Article

Multifractality in the Movement System When Adapting to Arm Cranking in Wheelchair Athletes, Able-Bodied Athletes, and Untrained People

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Abstract: Complexity science has helped neuroscientists shed new light on brain-body coordination during movement performance and motor learning in humans. A critical intuition based on monofractal approaches has been a fractal-like coordination in the movement system, more marked in motor-skilled people. Here we aimed to show that heterogeneity in scaling exponents of movements series, literally multifractality, may reflect a special kind of interactions spanning multiple temporal scales at once, which can be grasped by a focus-based multifractal detrended fluctuation analysis. We analyzed multifractality in the variability structure of a 10-min arm cranking movement series repeated as 3 sets a day for 3 days, comparatively with their linearized (phase-randomized) surrogate series in sedentary (SED) untrained people, wheelchair athletes (WATH), and able-bodied athletes (ATH). Arm cranking exercise was chosen to minimize external variations, which tend to interfere with internal origin of variability. Participants were asked to maintain a regular effort and torque output served as the performance variable. Our first hypothesis suggests greater multiscale interactions in trained (WATH, ATH) versus untrained (SED) people, reflected in a wider range of scaling exponents characterizing movement series, providing the system with significant robustness. As a second hypothesis, we addressed a possible advantage in WATH over ATH due to greater motor skills in upper-limbs. Multifractal metrics in original and surrogate series showed ubiquitous, but different, multifractal behaviors in expert (ATH and WATH indistinctively) versus novice (SED) people. Experts exhibited high multifractality during the first execution of the task; then multifractality dropped in following repetitions. We suggest an exacerbated robustness of the movement system coordination in experts when discovering the task. Once task novelty has worn off, poor external sources of variability and limited risks of task failure have been identified, which is reflected in the narrower range of scale interactions, possibly as an energy cost effective adaptation. Multifractal corollaries of movement adaptation may be helpful in sport training and motor rehabilitation programs.

Keywords: multifractal; nonlinear dynamics; motor skills; interaction-dominance

1. Introduction

The identification of biological systems exhibiting fractal-like dynamics in neurosciences has been a source of inspiration to explore health and adaptive capacity in humans [1–6]. From neurons to macroscopic behavior, fractal phenomena quantified by power laws in signal output have been experimentally evidenced [7] and now constitute a privileged substrate for psychologists [8], neuroscientists [9], and movement scientists [10] to gain a better understanding of the complex dynamics in systems linking the brain, body, and environment. A common observation in movement sciences has been the presence of scale-invariant, fractally structured fluctuations of cyclic motor instances [6,9,11]. Fractal fluctuations are believed to emerge from interdependencies between system components spanning a range of temporal scales. The system acquires functional unity because the activities of its components are not sequestered but dynamically assembled.
In the last few decades, a number of computational methods embracing the concept of fractal-like structures in movement series have been employed, with the promise to shed new light on the level of system complexity. Complexity is an essential property of biological systems that has been associated to robustness. A system is identified as complex on the basis of its structural and/or functional redundancies. This way, a few components may be unresponsive or defective without compromising functional integrity [12]. It is yet unclear how fractal properties speak about complexity in the movement system, mainly because monofractal and multifractal characteristics of the movement system reflect distinctive properties of the system [1]. Capturing mono- and multifractality in signal dynamics offer two ways of characterizing complexity of the dynamics: complexity of linear and nonlinear aspects of the captured dynamics.

The monofractal approach that quantifies a unique scaling exponent in movement series has been massively used to describe coordination among sensory, cognitive, and motor components [9,11]. Monofractal approaches have shown that the movement system in physically trained (expert) subjects exhibit higher scaling exponents in its architecture [13,14]. So, in context of the unique scaling exponent, motor learning has been conceived as the progressive installation of more coordinated dynamics in the movement system, rather the progressive elimination of alternative pathways and a shrink in networked interactions [14]. Although a single power-law function has provided important information about neurophysiological movement coordination [9,11], getting a unique fractal exponent is yet ambiguous as to whether the system exhibits interactivity unfolding similarly across many but an independent range of scales, or unfolding across a wide range of scales at once [8].

