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Multifractality, Interactivity, and the Adaptive Capacity of the Human Movement System: A Perspective for Advancing the Conceptual Basis of Neurologic Physical Therapy

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ABSTRACT

Background and Purpose:

Physical therapists seek to optimize movement as a means of reducing disability and improving health. The short-term effects of interventions designed to optimize movement ultimately are intended to be adapted for use across various future patterns of behavior, in potentially unpredictable ways, with varying frequency, and in the context of multiple tasks and environmental conditions. In this perspective article, we review and discuss the implications of recent evidence that optimal movement variability, which previously had been associated with adaptable motor behavior, contains a specific complex nonlinear feature known as "multifractality."

Summary of Key Points:

Multifractal movement fluctuation patterns reflect robust physiologic interactivity occurring within the movement system across multiple time scales. Such patterns provide conceptual support for the idea that patterns of motor behavior occurring in the moment are inextricably linked in complex, physiologic ways to patterns of motor behavior occurring over much longer periods. The human movement system appears to be particularly tuned to multifractal fluctuation patterns and exhibits the ability to reorganize its output in response to external stimulation embedded with multifractal features.

Recommendations for Clinical Practice:

As a fundamental feature of human movement, multifractality opens new avenues for conceptualizing the link between physiologic interactivity and adaptive capacity. Preliminary evidence supporting the positive influence of multifractal rhythmic auditory stimulation on the gait patterns of individuals with Parkinson disease is used to illustrate how physical therapy interventions might be devised to specifically target the adaptive capacity of the human movement system.

Video Abstract available for more insights from the authors (see Video, Supplemental Digital Content 1, https://links.lww.com/JNPT/A183).

Keywords:

intervention; measurement; motor control; nonlinear dynamics; variability

Optimizing movement is the fundamental therapeutic goal of the physical therapy profession.[1] As its core construct, the human movement system provides the profession with a scientific framework for understanding the nature of optimizing movement. The system, which "represents the collection of systems (cardiovascular, pulmonary, endocrine, integumentary, nervous, and musculoskeletal) that interact to move the body or its component parts,"[1] is by definition a dynamic one. When functioning optimally, the continuous interactions within the human movement system maximize an individual's ability to engage with and respond to his or her environment by virtue of functional capacity and performance.[1] Recent efforts by the American Physical Therapy Association[1–3] underscore the importance of integrating movement system concepts into physical therapist education, practice, and research.

Human movement is a complex behavior within a specific context.[1] If at any given moment, the movement-related functional capacity and performance of an individual are the product of interactions among physiologic systems, and if interactions among system components fluctuate continuously by definition, then one would expect that the behavior of the human movement system as a whole would fluctuate to some extent from one moment to the next; this is indeed the case. Across a range of physiologic and performance measures (eg, heart rate, respiratory rate, postural control sway, and gait strides),[4–14] variability in the output of the human movement system has been recognized as providing important information about the health of underlying physiologic systems and their interactions. Optimal human movement, in fact, exhibits complex, nonlinear fluctuation patterns in motor performance across multiple repetitions of a task that are suggestive of the capacity of the organism to adapt to changes in environmental conditions.[15,16]

Our purpose in this perspective article is to introduce neurologic physical therapists to the concept of "multifractality," a specific nonlinear feature of movement fluctuation patterns that recently has been identified as a mathematical descriptor of dynamic interactions among movement system components. We propose that multifractality characterizes the coordination of motor degrees of freedom and provides a window into understanding the adaptive capacity of the movement system as a whole. We begin by reviewing what is already known about movement variability in physical therapy clinical practice. We then review the basic idea of multifractality and evidence supporting its potential role in the movement system. In the final section, we translate multifractality concepts into neurologic physical therapy clinical practice by describing how various forms of mechanical stimulation currently in use might be augmented to promote greater interactivity, and therefore, enhanced adaptive capacity within the human movement system.

