based on a set of implicit and explicit assumptions of the perceptual, psychological, and physiological processes underlying human cognition.

Uncorrelated noise. An assumption of Fitts' law, as in the majority of psychological research, is that behavior can be considered highly stable and replicable across time. In this approach, noise (or trial-by-trial variability) is generally conceived of as a nuisance factor that discards the quality of a signal. Consequently, a signal to noise ratio can provide information about the efficiency of information processing. In this approach, skilled performance is equated with constancy and noise as a contaminating factor. It is assumed that the mean values of the variables of interest provide an important summary measure of human skill. Long-term prediction of a certain effect size improves as the number of observations increases. The assumption that fluctuations in successive measurements are randomly distributed and, as such, that they are uncorrelated in time implies that noise can be safely removed by averaging without cognitively relevant information being lost. For precision aiming, uncorrelated noise implies that all amplitudes within the accuracy tolerance range will be observed equally often. Also, all frequencies will be equally present in a movement time series obeying a Gaussian distribution.

An implication of the assumption is that in Fitts' paradigm temporal ordering of data points, that is, the motor variability over time, is ignored and the possibility of correlated structure of fluctuation is neglected. However, recent tests of the structure of movement variability from the perspective of nonlinear dynamical systems in behavioral research suggest that the information-processing assumption of random noise may well be the exception rather than the rule and that movement variability in precision aiming is not normally distributed (Lai, Mayer-Kress, Sosnoff and Newell, 2005; Slifkin & Newell, 1998). This effect is rather unexpected in the view of the current set of paradigms in cognitive psychology.

Task complexity. Another, related assumption of Fitts' law is that human behavior is identically replicable across context and that task complexity is solely determined by the task itself. In this approach, task complexity is a function of the number of distinct information cues that must be processed, the number of distinct processes that must be executed, and the relationship between tasks and cognitive processes. Although this assumption enables for an objective measure, its psychological valence is questionable because there is neither room for individuals with their particularities nor for explaining human movements as uniquely situated trajectories. A second approach (see Campbell 1988 for a review on the issue task complexity) considers task complexity to be a subjective experience. Thus, according to this approach, task performance is largely constrained by individual experience, but it lacks the appealing objectivity of the first approach. A means to study subjective complexity of a task is self-report (see e.g. Maynard & Hakel, 1997) A third approach considers the interaction between individual experience and objective task properties to be vital (see e.g., Gonzalez, 2005). I adhere to the validity of the assumption of the interaction between task and person, but will add a necessary source of constraint, namely, the context of task production, which includes the individual history of the participant. Thus, I take it that task complexity emerges from the interaction between task properties (target size, stimulus interval, modality, etc.), task conditions (time pressure, motivators, circadian rhythms, climate, social context, etc.), and participant variables (personal history, prior knowledge, practice effects, inter-individual differences, emotional state, age, etc.). Subtle inter-level relations and dependencies are created by the evolution of constrained motor behavior over time and these relations differ for different participants situated in different contexts. An interesting consequence of the fact that task difficulty changes with context is that task complexity can be manipulated simply by training a participant in a certain task, because a task becomes generally easier with practice. As such, participant variables are manipulated while the task remains constant.

Learning and variability

Information processing theory suggests that an increase of task complexity only occurs relative to the amount of information inherent in a task and specific task-processing characteristics. From an information-processing perspective a participant's performance becomes less variable as it improves. The motor signal driving successful performance becomes less perturbed by random noise in the channel. A reduction of motor noise or a change in its structure as a consequence of practice, however, is unexpected from Fitts' law. This approach to precision-aiming movements is particularly problematic pertaining to practice effects. Following Fitts' law, increases in variability are associated with a linear decline in the efficiency of the motor system in more difficult tasks, where task-dependent properties stand outside of practice. This, however, is not necessarily true. In fact, variability might be crucial for cognitive performance (Sliffkin & Newell, 1998). A tempting issue then is whether Fitts' law could incorporate the complexity of the coordination required for simple movements, and thus the inherent variability over time and practice.

Learning does not change just one thing (e.g., an increase in IP), it changes the interactions of processes at all scales throughout the cognitive system. Changes in learning behavior traditionally assessed as simple improvements in performance of the learning task, are now the outcome of modifications of the entire underlying system (Kelso, 1995). The interactions that connect every part of the cognitive system to everything else are called intrinsic dynamics. The intrinsic dynamics already present in the learner change, while the same task-dependent characteristics are present before and after learning.

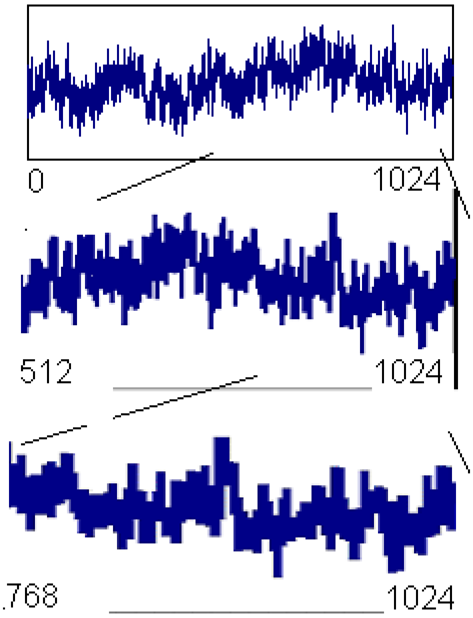
1/f scaling

The studies discussed above went no further than using static statistical measures such as mean, standard deviation, and correlation coefficient, all ignoring the temporal order of the data. In other words, the preceding studies paid no attention to a possible time-dependent property for variability in the sequence. One way to falsify the assumption that data are uncorrelated is testing for the presence of 1/f scaling also referred to as 1/f noise, pink noise or fractal noise.

To clarify this concept, think about measuring the length of a coastline at some scale of measurement, like kilometers, meters, or centimeters. New details keep appearing as the magnification increases from kilometers to meters to centimeters (see Figure 1b.). The length of the coastline will increase as progressively more detailed scales are used to measure its length. A power-law-scaling relation like 1/f scaling describes how the choice for a level of resolution affects the mean (Mandelbrot, 1982).

The same goes for behavioral data. In the case of 1/f scaling a time series shows a statistically self-similar organization of trial-by-trial fluctuation across many scales of measurement. By looking at a fewer number of trials in the series, smaller fluctuations appear embedded in lower frequency waves over longer time scales. This implies that nested fluctuations carry over the entire experiment; the trial-by-trial fluctuation is embedded in an overall trend. For an example of a how each data point uniquely participates in the larger patterns of the data set, see Figure 1a.

A



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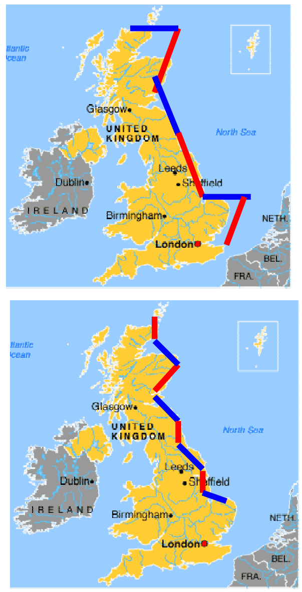


Figure 1a. **If characterized by 1/f scaling, a time series is self-similarly nested across timescales. When zooming in, the same statistical details occur at all scales of resolution. Such a time series cannot be described at a fixed scale. 1/f scaling is likely to emerge from the coordinated interaction between processes at many timescales.** ***Figure 1b.*** **A coastline has the same statistical properties as 1/f scaling, the length increases with the scale of resolution, which determines the mean and standard deviation.**

Most linear statistical tools and logic are frustrated by the presence of 1/f scaling because it is implied that the outcome of statistical measurements depends heavily on the location and resolution of the measurements. The mean and variance of a data series depends on the amount of data analyzed in the same way as the scale of resolution affects the length of a coastline.

The recurrence of 1/f scaling across various tasks and behaviors has even led researchers to speculate that 1/f scaling is a ubiquitous property of human behavior. To illustrate this ubiquity, 1/f scaling has been reported in tapping (Chen, Ding & Kelso, 1997; 2001; Lemoïne, Torres & Delignières, 2006), visual search (Aks, Zelinsky & Sprott, 2002), simple reaction times and word naming (Van Orden, et al. 2003), interval estimation (Gilden et al., 1995), mental rotation (Gilden, 2001), ratings of self-esteem (Delignieres, Fortes, & Ninot, 2004), simple classification (Clayton & Frey, 1997; Stamovlasis, 2005), decision making tasks (Ward & Richards, 2001), perceptual flippings (Aks & Sprott, 2003), spacing and timing of rhythmic movement (Schmidt, Beek, Treffner, & Turvey, 1991). postural sway (Duarte & Zatsiorsky, 2001; Riley, Wong, Mitra, & Turvey, 1997), swinging pendula (Schmidt et al., 1991), and human gait (Hausdorff et al., 1996). This list is not complete in any respect, long-range correlations over time in behavioral data can be conceived of as just as lawful as Fitts' law.

In these experiments the natural order of measurement has been kept intact instead of being randomized. The temporal-coherence characteristic of 1/f scaling disappears as it becomes shuffled into a random signal. Randomizing the stimuli prior to each run of an experimental session cannot prevent the appearance of 1/f scaling in any way. The appearance of coherence in trial-by-trial variation does not dependent upon properties of a task, rather 1/f scaling emerges from the dynamics of the participant performing the task. Observing 1/f scaling motivates another way of testing, another way to look at data and another set of questions to answer.

1/f scaling is not a phenomenon unique to behavioral data, but a generic theme across sciences. Examples include earthquakes, rainfall phenomena, rainforest growth, the architecture of cities, DNA sequences, galaxy structures, bird flight formations, and many others, up unto the structure of space-time. Although 1/f scaling appears to be ubiquitous across natural complex systems, the meaning of 1/f scaling remains an enigma throughout the physical, biological, and psychological sciences. The statistical pattern of 1/f scaling is intriguing because it suggests the presence of fractal processes; processes that are organized in relation to each other across all timescales indicating a cooperative effect. It is, however, essential to understand the dynamical mechanism generating 1/f scaling in human cognition.

Testing for the presence of 1/f scaling

Testing for 1/f scaling can be done simply by observing the evolution of a system over time. $1/f^{\alpha}$ scaling can be expressed as a function (x) with power exponent α (see Formula 2).

$$F(x) = x^{\alpha} \tag{2}$$

To assess the α value, the data from a time series can be plotted after spectral analysis, which consists of submitting data series to a Fast Fourier Transformation. A Fast Fourier Transformation linearly decomposes the series into component sine waves of varying amplitudes and frequencies, and examines the data for periodicity. The time domain of the series becomes transformed into a frequency domain. An analogy in this respect is a prism. A prism breaks down the mixed light waves into their composite-frequency bands, as reflected by the separated hues. The outcome of a spectral analysis can be expressed by a power-spectral-density plot that concerns the relationship between frequency and amplitude of the series on a log scale. These power spectra usually display log frequency on the x-axis and log amplitude (or power) on the y-axis; the relation between power (p) and frequency (f) can be expressed as in Formula 3, where α is the scaling exponent of x (in Formula 2) or the slope of the power spectrum.

$$\text{Log } p = -\alpha \log f \qquad (3)$$

If the regression line in a power spectrum has no slope (see Figure 2d), all frequencies are equally evident indicating random or white noise. There is no correlation between consequent trials, each measurement is independent of others taken at different points in time. In contrast, the case of $1/f^1$ scaling can be recognized in a power spectrum as an inverse correlation between the frequency of the composite waves and their power (or amplitude) on a log scale (see Figure 2b). It follows that the power spectrum has a negative slope. Self-similar fluctuations are nested across scales and are embedded in long-range correlations over time. If the slope of the power spectra equals two (see Figure 2f), the signal contains brown noise ($1/f^2$), indicating a random walk. Brown noise is a cumulative sum of white noise.

1/f scaling reflects a tendency of complex systems to develop correlations that decay more slowly and extend over larger distances in time and space than would be expected from random processes (Bak, 1996; Bassingthwaighte, Liebovitch, & West, 1994). Apart from spectral analysis, a strategy to identify 1/f scaling is to estimate the dispersion of the data over varying window sizes, also called sample or bin sizes. Measured over a duration T the standard deviation of a data series will increase as T^h where the exponent h exceeds the value 1/2 that would indicate randomness (Mandelbrot, 1982); an increase in variability with growing sample size indicates fractal scaling.