To gain a finer analysis of the kind of interactions emerging in movement system coordination, the introduction of multifractality in cognition, physiology, and movement has proven promising. The movement system has been theorized in terms of multiplicative cascade dynamics [8,10], a model of multiscale interdependencies between the system components. A significant amount of research considers that multiplicative interdependencies are consistent with the interaction-dominant perspective [5,15] and is reliably accounted for by the multifractal formalism [3,8,10]. Following this line of thought, it is suggested that complexity is rooted in interaction-dominance, understood as multiscale interdependencies among system components. Thus, grasping complexity in the movement system of sport experts needs to design a multifractal approach of their movement series [10].

From a methodological point of view, fractality (i.e., scale-free properties or scaling) in a linear time series can be fully characterized by a single scaling exponent (like H), where H is the measure of global (linear) correlation structuring in the series. In a nonlinear time series, correlation is not a global property but a local property. Hence its scaling is dependent on the degree of a statistical moment q, i.e., H(q). When H effectively varies with q, scaling singularities are admitted, which is the essence of multifractality. Monofractality, as captured by H, relates to q = 2, while multifractality relates to the difference in H(q) at extreme q-values and thus to the width of the multifractal spectrum. The presence of across-scale interactions, thereby a high level of system complexity, can be concluded after a last operation which consists in definitively ruling out the influence of linear phenomena in the multifractal spectrum [8,16]. For that, phase-randomized surrogate series of collected movements series must demonstrate a different spectrum when compared to original series because surrogates in this case mimic only the linear aspect of the series [15].

The link between the multifractal formalism and nonlinear dynamics that form the core of interaction–dominance in sensorimotor coupling has progressively gained coherence over the last few years [1,17,18]. Recent studies have attempted to show its functional significance, e.g., as a prospective coordination to improve perception [18,19]. As well, multifractal behaviors play a significant role in maintaining an equivalent performance during repeated motor instances of a task [20], or the quality of the executive function in a task where rules are progressively discovered by the participant [15]. Using gradual sensory feedback deprivation in healthy people, and a deafferented patient as a pathological limit-case, Torre et al. showed higher multifractality in movement series with sensory
They conclude that multifractality reflects effective adaptation when facing a task irrespective of chronic functional impairments. Facing unfamiliar functioning due to sensory deprivation, the system may have gained in complexity through interactivity unfolding across a larger spectrum of temporal scales to maintain task performance. In the same vein, changes in multifractal behavior of the movement system also found resonance when one must adapt to unfamiliar motor tasks, which is in direct connection with the aim of the present study. Faced with a new material on which they must carve, expert carvers are able to develop a more multifractal behavior in movement series where less qualified carvers cannot. This could mean that complexity in brain–body–environment coordination is more evident in motor-skilled than in less skilled people when facing a new task.

In the present study, we aimed at evaluating the emergence of scale-free, fractal characteristics of the movement system that links the brain and the body. Assuming interaction–dominant dynamics as a core model of functional coordination, we quantified multifractality in temporal fluctuations of torque output during repeated instances of an arm cranking exercise, repeated over several days under similar conditions. Our first hypothesis assumed that individuals with high motor skills might exhibit greater multifractality (as observed in expert carvers) when adapting to the unfamiliar arm cranking task. For that, participants were divided into three groups: sedentary, able-bodied athletes and wheelchair athletes. As a second hypothesis, we addressed a possible advantage in wheelchair-user basketball athletes due to greater daily use of their upper-limbs.

2. Materials and Methods

2.1. Participants

A total of 27 young adults gave their informed consent to participate to this study. The study was approved by the Institutional Review Board ‘Faculte des STAPS’. The study was conducted according to the guidelines of the Declaration of Helsinki. The participants were assigned to three experimental groups.