HUMAN MOVEMENT VARIABILITY IN CLINICAL PRACTICE: WHAT WE ALREADY KNOW

In some clinical contexts, the neurologic therapist's immediate goal is to reduce variability in the number of ways a patient might move. In an acute care setting, for example, a therapist's goal may be to constrain the movement of patients with balance impairment by training them to use an assistive device for added stability when walking. In an inpatient rehabilitation setting, a therapist's goal may be to train a patient with respiratory impairment using a distributed practice schedule, so as to avoid oxygen desaturation. In an outpatient setting, a therapist's goal might be to train a patient to avoid various activities that provoke noxious symptoms associated with mild traumatic brain injury. In these types of situations, therapists are likely to consider the patient's consistent, error-free adherence to a specific mobility restriction as serving to prevent injury, pain, and/or delayed recovery. In doing so, the therapist makes an informed tradeoff: the recommended behavioral constraints help ensure patient safety but leave the patient with fewer options for adapting movements to changes in environmental conditions.

In other clinical contexts, patients' relatively low risk of immediate harm during movement diminishes the need for highly restrictive, behavioral constraints to ensure safety. The therapist's main focus is to maximize patients' ability to engage with and respond to their customary environment by increasing functional capacity, improving task performance, and preventing injury. As reported previously using clinical examples,[15,16] the process of optimizing movement under these conditions typically involves 1 of 2 common approaches for addressing movement variability. The first approach is a traditional, linear approach in which the therapist assumes that decreasing movement variability is required to improve functional ability. The therapist has a safe, “correct” movement pattern in mind and provides feedback designed to reduce performance errors. Behavioral flexibility is discouraged during the learning process. A successful outcome is defined as the patient's ability to perform the correct pattern of movement with minimal errors under a narrow set of environmental conditions determined by the therapist.

The second approach is based on principles of nonlinearity, in which the therapist assumes that variations in a target movement pattern from one repetition to the next contain valuable information necessary for the movement system to develop adaptable motor skills. The therapist intentionally allows behavioral flexibility by encouraging the patient to explore a variety of ways to safely solve a given motor problem. The therapist strategically adds complexity to the intervention by varying environmental conditions across repetitions and encourages the patient to develop a repertoire of safe solutions for adapting the target behavior. A successful outcome is defined as the patient's ability to perform the target motor skill, not only under the environmental conditions under which it was acquired, but more importantly, under conditions in which it had not previously been attempted.

In both the approach wherein variability is limited and that wherein variability is encouraged, the patient's successful outcome is defined as improved performance of a safe pattern of movement. The approaches differ fundamentally, however, in how they address movement variability. In the first approach, optimized movement is error free. The therapist's likely assumption is that the patient, now knowing the “correct” movement pattern, will learn to adapt it on his or her own. In the second approach, optimized movement encompasses a repertoire of variations in performance of the motor skill. A calculated clinical decision is made to provide the patient with opportunities to learn how to adapt the target movement in the face of changing conditions. The therapist's likely assumption is that the patient, having learned general rules for adapting the target movement pattern, will apply the rules when encountering novel conditions in the future, outside of the clinic spotlight.

NEW DIRECTIONS IN HUMAN MOVEMENT VARIABILITY

Perhaps not surprisingly, each therapist in the aforementioned examples can make only tenuous assumptions about his or her patient's adaptive capacity. Two key reasons lie at the root of this limitation. First, the concept of “adaptive capacity,” although intuitively appealing, lacks a clear conceptual and empirical linkage to interactive mechanisms within the human movement system. Second, contemporary therapists lack the necessary tools with which foster and measure the development of adaptive capacity, and accordingly, are unable to make more definitive prognostic statements regarding the potential long-term success of their clinical interventions.