1/f scaling in tapping

1/f scaling has been observed in various tapping research, one of the fields of research next to line drawing that has been taken as a classical example of Fitts' law. Tapping constitutes an important and early topic in the study of motor control. In his pioneering work, Stevens (1886) observed that movement series from continuation tapping comprised both short-term fluctuations, which are low-amplitude and high-frequency fluctuations, and longer-term drifts, characterized by larger and less frequent waves. Such observations are epitomical to 1/f scaling.

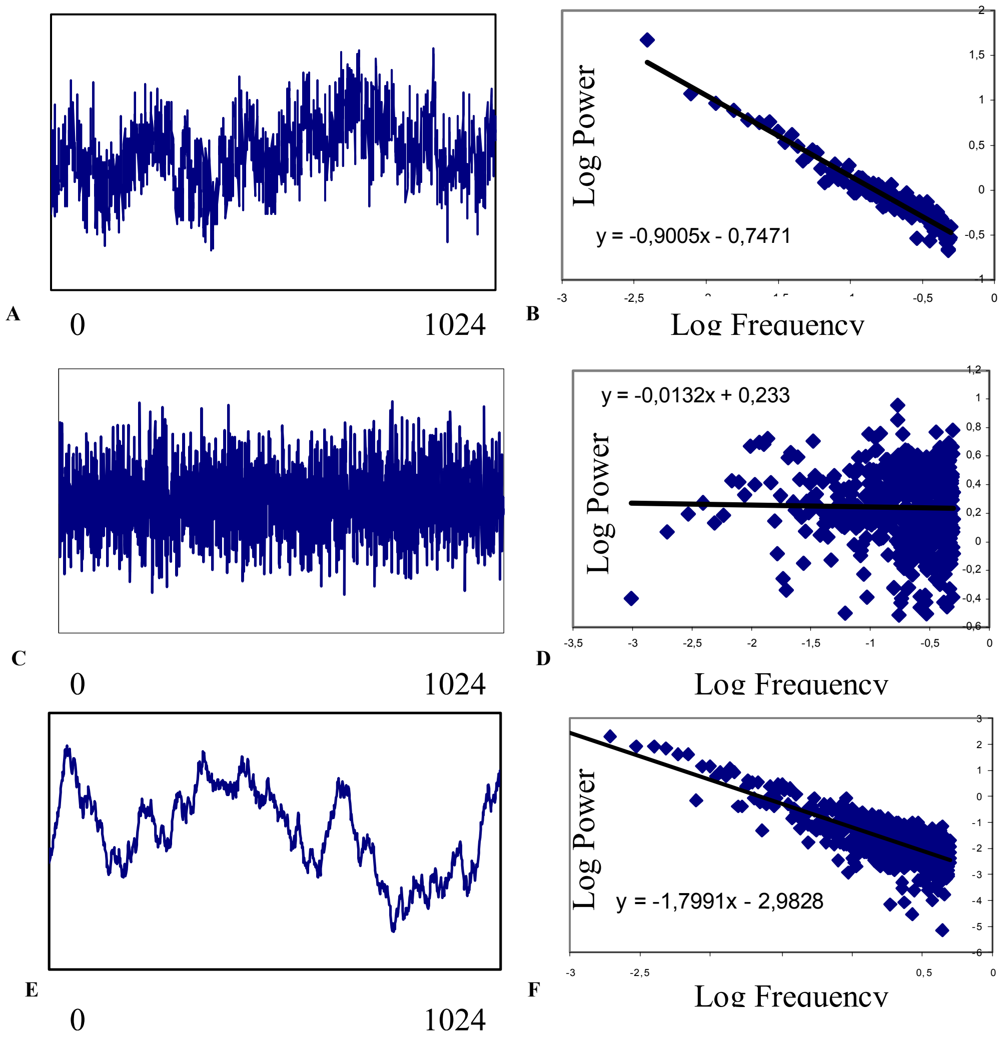


***Figure 2a.* A typical time series observed in human performance, 1/f scaling. *Figure 2b.* The power spectrum of a 1/f time series, α = 0.90. *Figure 2c.* A random time series created by randomizing the values of the 1/f time series from Figure 2a. *Figure 2d.* The power spectrum for the random time series, α = 0.01. *Figure 2e.* A time series that shows brown noise. *Figure 2f.* The power spectrum for brown noise. The slope is steeper than for 1/f scaling, α = 1.80.**

One of the first theories of 1/f scaling in human cognition reported by Gilden et al. (1995) concerned a time-estimation task, or equivalently a continuation-tapping task, in which participants were asked to repeatedly reproduce a rhythm from memory without feedback, so with the metronome that had presented the rhythm removed. 1/f scaling was observed in the deviations of the successive taps from the actual rhythm.

Another example of the presence of 1/f scaling in tapping data stems from Chen, Ding and Kelso (1997; 2001) who conducted a tapping experiment in which participants were presented a rhythm by a metronome. In contrast with Gilden et al.'s (1995) time-estimation task the metronome was not removed during the course of the experiment. In one condition, participants were asked to tap on the beat (synchronized), in a second condition they were asked to tap between two beats (syncopated). Analysis of the timing errors indicated slopes of the power spectrum of *-.54* for the synchronized condition, and *-.77* in the syncopated condition. The authors concluded that the syncopated condition that showed most pronounced 1/f scaling was more difficult, posing higher cognitive demands on the participants.

Tapping data recorded over continuous time appear to be characterized by 1/f scaling. If 1/f scaling is a phenomenon ubiquitous in natural systems and cognitive systems, it is likely to be observed in reciprocal-precision aiming as well. If the variability of successive movement times in a precision-aiming task scales with sample size, as in tapping, then that fact would speak to fundamental assumptions. It would not be appeased by ad hoc changes to Fitts' theory. 1/f scaling motivates changing some assumptions at the heart of behavioral science (Liebovitch, 2005; Van Orden et al, 2003; West & Deering, 1995). Thus, from a psychological point of view, it makes sense to ask what the empirical fact of 1/f scaling in cognitive and other human performance implies concerning the fundamental coupling of cognitive, bodily, and environmental processes.

In these studies, the scaling exponent characterizing fractal data has been proposed to be manipulable through task-dependent properties. Gilden et al. (1995) postulated that in a temporal-estimation task steeper slopes can be observed as the interval to be estimated increases. Chen et al. (1997, 2001) speculated that as task difficulty increases, defined by the task per se, the slope in the power spectrum decreases (becomes steeper). Van Orden et al. (2003) explained the tapping data differently. They postulated the theory that 1/f scaling originates from the spontaneous coordination of many component processes that all interact on multiple-time scales. These interactions are inherently sensitive to context. Van Orden et al. (2003) note that the cases where 1/f scaling is most pronounced are conditions where the same behavior is repeated many times with minimal external perturbation of cognitive performance. 1/f scaling is thought of to arise naturally in any set of human action, yet to be sensitive to perturbation. With respect to Chen et al.'s study (1997; 2001) specifically, Van Orden et al. (2003) argued that in the task conditions of the synchronized condition the inherent fluctuations are more obscured. This coordination cedes more control to the external driving force of the metronome, and the intrinsic dynamics of the cognitive system become obscured to more severe extent than in the synchronized-tapping condition. The example simply illustrates how changes in task demands are external factors that affect the capacity to measure 1/f scaling.

Task difficulty and 1/f scaling

A central issue of debate in the discussion about 1/f scaling has been whether more difficult tasks exhibit more or less pronounced 1/f scaling. Chen et al. (1997, 2001) observed a more pronounced 1/f signal in the syncopated-tapping condition, the assumed more difficult condition, than in the synchronized-tapping condition. In contrast to this finding, others reported more pronounced 1/f scaling in what appears to be a less difficult condition. Ward and Richard (2001) conducted a study of task difficulty that they equated with decision load; the number of stimulus and response alternatives (Ward, 2002; Ward & Richards, 2001). They observed more pronounced signals of 1/f scaling in what they considered to be less difficult task conditions, with minimal decision load (number of stimulus-response alternatives). Clayton and Frey (1997) also observed the clearest 1/f signal in their condition where task difficulty, in that study defined as memory load, was the lowest. Another interesting study of Kello, Beltz, Holden, and Van Orden (in press) suggests that task difficulty may have no effect on the appearance of 1/f scaling at all. Task difficulty certainly affects the scaling relation, yet it does not appear to be a unidirectional causal factor. It seems that 1/f scaling is co-determined by the context of task production.

These studies make clear that deciding upon task-dependent invariant levels of task difficulty clearly constitutes an ambiguous enterprise. It is concluded that other determinants must be considered. Here it is proposed to investigate the complexity of task performance as a moderating factor. This view is a challenge to Chen et al.'s (1997, 2001) encapsulated cognitive demands hypothesis that states that the exponent of 1/f scaling depends on task difficulty as well as to the belief that the effects of task difficulty are discarded by focusing on trial-by-trial variability (Wagenmakers, Farell, & Ratcliff, 2005).

The present study

Whereas the human cognitive system traditionally has been assumed a-temporal and context independent in its essential nature, it appears that the naturally occurring fluctuations in complex systems follow a lawful scaling relation, referred to as 1/f scaling. This has been observed in cognitive data to such extent that it has been claimed ubiquitous. If the ubiquity prediction holds, we might expect to observe 1/f scaling in precision-aiming data that are sampled continuously over time, over many consecutive trials. An implication of the presence of 1/f scaling in data is that relying just on the mean, the standard deviation or correlation coefficient under the assumption of a Gaussian distribution, one cannot adequately capture the dynamics of, and the presence of noise in, precision aiming movements. Lots of information can be gained from the issue of motor variability if the actual temporal order of the data is not discarded by means of averaging procedures.

It is proposed to investigate whether the scaling exponent characterizing 1/f scaling, as a reflection of the intrinsic dynamics of the cognitive system, perhaps constitutes that unique gauge for task complexity. Thus, not for the invariant task-dependant construct of task difficulty or objective-task complexity, but rather for the task complexity that naturally arises when a cognitive task is performed by a person in a context and in a history.

Inducing practice effects in a precision aiming task offers a hypothesis in this respect. The association between task complexity and the slope in the power spectrum leads to a testable prediction. If humans are trained in a hard task, it is very likely they will learn to perform the task better as practice increases. This means that the same task, for the same person will be easier to perform after practice. The task will be less perturbing as practice continues. If 1/f scaling in human motor data indeed arises from a fractal process, one would expect the ongoing activity to be disrupted by externally imposed perturbations.

Thus, as people get trained in precision aiming, first, steeper slopes in the power spectrum of the successive movement times, and secondly, a larger increase of standard deviation with sample size should be observed for equal levels of the Index of Difficulty inherent to the task. If the slope of power spectra derived from the data would change systematically over repeated-task performance, this would show that not only the task, but rather the context of human performance relates to the scaling relation observed in behavioral data. This, in turn, leads directly to the conclusion that the disruption of 1/f scaling in the cognitive system can be a gauge for how difficult a task actually is to a person in a context.

To investigate the effect of task on performance, we created two experimental conditions. In the first and easy condition, a large target size and a small target distance was used, whereas in the second and more difficult condition a small target size and a large target distance was used. In the second condition, there is a lot more coordination to gain than in the first condition where a ceiling effect of learning should occur earlier in the experiment. This was the reason for choosing such a high Index of Difficulty. An extra degree of coordination was achievable because training sessions were to be performed with the non-dominant hand.

An additional issue is the occurrence of concurrent streams of 1/f scaling. Apart from successive movement times, we also analyzed time series deriving from spatial variability, pen pressure and pen tilt. If the ubiquity prediction holds, 1/f scaling should also be observed in these data series. Following Kello et al. (in press), Kello, Anderson, and Van Orden (2007), and Anderson and Kello (2006), parallel streams of 1/f scaling are expected to be independently manipulable, in contrast to what may be expected if 1/f scaling pattern were a linear partition of amplitudes and frequency. If linear partitions of white noise just spuriously appear to look like 1/f scaling, each concurrent stream should reflect the spurious effect to a similar extent. Parallel streams of 1/f scaling would complete our evidence in favor of 1/f scaling in the variability of simple motor tasks as emergent and context-dependent.

Method

Participants

The participants were undergraduate students receiving a course credit for participating in the experiment. Thirty participants were randomly assigned to one of the two conditions. None suffered from any known motor impairment and all participants had normal or corrected to normal vision. All participants were right-handed as tested by the handedness subscale of the Lateral Preference Inventory (Coren, 1993).