Eight (4 females) of them (170 ± 9 cm, 66 ± 8 kg, 24 ± 3 year) did not practice physical activity on a regular basis and were assigned to the group ‘sedentary’ (SED). Eleven (4 females) participants (171 ± 5 cm, 65 ± 8 kg, 23 ± 2 year) were highly-trained athletes (ATH). Eight (3 females) participants (163 ± 14 cm, 59 ± 12 kg, 19 ± 1 year) were wheelchair-trained athletes (WATH) playing wheelchair basketball.

2.2. Arm Cranking Exercise

An arm cranking ergometer (Brachumera sport PFM, Lode B.V., Groningen, The Netherlands) was used to obtain the structure of variability of movement performance. A programmable unit was used to set the constant workload applied, imposed by an electromagnetic braking mechanism. Each crank handle is equipped with a torque sensor, allowing the recordings of torque output each 2 degrees of a total revolution (360 degrees). Movement variability was analyzed from series of successive values of the maximal torque output (curve peak) recorded during the push-off of the non-dominant hand.

2.3. Procedure

After ten minutes of warming up the muscles around the shoulder using rotation-circumduction and elastic bands, the participant was seated in front of the ergometer placed on a table, so that the shoulder (scapulohumeral joint) was at the same height as the axis of rotation of the cranks. The participant performed a few cranking movements to adjust a comfortable horizontal distance. For wheelchair users, they keep their own wheelchair that was firmly strapped to the ground and to the table to stay immobile during cranking.

During testing, the cranking velocity was capped at 58 revolutions per minute (rpm). During the first minute of the exercise, the participant was asked to use the visual feedback on the programmable unit of the ergometer displaying the averaged power output to adjust its movement on the target power. The target power was 35 W for males and 25 W for...
females. After one minute, the visual feedback was removed, and the participant was asked to concentrate on maintaining a regular power output corresponding to the prior target during the next nine minutes. Only the last 512 samples (after removing artifacts, see below) of this 9-min period served for the multifractal analysis.

The same procedure was repeated three times a day with five minutes rest between each repetition. These three sets were also repeated on 3 days separated by at least 24 h and no more than 72 h.

2.4. Data Preprocessing

Because spikes in series could significantly influence further computations based on variable fluctuations, visual inspection of the series identified obvious artifacts, i.e., an isolated abnormal push-off characterized by abnormally high/low torque output, which was subsequently removed. No more than 3 samples have been removed per series in less than 10 out of 270 series.

2.5. Multifractal Calculations

Multifractal characteristics in torque output time series were obtained by using a focus-based multifractal detrended fluctuation analysis, FMF-DFA, developed in [22].

The DFA algorithm follows the following steps for a signal \( x \) of length \( L \) (here \( L = 512 \)).

1. The cumulated sum from which the mean is subtracted is first computed:

   \[
   y(i) = \sum_{k=1}^{i} [x_k - \langle x \rangle], \quad i = 1, \ldots, L
   \]  

2. \( y(i) \) is divided into \( N_s = \text{floor}(L/s) \) nonoverlapping segments of length \( s \). Scales are constructed equidistantly on a logarithmic scale. For each box \( \nu \), a local trend \( y_\nu \) is calculated by a least-square fit.

3. The variance \( F^2(\nu, s) \) of the detrended series is calculated for each box \( \nu \) and scale \( s \):

   \[
   F^2(\nu, s) = \frac{1}{s} \int_{s} \{y[(\nu - 1)s + i] - y_\nu(i)\}^2
   \]  

4. Introducing a moment order \( q \), the \( q \)th order fluctuation function is calculated by averaging the variance \( F^2(\nu, s) \) over all the \( N_s \) boxes, with \( q = 0 \) being a special case.

   \[
   F_q(s) = \left\{ \frac{1}{N_s} \int_{v=1}^{N_s} F^2(v, s)^{\frac{1}{2}} \right\}^{\frac{1}{q}} \quad \text{for } q \neq 0
   \]

   \[
   F_q(s) = \exp\left\{ \frac{1}{2N_s} \ln \left[ F^2(v, s) \right] \right\} \quad \text{for } q = 0
   \]