Interactivity Begets Adaptive Capacity

Physiologic interactions within the human movement system are not directly observable. What clinicians observe instead are the external interactions of the person (ie, movement system as a whole) interacting with a given task in the context of a given environment. One key to understanding adaptive capacity is to recognize that the output of the movement system, when measured under certain conditions as a long series of repeated observations (eg, n = 1000), provides clues to the invisible interactivity occurring within the system itself.[6–8] The clues are contained within structured, “fractal,” patterns of variability in the sequence of emerging observations. In terms of their mathematical description, fractal objects reflect the systems-perspective idea that patterns of events captured at one measurement scale have a statistical and geometric resemblance to patterns of events captured at another scale. A fractal pattern of movement variability, therefore, means that movement fluctuations (ie, changes in the value of a specific movement parameter) measured at a fine scale (eg, milliseconds) resemble changes in the value of the parameter viewed at coarser scales (eg, seconds, minutes, and hours). Self-similar, fractal patterns are present in biological systems like the human movement system, in which physiologic interactions occur across a range of progressively longer time scales.[15–23]

Recent advances in movement science (see Supplemental Digital Content 2, https://links.lww.com/JNPT/A184, for selected examples) have revealed that a collection of multiple fractal fluctuation patterns, or “multifractality,” rather than a single fractal pattern, is a better indicator of an interaction-driven architecture in the human movement system.[24] The concept of multifractality arises from evidence that fractal patterns emerging from physiologic interactions across time scales will vary slightly from one another, depending on the nature and direction of the interactions under consideration. The variation is thought to occur as a result of differences in how finely-scale physiologic events influence various coarsely-scaled events (and vice versa).[25] For the interested reader, tutorials and basic information about fractal objects and multifractality are available elsewhere.[25–28]

The following is a conceptual example of temporal interactivity in the human movement system. Movement kinematics measured in milliseconds may influence physical activity patterns occurring over the course of an entire day. Daily physical activity patterns, in turn, may influence movement kinematics but not necessarily to the same extent. Furthermore, the extent to which movement kinematics and *hourly* physical activity patterns might influence one another, or the extent to which daily and *seasonal* physical activity patterns might influence one another, presumably is also not identical. When one considers that such differing, interdependent, bidirectional interactions can occur across many different time scales at once, it becomes apparent that a repertoire of interactivity may provide a better characterization of temporal events occurring within the human movement system than a single metric.

The idea that stable, adaptable human movement systems maintain a rich repertoire of movement strategies containing optimal movement variability is not new.[15,16] Similarly, the concept that fractal scaling promotes adaptability is also not new.[4,6–8] What is new here is that the adaptive capacity of the individual can now be conceptually and empirically linked to the *multifractal* characteristics of physiologic interactivity occurring within the system. Clinical understanding of a patient's capacity to adapt his or her motor behavior to changes in task demands and environmental conditions requires the recognition that such (1) behavioral changes are composed of changes in physiologic interactivity, (2) changes in interactivity can occur over many time scales, and (3) changes in interactivity can have differential, bidirectional influences on one another. Thus, we propose that clinicians seeking to foster the development of a patient's adaptive capacity should not limit their interventions to behavioral motor learning paradigms (eg, variable or random task practice).[29] Instead, the clinician should consider implementing additional interventions that directly enrich and diversify the patient's multifractal patterns of physiologic interactivity for a given task.

Measuring Multifractality

One widely used fractal analysis method is detrended fluctuation analysis (DFA),[30] which can provide unique insights into the patterns of fluctuation embedded in the temporal sequence of a movement. DFA begins with taking a measurement series $x(t)$, that is, measuring some variable x and doing so repeatedly (eg, $n \geq 1000$) over regular intervals or space—or even simply measuring attributes of isolated events as each consecutive event occurs. Examples of common time series on which DFA has been applied previously include center of pressure location collected during quiet standing[31,32]; the interval between consecutive heel strikes during overground walking in a laboratory or clinical environment[4]; and the number of steps per minute measured with an activity monitor during unconstrained, “free-living” walking in one's customary environment outside of a laboratory.[14]