Materials

Movement coordinates, axial pen pressure and pen tilt were recorded using a WACOM digitizer tablet connected to a regular Pentium PC. The tablet samples at temporal rate of 171Hz, with a spatial resolution of 1000 lines/cm. The input device was an inkless stylus used on a model sheet (A4). Kinematic records were converted into two dimensional coordinates using Oasis software (De Jong, Hulstijn, Kosterman, & Smits-Engelsman, 1996).

Procedure

Participants were seated on a height-adjustable chair in front of the digitizer tablet. Two visual targets were presented on a printed sheet of paper, one at the left side of the paper and one at the right side. The targets in the first condition (low ID) had a width of 2 cm and their middle points were separated by 8 cm. The Index of difficulty equals 3 bits for this condition. In the second condition (high ID) target width was 0.4 cm and the distance between targets was 24 cm. In this condition an Index of Difficulty of 6.9 bits was used. The participants were asked to draw lines between the targets, as fast and as accurately as possible. They were allowed to modify the distance to the digitizer tablet and the table orientation within a range of 30°. Participants had to complete 1100 trials in each session (for the spectral analysis, an uninterrupted time series of 1024 data points is required). Each session started with a calibration procedure. When the 1100^{th} trial in the session was reached a tone signaled the end of the session. The sequence of sessions was organized as follows. The first experimental block was completed with the dominant hand. After a three-minute break, a second experimental block started that had to be performed with the non-dominant hand. Then, after the standard three-minute breaks, participants were subjected to four identical training sessions, followed by a final session with the dominant hand.

Analyses

The movement times for successive lines were treated as a time series. To quantify the temporal structure of the successive fluctuations, we used power-spectral-density analysis, dispersion analysis, and detrended-fluctuation analysis using Matlab scripts (Mathworks Inc.). The correlations between concurrent streams of 1/f scaling, in this case successive effective line length, axial pen pressure, and pen tilt, are computed for the outcomes (scaling measures) of the spectral analysis, dispersion analysis, and the detrended-fluctuation analysis by calculating the correlation efficient for each session over fifteen participants averaged across sessions.

Power Spectral Density Analysis (PSDA). The power-spectral-density analysis, or spectral analysis, arises from the traditional linear perspective. Spectral analysis applies a Fast Fourier Transformation to the data, the output of this procedure results in a power spectrum; a log-log plot of frequency versus amplitude. This analysis, however, requires some preprocessing of the raw data. We treated the raw data in line with the data-massage that is usually given to these data, before they are submitted to spectral analysis (Van Orden et al, 2003). Essential steps include taking the raw data and excluding the extreme values. In the low-ID condition we excluded movement time below 150 ms and above 1200 ms. In the high-ID condition values below 50 ms and above 850 ms were excluded. For the tilt and pressure data, no extremes were removed because of their continuous character. Then, outliers were removed by means of a 3 * *SD* criterion. Next, after visual inspection of the time series it was decided to remove linear trends only. There were no reasons to remove higher-order trends, because this procedure might have discarded the signal in dramatic ways. Then the data series of movement times were truncated to 1024, as required for the spectral analysis. The time series from pen pressure and pen tilt were truncated to 32768 trials for the low-ID condition, and to 65536 trials for the high-ID condition. We left out the trials at the beginning of the experiment, until 1024 trials remained that were removed from extreme values, outliers, linear trends and that had a proper size for running the analysis. The truncating procedure was unrelated to the slope of the power spectrum. The number of estimated frequencies was 512 for movement times and line length, and 1024 for pen pressure and pen tilt.

Standardized Dispersion Analysis (SDA). Dispersion analysis can also characterize the degree of randomness in the data. It assesses the relative coherence of the patterns of fluctuations in 1/f scaling via the fractal-dimension statistic. The Fractal Dimension (FD) describes the change in variability attendant on changing-sample sizes. This estimate relates to the exponent of the spectral-scaling relation, a fractal dimension for a random-time series equals 1.5, time series characterized by 1/f scaling the fractal dimension equals 1.21. It is possible to recalculate the fractal dimension back into a scaling exponent. A fractal dimension equals $1+ (\alpha + 1) / 2$, where α is the spectral slope. Yet both analyses may not agree perfectly, because data are processed in a slightly different manner. For example, the fractal dimension is calculated over the entire range of frequencies as opposed to the spectral slope, for which a criterion has to be set. An advantage of applying dispersion analysis is that it captures the most important aspects of fractal data using the traditional statistical estimates readers will be familiar with. The dispersion analysis describes the changes in the variability of a measurement across a range of sample sizes (or measurement resolution), in terms of a power-law scaling relation. In other words, the dispersion analysis determines a scaling relation between sample size and sample variability.

The essential steps to compute FD using dispersion analysis are the following. Before the analysis, the linear trend is removed. Then data are standardized using the population standard deviation so that the mean becomes 0 and the standard deviation 1. Then, the mean of every two consecutive data points is computed, which yields 512 two-point means, and for these means the standard deviation is computed. Then, the standard deviation of the means of 256 four-point means is computed. Next the standard deviation is computed of 128 eight-point means, and so on. In case of 1/f scaling, for decreasing sample sizes 512, 256, 128, 64, 32, 16, 8, 4, 2, 1, the corresponding standard deviations increase dramatically. The fractal dimension can be computed by 1 - the slope of the plot of bin size against standardized dispersion (See Figure 3a and 3b). For the movement time series six bin sizes were used, for the pen pressure and pen tilt series, ten bin sizes were used.

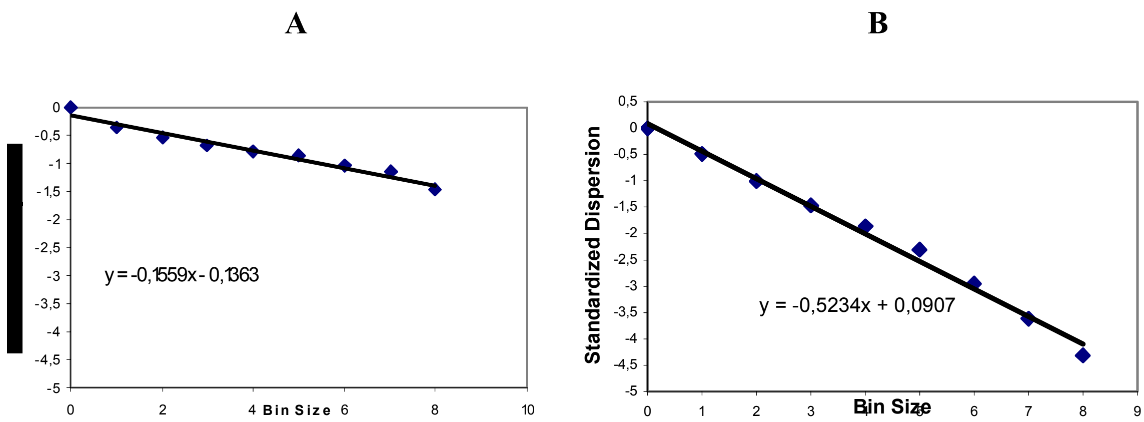


***Figure 3a.* A dispersion plot for a nearly 1/f scaled time series (*FD* = 1.16). *Figure 3b.* A dispersion plot for the same time series after randomization (*FD* = 1.52).**

Detrended Fluctuation Analysis (DFA). Detrended-fluctuation analysis is yet another scaling method commonly used for detecting long-range correlations in data series and was applied to the same time series as the PSDA (Peng, Mietus, Hausdorff, Havlin, Stanley, & Goldberger, 1993). The DFA method is briefly described here. First, the original time series is integrated by computing the accumulated departure from the mean of the whole series for each measurement. Then, detrending is performed locally, that is, the time series is subdivided into non-overlapping windows of equal length and, in each window, the local trend, the locally best-fit line is subtracted. Next, the standard deviations of the integrated and detrended time series are computed for windows of the same length and the mean of the standard deviations of all windows of the same length are computed. This process is repeated over increasing window sizes. We performed the DFA for window size ranges between 4 and 1024 for the trial series of movement time and movement amplitude, and between 4 and 32518 for the continuous time series of pen pressure and pen tilt.

The outcome of the DFA analysis is the fractal exponent α. It represents the slope of a line fitted to the mean-standard deviations versus the window sizes across the relevant range of scales on a log-log scale (See Figure 4a and 4b). If the alpha exponent is 0.5, the sequence is white noise. If alpha exceeds 0.5, the series is considered to have time correlation. In the case of an alpha value of 1, the sequence is scaled exactly as 1/f. The case of brown noise is characterized by an alpha exponent of 1.5.

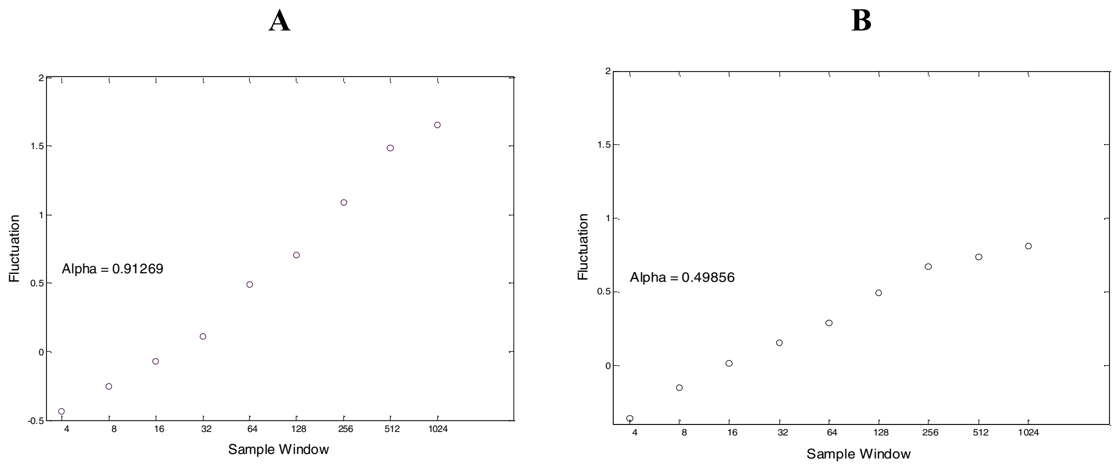


Figure 4a. **A diffusion plot from the DFA from a time series near 1/f scaling, $\alpha = 0.91$.** ***Figure 4b.*** **A diffusion plot from the same time series that was randomized, $\alpha = 0.50$.**

Strengths and weaknesses of each kind of analysis. The application of spectral analysis, standardized dispersion analysis, and detrended-fluctuation analyses is necessary not only to reveal the nature of a given process more clearly, but also to avoid the false conclusion of scaling behavior resulting from possible artifacts or wrong measurements. The power spectrum analysis and standardized-dispersion analysis applied are not optimal for the quantification of correlations in potentially nonstationary data. Long-range correlations can arise also as an artifact in case of nonstationary data. Thus, to further consolidate the presence of long-range correlations, we implemented the detrended-fluctuation analysis. If its assumptions are met, standardized-dispersion analysis is among the most reliable methods to estimate fractal dimension. But, if the fractal dimension is less than 1.2 (so, more indicative of brown noise), other methods, like DFA should be used to characterize the scaling relations. The spectral analysis and standardized-dispersion analysis are affected by simple trends, but careful examination of data or removing a linear trend can avoid this. Also detrended-fluctuation analysis is known to be reliable (Eke, Hermán, Kocsis, & Kozak, 2002), and does not require the same preprocessing of the data as the spectral analysis. The use of different methods of analysis as converging operations is recommended. Using spectral and fractal methods in tandem makes it very hard to misclassify coincidental artifacts for 1/f scaling (Van Orden et al., 2003).

Results

The discussion of the results starts with an overview of the traditional performance measures, then the spectral and fractal analyses will be discussed, followed by the correlations between concurrent streams of 1/f scaling.

Performance measures

The traditional performance measures provide evidence for the fact that performance improved over training sessions. The analyses in this paragraph pertain to the mean accuracy, the mean movement time, the mean *SD,* and the mean Index of Performance per session. In all analyses, the variable ID was treated as a between-subjects variable and session as a within-subjects variable.

Accuracy

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the mean accuracy of the participants using the dominant hand. The main effect of ID revealed a significantly higher accuracy in the low-ID condition (Mean = 85.15%, *SD* = 12.81) than in the high-ID condition (Mean = 27.2%, *SD* = 17.04), $F(1, 28) = 88.70$, $p < .0001$, partial $\eta^2 = .76$. The main effect of session was not significant, $F < 1$. The interaction effect between ID and session was, $F(1, 28) = 4.27$, $p < .05$, partial $\eta^2 = .13$. A subsequent paired-samples *t* test on the comparison between first and last session of the low-ID condition revealed no significant difference, $t(14) = -.94$, $p = .36$. The same analysis on the high-ID condition appeared to be significant, $t(14) = 2.37$, $p < .04$. Mean accuracy of the first session was higher (Mean = 32.4%, *SD* = 18.24) than of the last session (Mean = 22.1%, *SD* = 14.53).