5. The scaling function values (Equations (3) and (4)) are logarithmically plotted against the scales \( s \) for each value of \( q \) (Figure 1, top right), here with used \( q \)-values in the range \(-15 \leq q \leq 15 \) (Figure 1, bottom left). If the original signal \( x \) shows fractal scaling properties, the fluctuation function follows a power law for increasing scales \( s \):

   \[
   F_q(s) \propto s^{H(q)}
   \]
In order to calculate H(q) with a more robust and unbiased method, we use a reference point (focus) during the regression of scaling functions (Figure 1 top right) as developed in [22]. Briefly, the method is based on the fact that, for a signal with finite length, all qth order scaling functions converge towards an identical point when the signal length L is used as the scale s. Most importantly, it prevents the multifractal analysis of empirical time series (Figure 1 top left) from being corrupted by enforcing a family of scaling functions with the ideal fan-like geometry when fitting for H(q) (Figure 1 top right and bottom left),

2.5.1. Focus-Based Multifractal Formalism

The generalized Hurst exponent H(q) yields the multifractal characteristics of the series (Figure 1, bottom left). The width of the multifractal spectrum is also classically represented (Figure 1, bottom right). In the present study, multifractality was quantitatively assessed by the distance between H obtained for q = −15 and H obtained for q = +15, i.e., ΔH15; in Figure 1 (bottom left), one can read H(−15) = 1.26, H(15) = 0.81, so ΔH15 = 1.26 − 0.81 = 0.45. It is assumed that q = −15 and q = 15 are acceptable boundaries [23], outside of which q variations have limited effects on H (see Figure 1).
thus avoiding obtaining inverted spectra (Figure 1 bottom right) (also see Figure 4 C3 in [22]).

2.5.2. Monofractal Formalism

The monofractal scaling exponent was obtained from Equation (3) using $q = 2$. The scaling function values (Equation (3,4)) are logarithmically plotted against the scales $s$, with $s$ varying from 10 to $L/4$ (512/4) without using the focus point ($s = L$). The scaling exponent is the slope of the best least squares fit by a linear model.

2.6. Surrogate Data Testing

Phenomena such as linear autocorrelations, the finite size of the analyzed time series, or a heavy-tailed distribution of samples values can be part of the multifractal spectrum width [8,16], although their contribution in quantifying multifractality are unwanted. Here, to avoid spectrum corruption, each original time series was phase-randomized using the IAAFT method (Iterated Amplitude Adjusted Fourier Transform, [24]) to generate 50 surrogates of the initial series. True multifractality away from background noise in a series was admitted when $\Delta H_{15}$ of the empirical series was significantly higher than the averaged $\Delta H_{15}$ obtained from surrogate series.

2.7. Statistical Analyses

Statistical analyses were performed using Matlab (Matlab 2021b, Matworks, Natick, MA, USA). One-tail $t$-test was used for surrogate data testing with $p$-value 0.05 as a threshold for significance. Mean and standard deviation were calculated for all variables. Normality was checked by the Shapiro–Wilk test. A two-way (group $\times$ repetition) analysis of variance was used to compare the (multi)fractal profiles among the movement series. When no interaction effect was observed, the effect of the factor ‘repetition’ was tested in each group independently using repeated measures analysis of variance and tukey-kramer (hsd) post-hoc comparisons.

3. Results

3.1. Results of the Surrogate Data Testing

Overall, a great number of empirical series showed true multifractal characteristics. In SED, the average value by repetition reached 7.3/8 for a total of 66/72 (92%) series showing a higher multifractal parameter ($\Delta H_{15}$) than their 50 surrogates. In ATH, these values reached 10/11 and 90/99 (91%). In WAHN, these values reached 6.9/8 as the mean by repetition, for a total amounting to 62/72 (86%).