The DFA algorithm is applied to a given time series using computer programming languages such as Matlab (Mathworks, Natick, Massachusetts) or R (R Foundation for Statistical Computing, Vienna, Austria). The algorithm proceeds by constructing, from the measurement series $x(t)$, a random-walk series $y(t)$ and assessing standard deviation as the root mean square (RMS) fluctuations above and beyond local trends. See Supplemental Digital Content 3, https://links.lww.com/JNPT/A185, for an appendix containing a brief introduction to these concepts. DFA assesses these detrended RMS fluctuations over bins of many different sizes to estimate how much the standard deviation grows over different scales of the measurement (Figures 1 and 2). The resulting “fluctuation function” (see the bottom panel of Figure 2) depicts what is called a power-law relationship between RMS (ie, standard deviation) and measurement scale. The exponent on the power-law relationship provides the analytical key to diagnosing fractality. Typically, these power-law exponents estimated by DFA are denoted by a Greek letter α or by an upper-case *H*. A power-law exponent of 0.5 indicates temporally uncorrelated fluctuations, whereas temporal correlations will yield power-law exponents beyond 0.5.

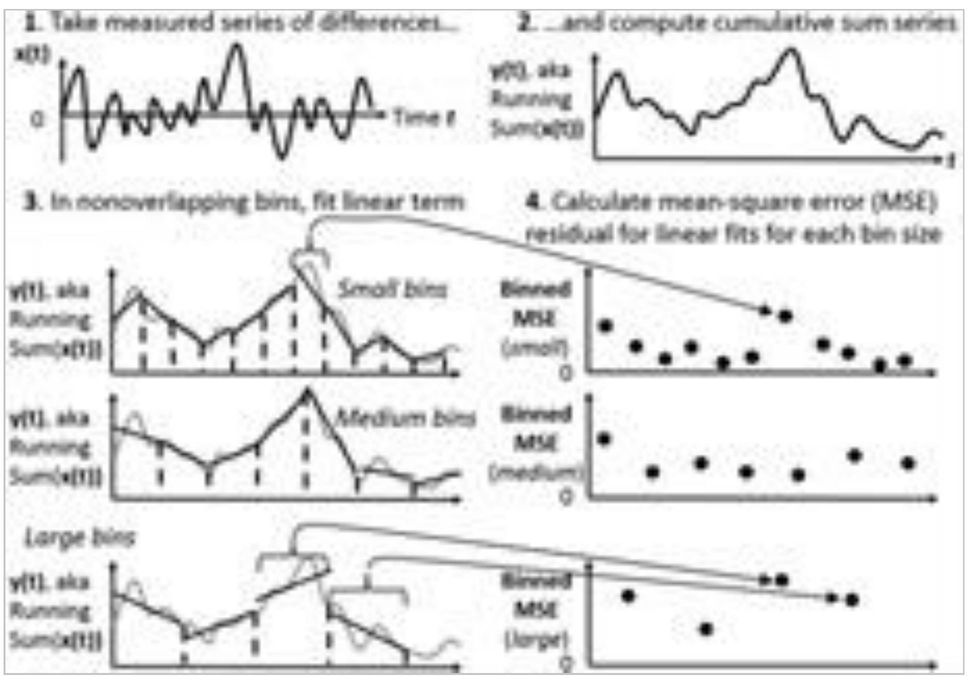

Figure 1.:

Schematic of initial steps in detrended fluctuation analysis. The first panel (top left) schematizes the measured series. The second panel (top right) schematizes the cumulative sum over time. The third panel (bottom left) schematizes the fitting of linear trends to nonoverlapping bins of the cumulative sum from the second panel, depicting the cumulative sum series in gray curves, the trend lines in solid black lines, and the bin boundaries in dashed black vertical lines. The fourth panel (bottom right) schematizes the MSE of residuals left over from each bin's linear fit in the bottom left panel. In both bottom panels, the MSEs on the right correspond to the linear fits on the left, for small, medium, and large bins. MSE, mean squared error.