A 2 (ID: high vs. low) by 5 (session: 2 vs. 3 vs. 4 vs. 5 vs. 6) ANOVA on the mean mean accuracy of the participants using the non-dominant hand. The main effect of ID revealed a significantly higher accuracy in the low-ID condition (Mean = 84.4%) than in the high-ID condition (Mean = 14.2%), $F(4, 112) = 598.12$, $p < .0001$, partial $\eta^2 = .96$. Neither the main effect of session nor the interaction reached significance, both *F*'s < 1.

A 2 (ID: high vs. low) by 7 (session: 1 vs. 2 vs. 3 vs. 4 vs. 5 vs. 6 vs. 7) MANOVA on the mean movement times of the participants in all seven sessions. Again, the main effect of ID reached significance, $F(1, 28) = 444.85$, $p < .0001$, partial $\eta^2 = .94$. The main effect of session was not significant, $F < 1$. The interaction effect, however, was significant, Pillai's trace = .41, $F(6, 23) = 4.72$, $p < .04$. To further investigate the source of this interaction, separate MANOVA's were conducted on the ID conditions. In the low-ID condition, no significant effect of session emerged, $F < 1$. This indicates that accuracy remained stable over all session, irrespective of hand preference. In the high-ID condition, a significant effect of session emerged with significant linear and quadratic trends, Pillai's trace = .89, $F(6, 9) = 12.01$, $p < .001$. The highest accuracy occurred in the first session with the dominant hand, a significant drop in accuracy emerged from the second to the sixth session performed with the non-dominant hand, followed by a significant increase in the last session again with the dominant hand, but was still performed less accurately than the first dominant-hand session.

Movement time

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the mean movement times (in seconds) of the participants using the dominant hand. The main effect of ID revealed significantly shorter movement times in the low-ID condition (Mean = 0.18s, *SD* = .06) than in the high-ID condition (Mean = 0.54s, *SD* = .09), $F(1, 28) = 214{,}90$, $p < .0001$, partial $\eta^2 = .89$. The main effect of session was significant, $F(1,28) = 15.94$, $p < .0001$, partial $\eta^2 = .36$. The interaction effect between ID and session was not, $F(1, 28) = 2.08$, $p = .16$.

A 2 (ID: high vs. low) by 5 (session: 2 vs. 3 vs. 4 vs. 5 vs. 6) ANOVA was run on the mean movement times (in seconds) of the participants using the non-dominant hand. The main effect of ID revealed a significantly shorter movement times in the low-ID condition (Mean = 0.21s, *SD* = .08) than in the high-ID condition (Mean = 0.56s, *SD* = .09), $F(4, 28) = 176.21$, $p < .0001$, partial $\eta^2 = .86$. The main effect of session was significant as well, $F(4, 112) = 3.27$, $p < .03$, revealing a significant linear trend. The interaction did not reach significance, $F(4, 112) = 1.29$, $p = .28$.

A 2 (ID: high vs. low) by 7 (session: 1 vs. 2 vs. 3 vs. 4 vs. 5 vs. 6 vs. 7) MANOVA was performed on the mean movement times (in seconds) of the participants in all seven sessions. Again, the main effect of ID reached significance, $F(1, 28) = 209.70$, $p < .0001$, partial $\eta^2 = .88$. The mean movement time in the low-ID condition was (Mean = .20s, *SD* = .07), the mean in the high-ID condition was (Mean = .55s, *SD* = .06). The main effect of session was significant, Pillai's Trace = .60, $F(6, 23) = 209.70$, $p < .0001$, partial $\eta^2 = .88$. The interaction effect was also significant, Pillai's trace = .43, $F(6, 23) = 2.92$, $p < .03$. To further investigate the source of this interaction, separate MANOVA's were conducted on the ID conditions. In the low-ID condition a significant effect of session emerged, Pillai's Trace = .78, $F(6, 9) = 5.19$, $p = .01$, revealing significant linear, quadratic, cubic and order-4 trends. In the high-ID condition no significant effect of session emerged, $p = .13$. This indicates that movement time remained stable over all sessions, irrespective of hand preference.

Standard deviation of movement time

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the standard deviation of movement times for the dominant hand sessions. The main effect of ID revealed a significantly lower standard deviation in the low-ID condition (Mean = 0.02, *SD* = 0.01) than in the high-ID condition (Mean = 0.16, *SD* = .10), $F(1, 28) = 39.69$, $p < .0001$, partial $\eta^2 = .59$. The main effect of session was significant $F(1, 28) = 6.17$, $p < .02$, partial $\eta^2 = .18$, revealing a higher standard deviation in the first session (Mean = 0.10, *SD* = .11) than in the last (Mean = 0.07, *SD* = .09). The interaction effect between ID and session was, $F(1, 28) = 5.73$, $p < .02$. A subsequent paired-samples *t* test on the comparison between first and last session of the low-ID condition revealed no significant difference, $t(14) = .49$, $p = .63$. The same analysis on the high-ID condition appeared to be significant, $t(14) = 2.45$, $p < .03$. The mean standard deviation of the first session was higher (Mean = .18, *SD* = .10) than of the last session (Mean = .11, *SD* = .11).

A 2 (ID: high vs. low) by 5 (session: 2 vs. 3 vs. 4 vs. 5 vs. 6) ANOVA was run on the mean standard deviation of the participants for the non-dominant hand training sessions. The main effect of ID revealed a significantly lower standard deviation in the low-ID condition (Mean = 0.02, *SD* = .02) than in the high-ID condition (Mean = .12, *SD* = .10), $F(1, 28) = 19.68$, $p < .0001$, partial $\eta^2 = .41$. Neither the main effect of session, $p = 0.10$, nor the interaction, $F < 1$, reached significance.

A 2 (ID: high vs. low) by 7 (session: 1 vs. 2 vs. 3 vs. 4 vs. 5 vs. 6 vs. 7) MANOVA was performed on the mean movement times of the participants in all seven sessions. Again, the main effect of ID reached significance, $F(1, 28) = 28.99$, $p < .0001$, partial $\eta^2 = .51$. The main effect of session was significant, Pillai's trace = .50, $F(6, 23) = 3.84$, $p < .009$. The interaction effect was also significant, Pillai's trace = .47, $F(6, 23) = 3.46$, $p < .001$. To further investigate the source of this interaction, separate MANOVA's were conducted on the ID conditions. In the low-ID condition, no significant effect of session emerged, $F(6, 9) = 2.13$, $p = .15$. This indicates that standard deviation remained stable over all sessions, irrespective of hand preference. In the high-ID condition, a marginally significant effect of session emerged, Pillai's trace = .68, $F(6, 9) = 3.12$, $p = .06$. A significant linear trend emerged, indicating a decrease in standard deviation.

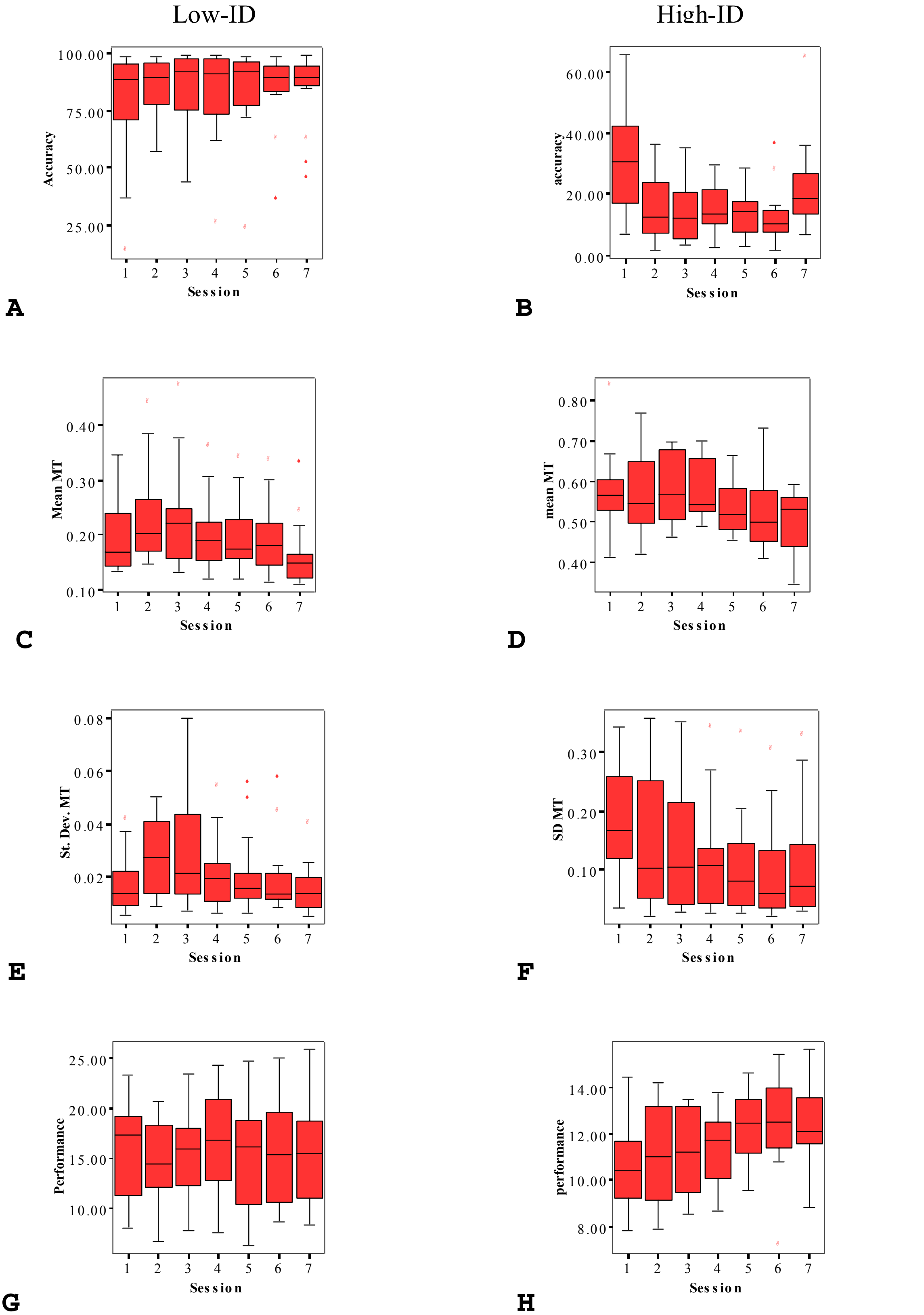


Figure 5 a-h. **The change in mean movement times, standard deviations, Index of Performance (IP) and accuracy levels over training sessions in the low-ID and high-ID condition. The first and the last session were completed with the dominant hand, the five middle sessions with the non-dominant hand. The corresponding effect size has been measured both with a seven level as with a five level ANOVA respectively. Note that the outer left and right bars are the sessions with the dominant hand.**

Index of Performance (IP)

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the Index of performance of the participants using the dominant hand. The main effect of ID revealed a significantly higher IP in the low-ID condition (Mean = 15.50, *SD* = 5.21) than in the high-ID condition (Mean = 11.50, *SD* = 2.10), $F(1, 28) = 10.19$, $p < .003$, partial $\eta^2 = .27$. Neither the main effect of session, $p = .21$, nor the interaction effect between ID and session, $p = .26$ was significant.

A 2 (ID: high vs. low) by 5 (session: 2 vs. 3 vs. 4 vs. 5 vs. 6) ANOVA on the Index of Performance of the participants using the non-dominant hand. The main effect of ID revealed a significantly higher IP in the low-ID condition (Mean = 15.55, *SD* = 5.00) than in the high-ID condition (Mean = 11.65, *SD* = 1.94), $F(1, 28) = 15.70$, $p < .001$, partial $\eta^2 = .36$. Neither the main effect of session nor the interaction reached significance, both *F*'s < 1. However, this is due to the fact that there where large differences in variances between the low-ID and the high-ID condition. Therefore, to further investigate the effect of rising IP with training, a repeated measures ANOVA for each condition was performed separately. In the high ID condition, a significant increase in IP was observed, $F(1, 14) = 4.00$, $p < .01$, partial $\eta^2 = .22$. In the low ID-condition however the effect was lacking, $F < 1$. This indicates that IP increases over the non-dominant hand training sessions.