3.2. Comparison of the Multifractal Profiles

The Shapiro–Wilk test indicated normality in 24 out of 27 samples of $\Delta H_{15}$ values and 25 out of 27 samples of values of the multifractal marker $\Delta H_{15}$. Hence, parametric statistics were used. A two-way (group $\times$ repetition) analysis of variance was used to compare the multifractal profiles among the movement series. There was no effect of the factor ‘population’ per se ($F = 0.18, p = 0.8349$) but a significant effect of the factor ‘repetition’ ($F = 4.93, p = 0.00001$). There was no interaction (population $\times$ repetition) effect ($F = 1.49, p = 0.1058$). This means that the factor ‘repetition’ has a singular effect within groups. A subsequent ANOVA with repeated-measurements performed independently within each group (SED, ATH and WATH) confirmed this observation. The value of $\Delta H_{15}$ decreased significantly with repetitions in group ATH ($F = 4.25, p = 0.0002$) and in group WATH ($F = 2.97, p = 0.0172$), but not in group SED ($F = 1.64, p = 0.1303$). Post-hoc comparisons in group ATH and in group WATH showed that athletes exhibit higher $\Delta H_{15}$ during the first repetition when compared to $\Delta H_{15}$ in the following repetitions (Figure 2).
3.3. Comparison of the Monofractal Profiles

A two-way (group × repetition) analysis of variance was used to compare the monofractal profiles (H2) among the movement series. There was no effect of the factor ‘population’ per se (F = 1.25, p = 0.2888) but a significant effect of the factor ‘repetition’ (F = 3.22, p = 0.0018). There was no interaction (population × repetition) effect (F = 0.88, p = 0.5881). This means that the factor ‘repetition’ has a singular effect within groups. A subsequent ANOVA with repeated-measurements performed independently within each group (SED, ATH and WATH) confirmed this observation only in group AHN. The value of H2 stays unchanged in successive repetitions of arm cranking exercises in group SED (F = 1.44, p = 0.1980), and in group WATH (F = 1.5, p = 0.174). In group AHN, the monofractal parameter H2 tended to change during repetitions (F = 2.13, p = 0.0409), where the highest value was observed during the first repetition. (Figure 3).

Figure 2. Multifractal-width of movement series in each repetition. Red lines represent mean values, dark grey 1SD, and light grey 2SD. Individual values are indicated as dots. From post-hoc tests, in ATH, MF-width of repetition 1 differed from 3, 4, 5, 6, 7, 8, 9. In WATH, MF-width of repetition 1 differed from 5, 6, 7, 8.

Figure 3. Monofractal scaling exponents of movement series in each repetition. Red lines represent mean values, dark grey 1SD, and light grey 2SD. Individual values are indicated as dots. From post-hoc tests, in ATH only, repetition 1 differed from 5 and 8.
4. Discussion

The present study shows that fractal-like temporal structures in cyclic movement fluctuations are obvious characteristics emerging from the movement system during repeated arm cranking exercises. As the main emergent form of coordination in this brain–body functional coupling, multifractal behaviors are evidenced here by a large variation of Hurst exponents when varying q-moments are present in a detrended fluctuation analysis (Figure 2). Importantly, we show that the phase-randomized surrogates of the original movement series, mimicking the linear aspects of the series, exhibit a different (narrower) multifractal spectrum (here $\Delta H_{15}$) in 218 out of 243 cases (90% of the collected series). As phase-randomization preserves only linear autocorrelations in a signal, a wider spectrum in original series pleads for the presence of nonlinear aspects, associated to interdependencies unfolding across multiple scales at once. Multiscale interactivity is far from trivial in movement neuroscience since it speaks right to the theorization of movement control. This has been highlighted in characterizing executive function [3,15], sensorimotor coupling [1,10,25], visuomotor coupling [20,26], or dexterous use of precision tools [21,27] by using a multifractal analysis of movement behavior.

Here, from changes in multifractal behavior, we elaborate on differences in coordination of the movement system among physically-trained (ATH and WATH) and untrained people (SED). As the main result, high complexity reflected in $\Delta H_{15}$ during the first execution of the task in trained participants only (Figure 2) might indicate an extreme robustness of the movement system during the initial execution of an unfamiliar motor task in experts, but not in novices. As an additional and original result, considering that $\Delta H_{15}$ rapidly decreased in following repetitions of the same task, one might suspect an extra cost of robustness, mitigated once experts have identified low external sources of variability, and the limited need for attention to the task environment, i.e., task familiarization.