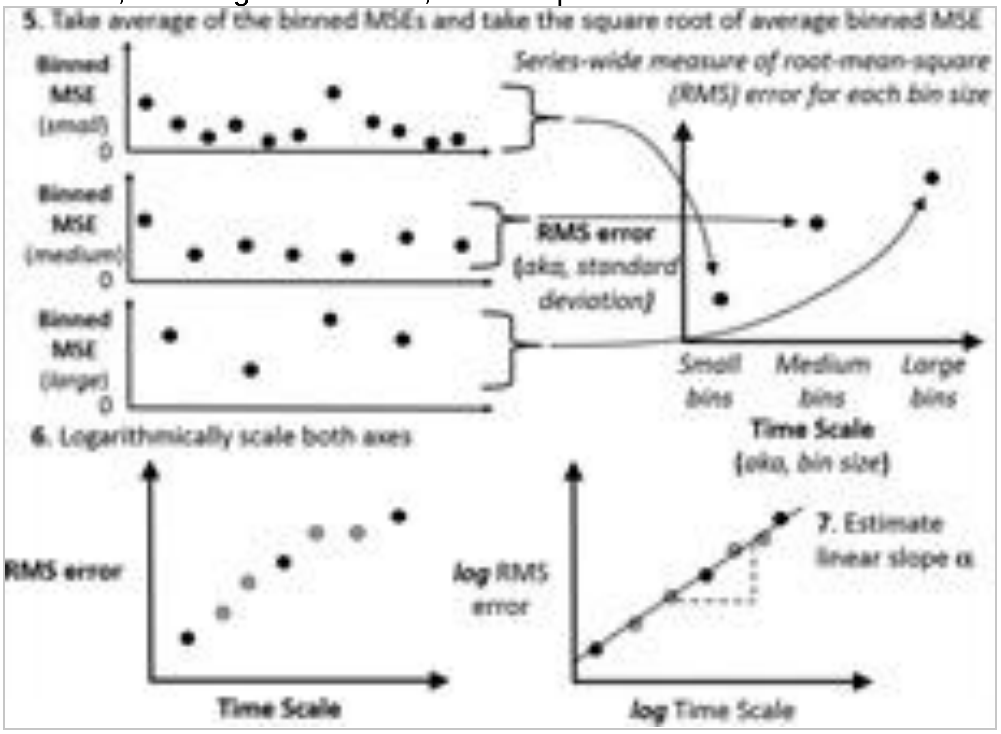

Figure 2.:

Schematic of concluding steps in DFA algorithm. As the top panels show, the MSE values depicted in Figure 1 contribute to an average whose square root is an RMS error statistic, and each bin size has a corresponding RMS statistic. The bottom panels schematize, on the left, the plot of RMS statistics for each bin size with newer gray circles representing other RMS values for intermediate bin sizes not schematized in these figures and, on the right, a logarithmic scaling of the RMS error and a logarithmic scaling of the time scale represented by the bin sizes. The lower right panel schematizes the possibility that this RMS function, once logarithmically transformed, can yield a linear relationship whose slope is an estimate of the power-law exponent. DFA, detrended fluctuation analysis; MSE, mean squared error; RMS, root mean square.

Multifractality is quantified as the variability in these power-law exponents within the same system (or person). If we measure multiple series from the same person, we can find evidence of multifractality in the variability of α from one measurement series to the next. In addition, we can estimate the variability of power-law exponents as a “multifractal spectrum” that serves as a sort of histogram indicating the relative frequency of α within a single series (Figure 3).[33]