A 2 (ID: high vs. low) by 7 (session: 1 vs. 2 vs. 3 vs. 4 vs. 5 vs. 6 vs. 7) MANOVA on the Index of Performance of the participants in all seven sessions. Again, the main effect of ID reached significance, $F(1, 28) = 16.11$, $p < .0001$, partial $\eta^2 = .37$, and the main effect of session as well as the interaction effect did not reach significance, both *F*'s < 1. To further investigate the effect of training on IP, separate MANOVA's were conducted on the ID conditions, because the lack of homogeneity of variances between the two ID conditions. In the low-ID condition, no significant effect of session emerged, $F < 1$. This indicates that IP remained stable over all session, irrespective of hand preference. In the high-ID condition however, a significant linear trend emerged, revealing an increase of performance, Pillai's trace = 0.65, $F(1, 14) = 4.14$, $p < .02$, partial $\eta^2 = .23$.

Spectral and fractal analyses

Apart from the traditional performance measures, the spectral and fractal analyses provide additional information about what happens to the intrinsic dynamics with learning. Focusing simultaneously on variability and stability by observing the evolution of a system over time can retrieve this information. It concerns unique information that is lost by applying traditional linear statistical logic.

The spectral analysis tests whether the amplitude and frequencies of fluctuations of the data are related so that fluctuations are self-similarly nested across different timescales, and as such, whether long-term correlations occur throughout the experiment. Additional information about the fractality of the data is provided by the SDA and the DFA. These analyses assess whether the standard deviation in the data grows with the amount of data, the window size, from the analyzed series. First, the focus is on whether fractal scaling occurs in precision-aiming data, then, the information about the learning process is presented, and finally, results that clarify the relation between the different streams of 1/f scaling are presented.

The occurrence of 1/f scaling in precision aiming data

In all sessions of all participants 1/f scaling was observed in the trial series of consecutive movement times, and in the time series of axial pen pressure and pen tilt. This is a clear indication precision-aiming movements are not randomly dispersed. In both the low-ID and in the high-ID condition the mean of the spectral-scaling exponents, as well as the fractal dimensions and the scaling exponents from the DFA varied for the different data sources, movement time series, axial pen pressure, and pen tilt. The average values for both conditions are presented in Table 1.

Table 1

The Fractal Scaling Measures for the Movement Time, Pen Pressure, and Pen Tilt Series.

Analysis/Variables	Movement time	Pen pressure	Pen tilt
		Low-ID	
PSDA	-.83	-1.60	-1.91
SDA	1.18	1.12	1.06
DFA	.90	1.00	1.11
		High-ID	
PSDA	-.85	-2.10	-1.93
SDA	1.19	1.08	1.05
DFA	.88	1.06	1.14

These results consistently indicate that that succesive data points were correlated in time. In all the measurements 1/f scaling is pronounced. The DFA analysis does not recognize pen pressure and tilt as nearly as brown noise as suggested by the spectral analysis and dispersion analysis, this is most likely due to a known weakness of these analyses. If the spectral analysis or the dispersion analysis suggests brown noise in the data, DFA is preferred. The scaling exponents coefficients of the DFA still exceed the value of exact 1/f scaling to some extent, yet the results contain values closer to 1/f scaling ($\alpha = 1$) then to brown noise ($\alpha = 1.5$).

The outcomes of the spectral analysis, dispersion analysis and detrended-fluctuation analysis were highly consistent as shown by overall correlations near 1 (See Table 2).

Table 2.

The Correlations between the Spectral and Fractal Analyses for the Movement Time Series.

		Spectral slope of MT averaged over training sessions	FD of MT averaged over training sessions	DFA exponents of MT averaged over training sessions
Spectral slope of MT averaged over training sessions	Pearson Correlation	-	.95**	-.92**
	p (2-tailed)	-	.0001	.0001
	N	-	15	15
FD of MT averaged over training sessions	Pearson Correlation	.85**	-	-.97**
	p (2-tailed)	.0001	-	.0001
	N	15	-	15
DFA exponents of MT averaged over training sessions	Pearson Correlation	.84**	-.97**	-
	p (2-tailed)	.0001	.0001	-
	N	15	15	-

Note: The correlations in the upper triangle correspond to the high-ID condition, and the correlations in the lower triangle to the low-ID condition.

Average changes with practice

If scaling exponents or fractal dimensions become averaged over training sessions the variance introduced by the acquisition of coordination is discarded. Therefore changes in fractality with practice were investigated. The results from the spectral analysis, the dispersion analysis and the detrended-Fluctuation analysis were subjected to a repeated measures (M)ANOVA. The mean spectral slopes, fractal dimensions and, DFA scaling exponents for consecutive training sessions in both experiments, for movement times, pen pressure and pen tilt can be found in Table 3.

Spectral analysis. All streams of 1/f scaling, that is, movement time, pen pressure, and pen tilt, were subjected to a spectral analysis. The first analyses pertained to the transfer from the first to the last training session, the second analyses concern the effect of practice on task performance with the non-dominant hand.

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the spectral slopes of movement times for the dominant hand sessions. Neither significant main effects of ID, $p = .18$, and session, $p = .14$, nor a significant interaction emerged, $F < 1$. The same analysis on pen pressure series revealed a significant effect of ID only, $F(1, 28) = 43.49$, $p < .0001$, partial $\eta^2 = .61$. The mean spectral slope of pen pressure in the first session (Mean = -1.82, SD =.49) was higher (more near brown noise than to 1/f scaling) then in the last session (Mean = -1.75, SD =.48). For the pen tilt series, no main effect of ID was observed, p =.30. No significant interaction effect occurred, $F < 1$. The main effect of session was marginally significant, $F(1, 28) = 3.88$, $p < .06$, partial $\eta^2 = .12$. The spectral slope increases, so becomes steeper in the last session (Mean = -1.80, SD =.36) compared to the first (Mean = -1.68, SD =.27).

A repeated measures ANOVA on spectral slopes from the movement time series of each of the participants in the five non-dominant hand conditions was performed on the high-ID and the low-ID conditions separately. No main effect of session occurred in the low-ID condition, $p = .38$. In the high-ID condition however, the main effect of session was significant, $F(4, 56) = 4.65$, $p < .003$, partial $\eta^2 = .25$, revealing a significant linear trend with decreasing scaling exponents (the slopes become steeper with practice), $F(1, 14) = 11.07$, $p < .005$, partial $\eta^2 = .44$. This indicates hat the spectral scaling exponents get larger with practice. The same analysis were performed on the pen pressure data, no significant effect of session was observed in the low-ID condition, $p = .28$, but there was in the high-ID condition, $F(4, 56) = 3.04$, $p < .02$, partial $\eta^2 = .18$, revealing a significant linear trend, with decreasing slopes of the pen pressure data. For pen tilt, the analysis did not reveal such an effect in the high-ID condition, $F < 1$. In the low-ID condition however, a significant effect was observed, $F(4, 56) = 2.59$, $p < .05$, partial $\eta^2 = .16$.

Fractal dimension. A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the fractal dimensions of the movement times for the dominant hand sessions. Neither significant main effects of ID, $p = .17$, and session, $p = .14$, nor a significant interaction emerged, $F < 1$. The same analysis on the pen pressure data revealed no significant effects at all, all F's < 1. Also for the pen tilt data, no significant effects were observed, all F's < 1.

A repeated measures ANOVA on fractal dimensions of each of the participants in the five non-dominant hand conditions was performed on the high-ID and the low-ID conditions separately for the movement time series. No main effect of session occurred in the low-ID condition, p = .23. In the high-ID condition however, the main effect of session was significant, $F(4, 56) = 3.55$, $p < .01$, partial $\eta^2 = .20$, revealing a significant linear trend with decreasing fractal dimensions, $F(1, 14) = 9.74$, $p < .008$, partial $\eta^2 = .41$. This confirms the result of the PSDA. The same analysis were performed on the pen pressure data, neither in the low-ID condition, $p = .14$ nor in the high-ID condition, $F < 1$, a significant effect of session was observed. For pen tilt, the analysis did not reveal such an effect in the high-ID condition, $p = .30$. In the low-ID condition however, a significant effect was observed, $F(4, 56) = 2.80$, $p < .03$, partial $\eta^2 = .17$, revealing a linear and quadratic trend.

A 2 (ID: high vs. low) by 2 (session: first vs. last) ANOVA was performed on the DFA scaling exponents of the movement time series for the dominant hand sessions. Neither significant main effects of ID, $p = .18$, and session, $p = .21$, nor a significant interaction emerged, $F < 1$. For pen pressure only a significant effect of ID was observed, $F(1, 28) = 8.88$, $p < .006$, partial $\eta^2 = .24$. In the low-ID condition, the scaling exponent for pen pressure was lower (Mean = 1.00, *SD* =.09) than in the high-ID condition (Mean = 1.07, *SD* =.07). The analysis for pen tilt revealed that no significant effects occurred, all F's < 1.

DFA scaling exponents. Also the alpha exponents of the DFA from the movement time series indicate clearer examples of 1/f scaling (and thus increases, the slope gets steeper) as people perform the task more often. A repeated measures on the fractal scaling exponents of the DFA of each of the participants in the five non-dominant hand conditions was performed on the high-ID and the low-ID conditions separately. No main effect of session occurred in the low-ID condition, $p = .28$. In the high-ID condition however, the main effect of session was significant, $F(4, 56) = 2.63$, $p < .04$, partial $\eta^2 = .16$, revealing a significant linear trend with increasing scaling exponents, $F(1, 14) = 4.48$, $p < .05$, partial $\eta^2 = .24$. Herby, the outcome of the PSDA and SDA are confirmed. The same analyses were performed on the pen pressure DFA exponents, no main effect of session occurred in either the low-ID ($p = .22$) or the high-ID conditions $F < 1$. The analyses for pen tilt showed a significant effect of session in the low-ID condition, $F(4, 56) = 2.64$, $p < .04$, partial $\eta^2 = .16$, revealing a significant linear trend. The DFA slopes decreased with practice. In the high-ID condition however, such an effect was lacking, $F < 1$.

Table 3

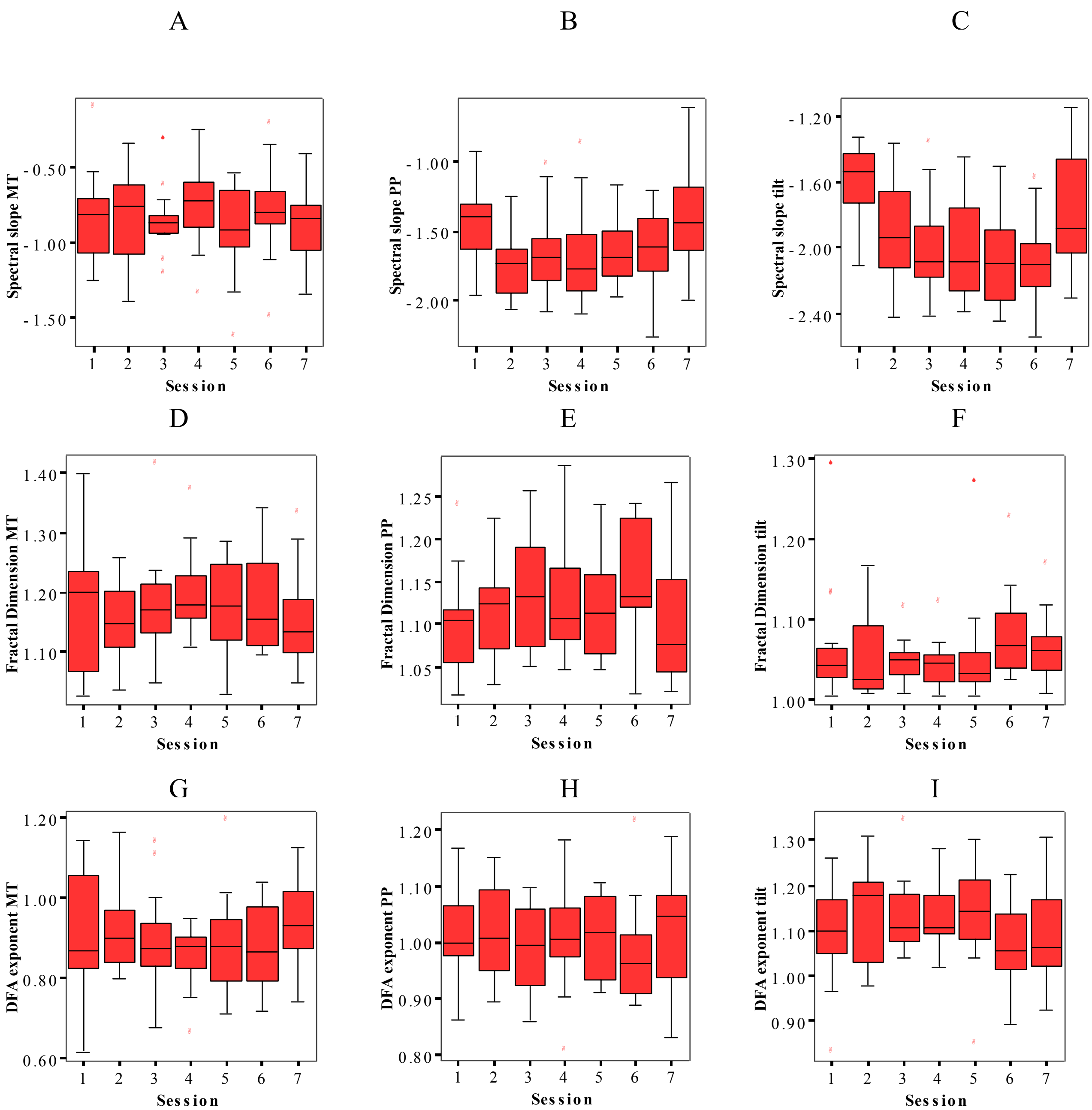
Mean Spectral Slopes, Fractal Dimensions and DFA Exponents for all Training Sessions in Both Experiments and for all Streams of 1/f Scaling. R1 and R2 are the Dominant Hand Sessions, L1-L5 are the Non-Dominant Hand Training Sessions.