The emergence of multifractality in cognitive, physiological, and movement systems has a recent but rich history. Central in this approach, researchers have promoted nonlinear dynamics supported by multiscale interdependencies between the activities of components that must cohere to form a functional system [8,10]. In our conditions, the emergence of multifractal behaviors was obvious in each experimental group indistinctively, and in each repetition of the task (Figure 2). In addition, the surrogate data testing indicated an evenly distributed presence of nonlinear dynamics, reflected in wider multifractal spectrum in original series, across all repeated movement series (see Section 3.1). These results illustrate the ubiquity of the multifractal behavior in our conditions, thereby strengthening the concept of multiscale interdependencies in components activity to support an optimized functional coordination in upper-limb movements.

A critical result in the present experiment was the specific profile observed in trained people, when compared to untrained individuals. While athletes (ATH and WATH) exhibited high multifractality ($\Delta H_{15}$) during the first execution of arm cranking, SED performed all the task sessions at rather low and similar $\Delta H_{15}$ (Figure 2). The monofractal approach showed a similar tendency but with much less discriminatory power (Figure 3). An interpretative hypothesis is that the monofractal approach captures a power-law behavior that is a global property of the system, blind to the specific behavior that emerges from nonlinear contingencies. Previous works evaluating the global power-law in movement series have shown a higher scaling exponent in experts, e.g., during oscillating movements on a ski simulator [14]. Based on a detrended fluctuation analysis without q-moments testing, Nourrit et al. showed that experts exhibit oscillation behavior with scaling exponents near 1.0 (pink noise), far from the white noise–like structures of temporal fluctuations observed in movement series of novices. The authors suggested a lack of optimally coordinated interactions in the movement system of novices, while years of practice in experts might have been accompanied with the progressive installation of degeneracy, or a greater repertoire of interactions in the operating system [14]. In the same vein, the variability structure obtained during rowing series demonstrated the obvious influence of motor skills on pink noise emergence, since such fractal-like behavior was clearly observed in elite but not
sub-elite (but trained) rowers [13]. One may conclude that a refined temporal structure of fluctuations, with clearer fractal-like structuring in the movement system is a characteristic of elite performers. As above studies have used a monofractal approach, one can hardly infer the kind of coordination that is responsible for clearer 1/f scaling in experts. Different kinds of interactivity can support a given monofractal system behavior [8], which leaves us without convincing information on the presence of separable components acting independently at one scale or obvious interactions across many scales at once. Here we suggest that the analysis of $\Delta H_{15}$ (multifractal) provides a clearer picture of interaction–dominance than the analysis of $H_2$ (monofractal) alone.

Perhaps in greater proximity with our $\Delta H_{15}$ analysis in movement series, the multifractal hammering behavior observed in expert versus less qualified carvers when shaping unfamiliar material [21] is appealing. First, it must be said that original series of hammering behavior have been compared with their linearized surrogates, which shows the dominance of nonlinear phenomena. The singularity spectrum width obtained in carvers (which is equivalent to $\Delta H_{15}$ metrics quantified here) significantly narrowed in the unfamiliar condition only in poorly qualified craftsmen. Mirroring this, when facing the same task novelty, multifractality was high in most prominent experts, a phenomenon that resembles high $\Delta H_{15}$ in ATH and WATH (but not SED) when they discovered arm cranking for the first time. Taken together, these observations argue for skill-dependent movement coordination when facing novelty in motor tasking: only experts exploit a complex coordination of nonlinear contingencies across temporal scales, providing the system with significant robustness in case of unanticipated external disturbances.