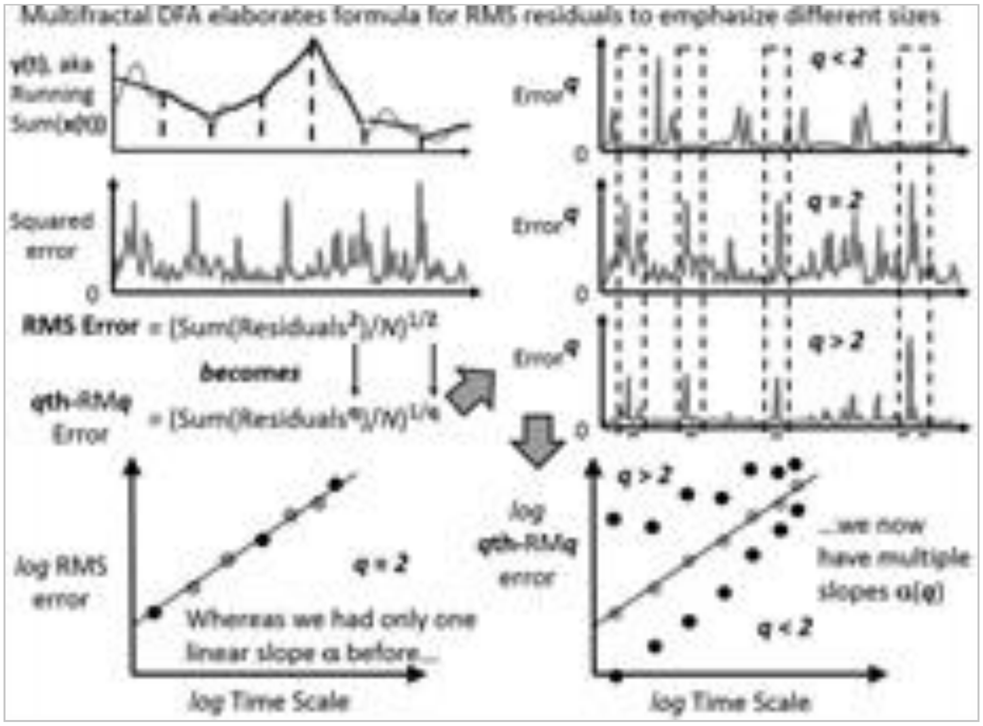

Figure 3.:

Schematic of multifractal elaboration of the DFA algorithm. In this schematic, we consider the entire series of squared residuals left over from the binned detrending (top left panel). What multifractal DFA does is to introduce a parameter *q* that, for standard DFA, only equals 2. Different values of *q* amplify residuals of different size. As the top right panel shows, residuals raised to the exponent *q* is equivalent to squared residuals for standard DFA, residuals raised to exponents *q* greater than 2 leave large errors relatively large while diminishing smaller errors, and residuals raised to exponents *q* less than 2 amplify small errors and diminish larger errors. The bottom panels show how, whereas DFA uses a single series of squared residuals, multifractal DFA uses as many series of error-raised-to-exponent *q* as there are values of *q*. Each series of error-raised-to-exponent *q* contributes to a specific relationship between *q*th-RM*q* and bin size, yielding potentially many linear relationships on logarithmic axes and so potentially many slopes. DFA, detrended fluctuation analysis.

TRANSLATING MULTIFRACTALITY INTO NEUROLOGIC PHYSICAL THERAPY CLINICAL PRACTICE

An empirical example of movement synchronization serves as a useful vehicle for envisioning how physical therapists might begin to incorporate an awareness of multifractality into clinical interventions designed to enhance adaptive capacity. When movement scientists employ a traditional paradigm to study repetitive finger tapping, they ask participants to entrain their tapping movements to periodic (ie, perfectly regular) metronome signals. The traditional interpretation of this ability has been that it reveals the production and use of a motor program that participants can use to synchronize their future movements with the metronome on the basis of their previous experiences with the metronome. The motor program allows the participants to predict when the next metronome beat will be. However, sometimes experimenters will present their participants with metronome signals that fluctuate in their timing from one beat to the next. The pattern of fluctuating interbeat intervals contains a complex organizational structure that features multifractal fluctuation patterns. To the participants, the metronome signals simply seem to fluctuate in random and unpredictable ways. As a result, the standard expectation, that the beat-by-beat performance of the participant reflects a gradually fine-tuned predictive model of when it is most appropriate to tap the response button next, goes directly out the theoretical window. Participants will omit to tap, or sometimes, in a mix of clumsy anticipation and reaction, tap multiple times for individual beats. Surprisingly, however, when viewed over the wider time scale of the entire experiment, participants seem able to generate a series of taps (ie, some accurate, some missing, and some extra) with intertap intervals that fluctuated according to a rule similar to the one which generated the complex, interbeat series of the metronome.[34] That is, despite failing to coordinate their taps with a variable metronome on a beat-by-beat basis, participants' tapping behavior displays a similar multifractal pattern to that of the metronome signal.[35] The closeness of the match, especially given that it occurred across a *collection* of complex fluctuation patterns, could not have been produced by the participant simply attempting to roughly approximate the series of interbeat intervals.