		Index of Difficulty													
MEAN SPECTRAL SLOPES		**Low**							**High**						
		R1	**L1**	**L2**	**L3**	**L4**	**L5**	**R2**	**R1**	**L1**	**L2**	**L3**	**L4**	**L5**	**R2**
Movement Time															
	M	-.83	-.81	-.85	-.74	-.89	-.77	-.89	-.67	-.77	-.88	-.82	-1.01	-.99	-.83
	SD	.31	.30	.20	.28	.31	.31	.25	.29	.30	.29	.28	.26	.29	.36
Pen pressure															
	M	-1.44	-1.75	-1.65	-1.68	-1.64	-1.63	-1.41	-2.19	-2.15	-2.16	-2.09	-2.04	-1.99	-2.08
	SD	.26	.25	.30	.34	.25	.28	.37	.35	.33	.31	.27	.26	.28	.34
Tilt															
	M	-1.61	-1.91	-1.98	-2.00	-2.06	-2.07	-1.77	-1.76	-1.96	-1.98	-2.02	-1.97	-1.96	-1.84
	SD	.24	.30	.30	.31	.29	.26	.38	.29	.32	.32	.36	.37	.38	.35

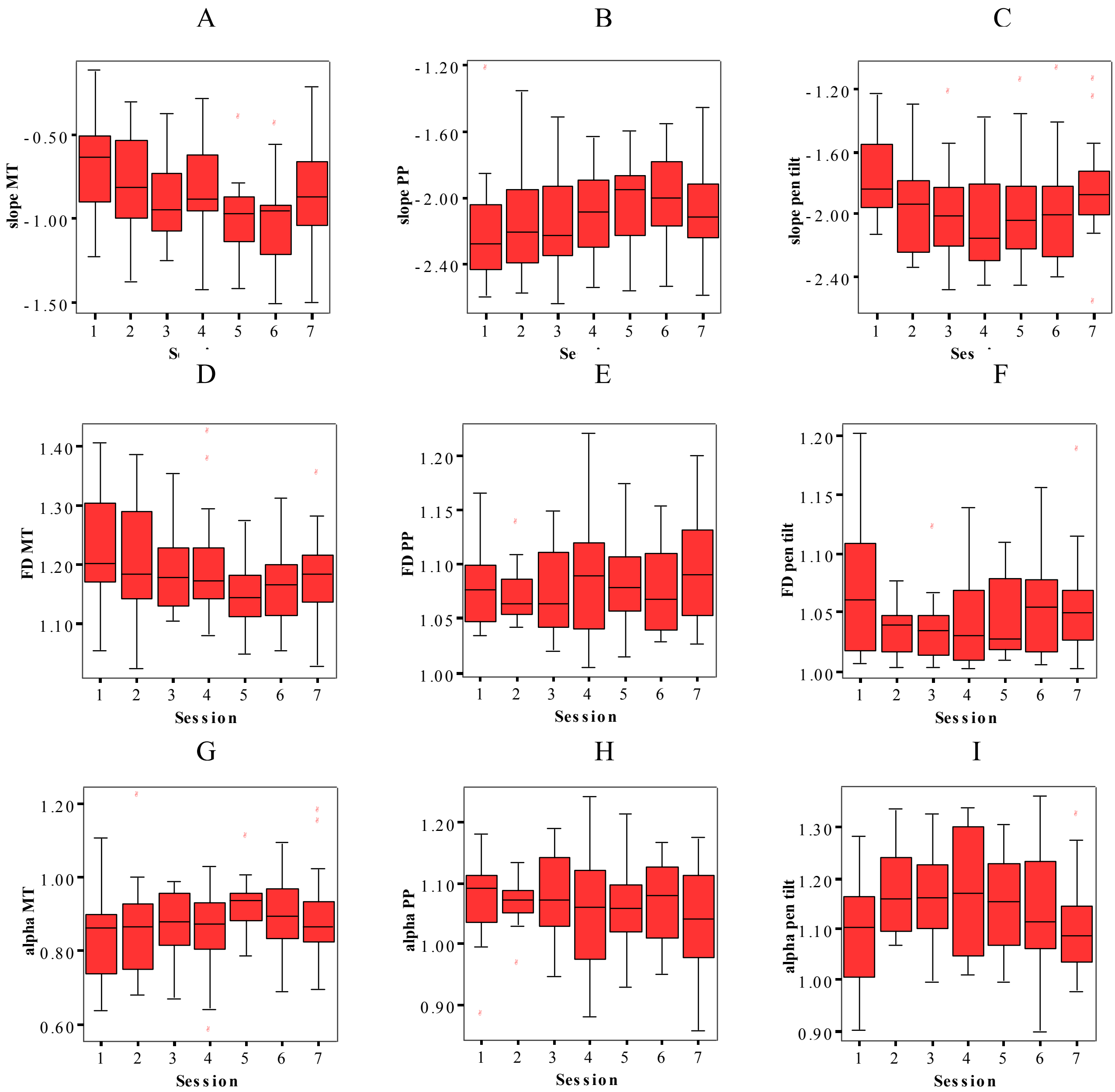
Table 2 (continued)

		Index of Difficulty													
FRACTAL DIMENSIONS SDA		**Low**							**High**						
		R1	L1	L2	L3	L4	L5	R2	R1	L1	L2	L3	L4	L5	R2
Movement Time															
	M	1.17	1.15	1.18	1.20	1.18	1.19	1.16	1.23	1.21	1.19	1.21	1.15	1.16	1.18
	SD	.11	.07	.09	.07	.08	.09	.08	.11	.10	.09	.09	.06	.07	.09
Pen pressure															
	M	1.10	1.12	1.14	1.13	1.12	1.15	1.10	1.08	1.07	1.08	1.09	1.08	1.08	1.09
	SD	.06	0.6	.07	.07	.06	.07	.08	.04	.03	.04	.06	.04	.04	.05
Tilt															
	M	1.06	1.05	1.05	1.04	1.05	1.08	1.06	1.07	1.04	1.04	1.05	1.05	1.06	1.06
	SD	.07	.05	.03	.03	.07	.05	.04	.06	.02	.03	.04	.04	.04	.05

		Index of Difficulty													
MEAN DFA EXPONENTS		Low							High						
		R1	L1	L2	L3	L4	L5	R2	R1	L1	L2	L3	L4	L5	R2
Movement Time															
	M	.91	.93	.89	..85	.89	.87	.94	.85	.87	.87	.84	.93	.91	.90
	SD	.15	.12	.13	.07	.12	.11	.11	.14	.14	.10	.13	.08	.12	.13
Pen pressure															
	M	1.02	1.02	.99	1.00	1.00	.98	1.02	1.07	1.07	1.08	1.06	1.06	1.07	1.04
	SD	.08	.09	.09	.09	.08	.09	.10	.07	.41	.08	.10	.08	.07	.09
Tilt															
	M	1.09	1.14	1.13	1.13	1.13	1.07	1.09	1.09	1.17	1.17	1.17	1.15	1.14	1.11
	SD	.11	.11	.08	.07	.11	.09	.11	.11	.08	.98	.13	.10	.13	.10



Figures 6a-i. **The changes in the spectral slopes, fractal dimensions and slope of the detrended-fluctuation analysis over training sessions for the movement time, pen pressure, and pen tilt series in the low-ID condition. Note that the outer left and right bars are the sessions with the dominant hand.**



Figures 7 a-i. **The changes in the spectral slopes, Fractal Dimensions and slope of the Detrended Fluctuation Analysis over training sessions for the movement time series in the high-ID condition.**

Correlations between scaling measures and SD. Another observation was a robust correlation between fractal scaling exponents and fractal dimension with the standard deviation of the movement time series. In the low-ID condition, the correlations were -.26, $p < .01$; .29, $p < .01$; and -.31, $p < .01$ for the PSDA, SDA and DFA respectively. In the high-ID condition the correlations were .30, $p < .01$, -.32, $p < .01$, and .34, $p < .00$. As participants move more consistently, the data become more scaled as 1/f, indicating their coordination settles as participants get more in tune with the task.

Correlations between concurrent streams of 1/f scaling

In the low-ID condition, a fair number of the correlation coefficients for the slopes of movement time , pen pressure, and pen tilt (See Table 4) are moderate to high. Values near zero were expected. The average correlation coefficients were calculated over the different training sessions. The same correlation coefficients for the high-ID condition and pen tilt slopes are shown in Table 5.

Table 4.
Correlations between the Scaling Measures for the Different Streams of 1/f Scaling in the Low-ID condition.

Correlations between concurrent spectral slopes		slope MT averaged over training sessions	slope PP averaged over training sessions	slope tilt averaged over training sessions
slope MT averaged over training sessions	Pearson Correlation	-	.06	.63*
	P (2-tailed)	-	.82	.01
	N	-	15	15
slope PP averaged over training sessions	Pearson Correlation	.06	-	-.20
	P (2-tailed)	.82	-	.47
	N	15	-	15
slope tilt averaged over training sessions	Pearson Correlation	.63*	-.20	-
	P (2-tailed)	.01	.47	-
	N	15	15	-
Correlations between concurrent Fractal Dimensions		FD of MT averaged over training sessions	FD of PP averaged over training sessions	FD of tilt averaged over training sessions
FD of MT averaged over training sessions	Pearson Correlation	-	.49	.36
	P (2-tailed)	-	.065	.19
	N	-	15	15
FD of PP averaged over training sessions	Pearson Correlation	.49	-	.27
	P (2-tailed)	.07	-	.33
	N	15	-	15
FD of tilt averaged over training sessions	Pearson Correlation	.36	.27	-
	P (2-tailed)	.19	.33	-
	N	15	15	-

Correlations between concurrent DFA exponents		DFA exponent of MT averaged over training sessions	DFA exponent of PP averaged over training sessions	DFA exponent of tilt averaged over training sessions
DFA exponent of MT averaged over training sessions	Pearson Correlation	-	.37	.41
	p (2-tailed)	-	.18	.13
	n	-	15	15
DFA exponent of PP averaged over training sessions	Pearson Correlation	.37	-	.51
	p (2-tailed)	.18	-	.05
	n	15	-	15
DFA exponent of tilt averaged over training sessions	Pearson Correlation	.41	.51	-
	p (2-tailed)	.13	.05	-
	n	15	15	-

* Correlation is significant at the 0.05 level.

Table 5.
Correlations between the Spectral Slopes, the Fractal Dimensions and the Slopes of the Detrended Fluctuation Analysis for the Different Streams of 1/f Scaling in the High-ID condition.