A somewhat puzzling observation in the present study was the progressive decline in $\Delta H_{15}$ in the following repetitions. Assuming high $\Delta H_{15}$ as an asset during the initial execution of the task, in relation with greater system complexity and robustness, the question arises why such level of complexity is not maintained during the following repetitions of the same task. As a first consequence of observing a drop in $\Delta H_{15}$, one can hardly interpret the exacerbated multifractality observed during the initial repetitions in physically trained people as the definitive installation of a new and definitively anchored kind of coordination, resulting from years of training. With an anchored, encoded, and consolidated coordination, $\Delta H_{15}$ would not have changed in following repetitions of the task. The question is therefore, in what extent the drop in $\Delta H_{15}$ should be considered an adequate behavior in the sense that it is observable in our most skilled participants. Two complementary arguments could be put forward: the kind of interactivity spanning a wide range of scales provides excellent robustness but has an energy cost; meanwhile, adapting to a new motor task, experts progressively identify if the risk of failure to maintain force output (the main goal of the task) is high or low.

It must be remembered that arm cranking was chosen because of limited sources of external sources of variation, due to strict movement trajectory imposed by crank rotations. External sources of variation are usually linked to degraded behavioral complexity [9]. Performing a task requires focusing on task constraints and adjusting behavioral degrees of freedom. This does not exhaust all the scales at which the participant is able to behave, especially when constraints are minimal. So, the cognitive system operates through the ability to complete the task and the ability to detach from the task constraints to attend to other details or event that may arise [28]. The latter might be exacerbated in the movement system of our experts when adapting for the first time to arm cranking. It would mean that only the cognitive system of experts spontaneously exploits this wider range of interdependencies to gain a robust system, at a time when risks of task failure have not yet been identified. Figure 2 seems to indicate that the phenomenon does not obey ‘all or nothing’ since $\Delta H_{15}$ dropped somewhat gradually during initial repetitions of the task. Once the task and the context have been identified by experts as unlikely sources of variability, then interactivity unfolds across a narrower range of scales. The system is progressively simplified, at last over a 3-day period of observation, although it preserves a multifractal behavior for relative robustness. This line of reasoning might imply that nonlinear dynam-
ics during familiarization reflects the presence of proactive cascades in movement control. The link between multifractality and proactive cascades has received recent experimental highlights [18,28,29]. It also implies that it is not the task constraints per se that imposes behavioral complexity, otherwise a similar behavior would have been observed in SED, but that the particular system dynamics are codetermined by the context of the task and the individual dispositions, which has also received experimental evidence [30].

In the second step of our reasoning, it is hypothesized that reducing the range of scales among which interactivity unfolds is cost effective. Hence, it becomes evident that maintaining high system complexity when facing poorly demanding tasks would have been vain and inadequate. In support of this hypothesis, a parallel has been drawn between diffusive properties of information in the cognitive system and the broader formalism of energy flow [3]. Diffusion only occurs when there is a gradient of energy. When diffusion takes the form of multiplicative cascades through a biological medium, multiplicity might be a source of energy demand. When progressively reducing attention on the poorly demanded context of the task, thereby simplifying cascade dynamics, the overall behavior becomes progressively less demanding in experts.

This study is not without limitations. It must be said that although multifractality presents obvious promise to deal with movement adaptation, the identification of underlying processes at the origin of a rearrangement in multiplicative interactions is beyond the limits of the present study. We also failed to identify distinctive behaviors between ATH and WATH (Hypothesis 2). On one hand, this might be due to a limited number of participants in each group, and the issue remains rather inconclusive. On the other hand, the basic situation of arm cranking is not comparable with the complex gesture of wheelchair maneuvering, especially for basketball training in our participants. Increasing task difficulty may enforce more focal adaptation to the task, which could help in being more discriminant when capturing multifractal resources in wheelchair users.

In conclusion, we have shown that a large number of scaling exponents is needed to finely characterize movement dynamics when adapting to arm cranking, which is well reflected in a focus-based multifractal detrended fluctuation analysis. This is in line with the concept of interaction-dominance in the coordination of perception, cognition, and action, provided that our investigation points to the special kind of interactivity where interactions unfold across a wide range of temporal scales. Such a behavior is exacerbated in experts to get the most robust movement system as far as risks of task failure are not well identified.

On the basis of these novel findings, multifractality could serve in future studies of rehabilitation populations who, in order to achieve autonomy, must adapt to other forms of motor skills, e.g., maneuvering a wheelchair or returning to walking with a prosthesis after amputation.

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