Correlations between concurrent spectral slopes		slope MT averaged over training sessions	slope PP averaged over training sessions	slope tilt averaged over training sessions
slope MT averaged over training sessions	Pearson Correlation	-	-.18	.69**
	P (2-tailed)	-	.52	.004
	N	-	15	15
slope PP averaged over training sessions	Pearson Correlation	-.18	-	.06
	P (2-tailed)	.52	-	.82
	N	15	-	15
slope tilt averaged over training sessions	Pearson Correlation	.69**	.06	-
	P (2-tailed)	.004	.82	-
	N	15	15	-

Correlations between concurrent Fractal Dimensions		FD of MT averaged over training sessions	FD of PP averaged over training sessions	FD of tilt averaged over training sessions
FD of MT averaged over training sessions	Pearson Correlation	-	.31	.53*
	P (2-tailed)	-	.26	.04
	N	-	15	15
FD of PP averaged over training sessions	Pearson Correlation	.31	-	.42
	p (2-tailed)	.26	-	.12
	N	15	-	15
FD of tilt averaged over training sessions	Pearson Correlation	.53*	.42	-
	p (2-tailed)	.04	.12	-
	N	15	15	-

Correlations between concurrent DFA exponents		DFA exponent of MT averaged over training sessions	DFA exponent of PP averaged over training sessions	DFA exponent of tilt averaged over training sessions
DFA exponent of MT averaged over training sessions	Pearson Correlation	-	.20	.70**
	p (2-tailed)	-	.48	.004
	N	-	15	15
DFA exponent of PP averaged over training sessions	Pearson Correlation	.20	-	.55*
	p (2-tailed)	.48	-	.03
	N	15	-	15
DFA exponent of tilt averaged over training sessions	Pearson Correlation	.70**	.55*	-
	p (2-tailed)	.004	.03	-
	N	15	15	-

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.

Discussion

The results presented provide clear evidence for 1/f scaling in successive movement times in precision aiming, as well as in axial pen pressure and pen tilt. The data of these behavioral measures are self-similarly nested across many timescales. The analyses solely focused on the intrinsic sources of variation and on how these intrinsic sources vary with practice. This manipulation questions psychological constructs based solely upon task properties. The use of the non-dominant hand is aimed at controlling for previous practice effects that may vary among participants. For instance, graphical designers or artists may be trained in line drawing. However, none of the participants reported special abilities with their non-dominant hand. The choice of ID was very high for the second condition for minimizing overlearning to occur.

Specifically, it is shown that 1/f structure in the movement time data is degraded by perturbation of the task. 1/f scaling becomes more pronounced with practice, or equivalently, if perturbation of task performance decreases, participants get more in tune with the task. Note however that the scaling measures only increased with practice in the high-ID condition. If a task is so easy that it is almost impossible to increase performance with practice, the fractal scaling measures do not change. The outcomes of each of the three methods supported the outcome of each other in this respect. The training manipulation was aimed at manipulating participant variables by introducing practice effects. The observation that the scaling relation changes as the context of task production (task complexity) changes and that changes in task per se do not induce this effect, expresses that the intrinsic dynamics of cognitive performance are inherently contextually constrained. The task constitutes an external factor that perturbs the intrinsic dynamics of cognitive performance. As participants get practiced, the data are more clearly characterized by 1/f scaling. Van Orden et al.'s hypothesis (2003) is supported.

The assessment of multiple streams of 1/f scaling was aimed at determining whether multiple streams of 1/f scaling run in parallel and are independent or whether they were uniformly manipulable. Cognitive functions less perturbed by task demands, pen pressure, and pen tilt, were not consistently characterized with more pronounced examples of 1/f scaling with practice. No one-on-one relation between concurrent streams was observed. However, the occurrence of temporal scaling relations in movement time and pen tilt series showed surprisingly high correlations compared to those observed by Kello et al. (in press). Linear accounts must come up with additional sources of 1/f scaling post-hoc. This discredits their viability of serving as a general explanation for the observation of 1/f scaling in human cognition. We observed that Kello et al.'s (in press) prediction is supported to some extent, concurrent streams of 1/f scaling were independently manipulated. Yet, the conclusion of independence among concurrent streams of 1/f scaling cannot be drawn.

In terms of the paradigm of Fitts' law, these findings are surprising. Over time, consecutive runs are characterized by unique variations, each data point participates in the larger pattern. Fractal dynamics are unexpected from an information-processing perspective, moreover, changes over context require an extraordinary explanation.

Fitts' model is rather robust with respect to average-movement times, as in the prediction of the variability that comes about in precision aiming. In this thesis, however, it is emphasized that discarding temporal structure in behavioral data, also ignores a considerable amount of the variance to be explained in the data (cf. Gilden, 2001). Standard-inferential statistical techniques and logic rely on the assumption of white noise to estimate population parameters and confidence intervals, and as implied, on the assumption of static and stable variance and mean values. Fractal data, however, imply that estimates like the mean and standard deviation are not static, they largely depend upon the scale of magnitude; the ruler size in the coastline example, the number of intervenient trials in cognitive research. In fractal data, it simply does not make sense to assume one static average level of performance; static summary functions constitute an oversimplification. The mean value and standard deviation may be efficient in communicating numbers if the assumptions underlying their application are met. In fractal data, however, means and standard deviations do not fulfill their theoretical function as a summary function. They should be conceived as useful tools, within boundaries of their limitations.

The observation that precision aiming data have fractal structure calls Fitts' hallmark, a constant flow of information (an IP that is constant), into question as a theoretical explanation for the variation of human movement. In fact, the increase in performance observed indicates that Fitts' Index of Performance increases with practice for the same task. Thus, it is clear that performance improves with practice, but only in the more 'difficult' or high-ID condition. In the low-ID condition, such an effect is lacking. In the low-ID condition, people gained less coordination than in the high-ID condition. The findings presented suggest that coordinated-human performance is not constant or stable. For the same task and for stable levels of accuracy, significant decreases in movement time and nearly significant decreases in standard deviation of the movement times occurred. The improvement in performance measures for stable levels of accuracy was more pronounced in the high-ID condition. Therefore, it is not surprising in the light of our hypothesis that the scaling measures show a change in the high-ID condition, but not in the low-ID condition where overlearning occurred. The appearance of 1/f scaling suggests that motor variability is not random but rather a structured-scaling relation that connects processes at all timescales. The fact that data points are embedded in overall dynamics suggests that coordination in simple motor tasks goes along with fractality and calls into question the assumptions of component dominant dynamics and random noise.

It is, however, impossible to assess whether the data presented here converge with Fitts' law. A full investigation of all Indices of Difficulty goes beyond the scope of this paper, only two ID's have been investigated and each participant completed one of them. This makes it impossible to assess whether our data converge with Fitts' law. Another issue in this respect is the fact that a tacit assumption of Fitts' law is that an accuracy level of 96% should be reached. Although this level of accuracy was generally achieved in the low-ID condition, it was not in the high-ID condition. In case the accuracy level is below 96%, a post-hoc adjustment to the target width should be introduced (MacKenzie, 1992). Note that a difference with mainstream precision aiming research and the experiments presented here is that typically only 30 runs or so are taken, while in 1/f experiments usually at least 1024 trials must be measured continuously over time. It was not expected that participants in the high-ID condition would meet a criterion of 96% accuracy.

In order to account for the results, Fitts' explanatory framework should at least be able to reconcile the presence of non-randomness in the form of long-range correlations with the appearance of 1/f scaling in movement data. This is possible to some extent, because it does not necessarily hold that because data appear to scale as 1/f scaling their underlying mechanism is fractal in nature, the effect may be a statistical artifact. This point is relevant since many models can produce 1/f scaling, and also some linear models can deal with a possible time-dependent property for the variability sequence. (Granger, 1980; Pressing, 1999; Pressing and Jolley-Rogers, 1997; Wagenmakers, Farrell and Ratcliff, 2004; Ward, 2002). Any complex pattern in data can be modeled by linear decomposition into smaller patterns. This means that it will always be possible to model a particular 1/f pattern of a particular data set.

A popular approach in this respect is to identify three sources of cognitive activity that may be summed to create 1/f scaling. These summation accounts of 1/f scaling may be appealing because they demystify the phenomenon by applying well-understood mathematical models and the fact that many conventional assumptions can be kept. 1/f scaling in human cognition would be produced by the coincidental activity of specific cognitive components. One such model that can produce 1/f scaling has been proposed by Ward and Richards (2001). They suggested that a multiscaled randomness model with three summed independent streams of white noise at different timescales that produces a signal that closely mimics 1/f scaling. The authors postulated that these processes correspond to (fast) preconscious processes, (intermediate) unconscious processes, and (slow) conscious processes. Their model renders an equal fit of the data compared to Gilden et al.'s model (1995), but unfortunately the model can only be fitted post-hoc. In the same line of thinking, Wagenmakers et al (2004, 2005) proposed that aggregation of random noises could mimic 1/f scaling.

In the case of 1/f scaling, variation will grow in amplitude as more data are collected because the 1/f scaling pattern will extend outside the limits of sampled data points and a new larger sample will pick up more of the scaling relation. A longer data set reveals more of the lowest frequencies, which are associated with much larger amplitudes of variation. The new data will reveal new and larger variations, so variation will grow in the larger sample. The models proposed by Wagenmakers et al (2004; 2005) predict that the 1/f scaling relation must break down at some long time scale where random variation appears; outside a certain parameterization. Particularly in the lowest frequencies, a flat plateau of random variation should appear in the power spectrum, however, such plateaus are almost never observed (Van Orden et al., 2005). Van Orden et al. (2005) convincingly discredit the conjecture of Wagenmakers et al. (2004; 2005), that the signal whitens as more and more data are collected. In fact, the opposite occurs. Variability and mean values keep on increasing, even after 8192 trials; a clear hallmark for 1/f scaling. The most severe limitation also for the models proposed by Wagenmakers et al. (2005) is that parameters must be fit post-hoc to each measurement series.

The main finding presented here is that embedded-coordination dynamics become more clearly characterized by 1/f scaling as the task constitutes less of a perturbation for task performance. As task complexity decreases with practice, the perturbation created by the experimental context will impinge less upon the intrinsic dynamics. If independent cognitive components produce white noise, why is there such a coherent change in the background 'noise'?

A plausible suggestion is that 1/f scaling emerges from self-organization. Self-organization is an emergent process that leads to irregular pattern formation and that involves the cooperation of multiple systems stacked at different time scales. The assumption of component-dominant dynamics, along with its methodological implications discards any multilevel interactions present in the system. The presence of 1/f scaling in precision-aiming data suggests the presence of interaction dominant dynamics. Interaction-dominant dynamics have been proposed to establish a metastable basis for the functional organization of human behavior (Kello et al., in press; Van Orden et al., 2003), a hallmark of coordination as opposed to a nuisance factor. The theory postulated by Van Orden et al. (2003) is based on the fundamental idea that the structure and complexity seen in human behavior is a phenomenon of self-organization. The theory equates the presence of 1/f scaling in human cognition with the coordination and coherence of human behavior, and external manipulations with external sources of white noise that perturb the system. This leads to the hypothesis that 1/f scaling originates in the internal fractal dynamics of the cognitive system, which implies that perturbations, such as task demands constitute an external factor that affect the capacity to measure pink noise. It follows from the account that 1/f scaling should be present in the entire set of cognitive activity. This account contrasts the idea that 1/f scaling is associated with specific cortical mechanisms as isolable processes (Chen et al. 1997; 2001; Gilden, 2001) or the summation of these components' noises (Pressing, 1999; Wagenmakers et al., 2004; Ward, 2002).

The best candidate (Aks et al., 2002; Chen et al. 1997; Gilden, 2001; Kello et al., in press; Van Orden et al. 2003) for explaining the ubiquity of 1/f scaling throughout nature is the Self-Organized Criticality model (Bak, Tang and Wiesenfeld, 1987). The model proposed by Bak et al. yields a plausible explanation of how even the most minimal complex systems in nature that reside from the interaction among their components, like a pile of sand, are complex adaptive systems. Self-Organized Criticality associates 1/f scaling with a system's spontaneous internal reorganization near critical points. At such critical point extremely flexible adaptive behavior emerges, that is neither random nor overly persistent. The dynamics may be viewed as balancing between a predictable stable pattern of activity and uncorrelated random behavior by the interplay of the intrinsic and extrinsic dynamics. In the critical state, the internal spatiotemporal correlations are highly susceptible to external perturbations. The system responds to any perturbation, randomness, etc., by returning to the critical state after a transient period.

The appeal of self-organized criticality is that systems near critical points are poised to access all potential behavioral trajectories (within the boundary conditions). In the case of 1/f scaling as a consequence of SOC, a system becomes exquisitely context sensitive and is characterized by multiple realizability. Context specificity in self-organizing situates behavior within the flow of circumstances. all potential behavioural trajectories within boundary conditions can be accessed while balancing precisely among constraints. The emergence of complexity from simple local interactions in the self-organized criticality model happens spontaneously and therefore it constitues a plausible source of natural complexity, rather than a phenomenon arising from a specific tuning of control parameters to precise values. There is no external control. Through Self-Organized Criticality 1/f scaling becomes associated with complex systems whose components interact across multiple temporal and spatial scales to self-organize their behavior. However, observing 1/f scaling is regarded as an important but on itself insufficient fingerprint of SOC (Aks, 2005; Stamovlasis, 2005), though it is conceived as a necessary consequence (Bak et al., 1987; Gilden 2001; Van Orden et al., 2003; Van Orden et al., 2005).

Another argument in favor for 1/f scaling, in contrast with non-emergent explanations, presented here has been inspired by Kello et al. (in press). They measured multiple concurrent streams of 1/f scaling, and did not only assess reaction times, but also key press durations, that is the brief duration of time from contact to release of the key. Kello et al. showed that concurrent streams were independently manipulable and uncorrelated. The most straightforward prediction from the summation and strategy change accounts is, however, that reaction times and key contact durations exhibit correlated 1/f fluctuations. The prediction stems from the assumption that whatever physiological or cognitive processes impinge on key-presses and key releases to create 1/f scaling, they will impinge on both aspects of performance in a correlated manner. If, for example, practice and fatigue would induce different amplitude fluctuations (Wagenmakers et al., 2005), they should create the same 1/f fluctuation in all behavioral measures. If seperate streams do not correlate, non-emergent hypotheses must come up with post-hoc sources of 1/f scaling for every uncorrelated stream. Thus, in conclusion, an information-processing approach would need an extraordinary explanation, after the fact, to postulate that the appearance of 1/f scaling in behavioral data is a coincidental phenomenon.

The evidence is in favor of the Self-Organized Criticality hypotheses. As said, observing 1/f scaling at first sight in some complex process does not necessarily means Self-Organized Criticality is at play. Our results support the hypothesis that 1/f scaling is a ubiquitous and emergent phenomenon in human cognition. We conclude that 1/f scaling is very unlikely to come apart as a linear partition of power among frequencies. “It is not clear how much sense it makes to develop models and theories of strongly correlated processes and then to describe them as a linear superposition of independent events” (Jensen, 1998, p.10). “How do intrinsic dynamics align power and frequency in such a coherent fashion? In linear account, the implied coincidence of the scaling relation becomes an extraordinary hypothesis that would itself require extraordinary evidence” (Van Orden et al, 2003, p.19).

The presented results along with those of a recent line of research express the need for a turn-away from the machine or computer metaphor. A machine metaphor suggests central organization, random noise, independence among components, separate processing stages, component-dominant dynamics and system decomposability. Rather, 1/f scaling suggests the cognitive system to depend upon interaction-dominant dynamics. The only assumption made in this respect is that the cognitive system is a complex system. This constitutes an innovative conceptual framework to view cognitive performance and has got to have a big effect on behavioral research.

For human performance the presented results imply that task per se is not a single factor that causes specific, stable (alternations of) performance levels. Participants do not only bring into the experiment some outputs from the inputs presented. The subject of study always involves the coupling between task and participant embedded in a context, a coupling always more complex than just task-dependent properties. Fractal dynamics are highly informative in this respect. Think for instance about the assessment of cognitive workload. Measuring how difficult something is in a context generally is investigated through self-report or physiological measures. Now, it is shown, information about the development of human skills can be deuced from the application of tools from nonlinear-dynamical-systems theory.

References

Aks, D. J. (2005). 1/f dynamic in complex visual search: Evidence for self-organized criticality in human perception. In M. A. Riley & G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 319-353): Retrieved January 7, 2006, from http://www.nsf.gov/sbe/bcs/pac/nmbs/nmbs.jsp.

Aks, D. J., & Sprott, J. C. (2003). The role of depth and 1/f dynamics in perceiving reversible figures. *Nonlinear Dynamics, Psychology, and Life Sciences, 7*(2), 161-180.

Aks, D. J., Zelinsky, G. J., & Sprott, J. C. (2002). Memory Across Eye-Movements: 1/f Dynamic in Visual Search. *Nonlinear Dynamics, Psychology, and Life Sciences, 6*(1), 1-25.

Anderson, G., & Kello, C. T. (2006). The fractal frabric of speech. In *Proceedings of the 28th annual meeting of the cognitive science society*. Vancouver: Lawrence Erlbaum.

Bak, P. (1996). *How nature works.* New York: Springer-Verlag.

Bak, P., Tang, C. and Wiesenfeld, K. (1987). Self-organized criticality: an explanation of 1 / f noise. *Physical Review Letters, 59,* 381–384.

Bassingthwaite, J. B., Liebovitch, L. S., and West B. J. (1994). *Fractal Physiology.* New York: Oxford University Press.

Bernstein, N. (1967). *The coordination and regulation of movements.* London: Pergamon Press.

Campbell, D. J. (1988). Task complexity: A review and analysis. *Academy of Management Review, 13*, 40-52.

Chen, Y., Ding, M., & Kelso, J. A. S. (1997). Long memory processes (1/f type) in human coordination. *Physical Review Letters, 79,* 4501–4504.

Chen, Y., Ding, M., & Kelso, J. A. S. (2001). Origins of time errors in human sensorimotor coordination. *Journal of Motor Behavior, 33,* 3–8.

Clayton, K., & Frey, B. B. (1997). Studies of mental "noise." *NonlinearDynamics, Psychology, and Life Sciences, 1,* 173–180.

Coren, S. (1993). The lateral preference inventory for the measurement of handedness, footedness, eyedness, and earedness: Norms for young adults. *Bull. Psychon. Soc, 31*, 1–3.

Cox, R. F. A., Smitsman, A. W. (2006). Action planning in young children's tool use. *Developmental Science, 9*(6), 628-641.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52*, 281-302.

De Jong, W. P., Hulstijn, W., Kosterman, B. J. M., & Smits-Engelsman, B. C. M. (1996). Oasis software and its applications in experimental handwriting research. In M. L. Simner, C. G. Leedham, & A. J. W. M. Thomassen (Eds.), Handwriting and drawing research, basic and applied issues (pp. 429–440). Amsterdam: IOS Press.

Delignières, D., Fortes, M. & Ninot, G. (2004). *Nonlinear Dynamics in Psychology and Life Sciences,* 8, 479-510

Duarte, M., Zatsiorsky V. M. (2001). Long-range correlations in human standing. *Physics Letters A, 283,* 124-128.

Eke, A., Hermán, P., Kocsis, L., & Kozak, L. R. (2002). Fractal characterization of complexity in temporal physiological signals. *Physiological Measurement, 23,* 1–38.

Embretson, S. E. (2006). The continued search for nonarbitrary metrics in psychology. *American Psychologist, 61*, 50-55.

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement, *Journal of Experimental Psychology, 47*, 381–391.

Gilden, D. L. (1997). Fluctuations in the time required for elementary decisions. *Psychological Science, 8,* 296–301.

Gilden, D. L. (2001). Cognitive emissions of 1/f noise. *Psychological Reviews, 106*, 33-35.

Gilden, D. L., Thornton, T. L., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science, 267*, 1837-1839.

Granger, C. W. J. (1980). Long memory relationships and the aggregation of dynamic models. *Journal of Econometrics*, *14*, 227–238.

Gonzalez, C. (2005). Task workload and cognitive abilities in dynamic decision making. *Human Factors*, *47*(1), 92-101.

Haken, H. (2006). Synergetics of brain function. *International Journal of Psychophysiology Models and Theories of Brain Function with Special Emphasis on Cognitive Processing, 60*(2), 110-124.

Hausdorff, J. M., Purdon, P. L., Peng, C.-K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: Stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology, 80,* 1448–1457.

Jensen, H. J. (1998). *Self-organized criticality.* Cambridge, England: Cambridge University Press.

Kello, C. T., Anderson, G. G., & Van Orden, G. C. (2007). *Intrinsic fluctuations of speech reveal the coordinative basis of cognition*. (submitted for publication).

Kello, C. T., Beltz, B. C., Holden, J. G., & Van Orden, G. C. (in press). The emergent coordination of cognitive function. *Journal of Experimental Psychology: General*.

Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior.* Cambridge, MA: MIT Press.

Kloos, H. & Van Orden, G.C. (in press). Soft-assembled mechanisms for the grand theory. In J.P. Spencer, M. Thomas, & J. McClelland (Eds.), *Toward a New Grand Theory of Development? Connectionism and Dynamics Systems Theory Reconsidered.* Oxford University Press.

Kugler, P. and Turvey, M. (1987*). Information, natural law, and the self-assembly of rhythmic movement*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Lai, S-C, Mayer-Kress, G, Sosnoff, JJ, & Newell, KM. (2005). Information entropy analysis of discrete aiming movements. *Acta Psychologica, 119*(3), 283-304.

Lemoine, L., Torre, K., & Delignières, D. (2006). Testing for the presence of 1/*f* noise in continuation tapping data. *Canadian Journal of Experimental Psychology, 60*(4), 247-257.

Liebovitch, L. S., & Shehadeh, L. A. (2005). Introduction to fractals. In M. A. Riley & G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 178-266): Retrieved January 7, 2006, from http://www.nsf.gov/sbe/bcs/pac/nmbs/nmbs.jsp.

MacKenzie, I. S. (1992). Fitts' law as a research and design tool in human–computer interaction. *Human–Computer Interaction, 7*, 91–139.

Mandelbrot, B. (1982). *The fractal geometry of nature*. New York: Freeman.

Maynard, D. C., & Hakel, M. D. (1997). Effects of objective and subjective task complexity on performance. *Human Performance, 10*(4), 303-330.

Mottet, D. & Bootsma, R. J. (1999). The dynamics of goal-directed rhythmical aiming. *Biological Cybernetics, 80,* 235–245.

Peng, C. K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical Review Letters, 70*, 1343–1346.

Plamondon, R., & Alimi, A.M. (1997). Speed/accuracy trade-offs in target-directed movements. *Behavioral and Brain Sciences, 20*, 279–349.

Pressing, J. (1999). Sources for 1/f noise effects in human cognition and performance. Proceedings of the 4th Conference of the Australasian Cognitive Science Society, Newcastle.

Pressing, J., & Jolley-Rogers, G. (1997). Spectral properties of human cognition and skill. *Biological Cybernetics, 76*(5), 339-347.

Riley, M. A., Wong, S., Mitra, S., & Turvey, M. T. (1997). Common effects of touch and vision on postural parameters. *Experimental Brain Research, 117*, 165-170.

Schmidt, R. C., Beek, P. J., Treffner, P. J., & Turvey, M. T. (1991). Dynamical substructure of coordinated rhythmic movements. *Journal of Experimental Psychology: Human perception and performance, 17*, 636-651.

Schmidt R.A., & Lee, T.D. (2005). *Motor control and learning: A behavioral emphasis.* Champaign, IL: Human Kinetics.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Tech. J., 27*, 379-423, 623-656.

Slifkin, A. B., & Newell, K. M. (1998). Is variability in human performance a reflection of system noise? *Current Directions in Psychological Science, 7,* 170-177.

Stamovlasis, D. (2005, June 2005). *Nonlinearity, thresholds and bifurcations in knowledge acquisition and problem solving: Towards a paradigm shift in educational research.* Paper presented at the International Symposium on Adaptive Models of Knowledge, Language and Cognition, Espoo, Finland.

Stevens, L.T. (1886). On the time sense. *Mind, 11*, 393-404.

Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. Cambridge: MIT Press.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organisation of cognitive performance. *Journal of Experimental Psychology, 132*, 331-350.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2005). Human cognition and 1/f scaling. *Journal of Experimental Psychology, 134*, 117-123.

Van Orden, G. C., Pennington, B. F., & Stone, G. O. (2001). What do double dissociations prove? *Cognitive Science, 25*, 111-172.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of 1/*fα* noise in human cognition. *Psychonomic Bulletin & Review, 11*, 579–615.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2005). Human cognition and a pile of sand: A discussion on serial correlations and self-organized criticality. *Journal of Experimental Psychology: General, 135*, 108-116.

Ward, L. M. (2002). *Dynamical cognitive science*. Cambridge: MIT Press.

West, B. J., & Deering, W. (1995). *The lure of modern science: Fractal thinking*. River Edge, NJ: World Scientific.

Woodworth, R. S. (1899). The accuracy of voluntary movement. *Psychological Review, 3*, 1–106.