The metronome experiment offers a potentially intriguing example of how smoothly and easily multifractal fluctuations might spread from the task environment into the movement system. It offers a springboard into a novel way of thinking about the control of movement; that is, if multifractal fluctuations can spread from a metronome to a tapping hand, perhaps they can also influence motor coordination in neurologic patient populations for whom movement retraining is a common focus of rehabilitation. For example, it is well established that healthy human gait is characterized by naturally occurring fractal dynamics that are thought to allow humans to ambulate in a stable yet flexible manner, ready to adapt to unpredictable changes in the environment.[4] Moreover, abnormal gait patterns associated with a variety of neuromuscular disorders are characterized by alterations in fractal dynamics.[4] For individuals with Parkinson disease (PD), rhythmic auditory stimulation (RAS) delivered via a fixed-tempo metronome can be used to temporarily improve gait velocity, stride length, cadence, and symmetry.[4,36] Conceptually, however, fixed-tempo RAS has the potential to overtrain 1 tempo during rehabilitation, thereby reducing adaptability.[37] Moreover, fixed-tempo RAS does not appear to restore the diminished fractal scaling of PD gait dynamics, and, in fact, appears to *induce* diminished fractal scaling in healthy adults.[4] If the diminished fractal scaling properties of PD gait dynamics are indicative of defective movement system interactivity attributable to basal ganglia pathology,[6–8] and if an important goal of PD rehabilitation is to optimize movement by restoring adaptive capacity via movement system interactivity, then it follows that the therapeutic value of fixed-tempo RAS may be inherently limited. Perhaps this limitation helps explain why the therapeutic effect of fixed-tempo RAS on gait biomechanics appears to be relatively short-lived.[38]

Can the benefits of RAS be amplified in individuals with PD if the cueing stimulus contains multifractal dynamics? Preliminary evidence suggests that this might be the case. In 2013, Hove et al[37] asked a small sample of individuals with PD and healthy individuals to walk over ground under 3 conditions: no auditory stimulus, fixed-tempo RAS, and interactive RAS embedded with nonlinear temporal structure. Their results revealed that the diminished fractal scaling properties of gait dynamics of individuals with PD were restored to healthy levels only with exposure to an interactive, nonlinear auditory stimulus. Furthermore, the gait patterns retained the restored fractal scaling 5 minutes after removing the interactive RAS, suggesting that the interaction stabilized the internal rhythm-generating system and reintegrated timing networks of the participants with PD. A meaningful additional outcome of the study was that the participants with PD reported greater perceived stability when walking with the nonlinear RAS compared with a fixed-tempo RAS.

Several more recent studies provide preliminary evidence that RAS embedded with nonlinear features can indeed alter the naturally occurring fractal characteristics of human gait.[34,39,40] Importantly, however, the methods used across studies varied in key ways (eg, whether participants were explicitly instructed to synchronize their gait with the metronome and whether walking was assessed on a treadmill or over ground). Furthermore, the extent to which the RAS used in each study may have been multifractal was either limited or unclear. Nonetheless, the studies collectively support the general proposition that movement retraining interventions promoting interactivity among system components may be a potent stimulus for building adaptive capacity of the system as a whole.

FUTURE DIRECTIONS

In contemporary neurologic clinical practice, physical therapists have opportunities to augment their patients' movement training routines by using devices to deliver subtle, repetitive, auditory, visual, or tactile stimulation. Examples (other than a metronome) include movements influenced by virtual reality,[41] robotic cues,[42] whole body vibration,[43–46] vibratory insoles to the feet,[47,48] and neuromuscular electrical stimulation).[49] Very recently, noninvasive brain stimulation has also been added to the array of stimulation-based tools that might augment neurorehabilitation practices.[50] Generally speaking, these devices are designed to deliver predictable, linear patterns of stimulation for the purpose of facilitating movement (eg, muscle activation and kinematics). In the future, such devices could potentially be designed to deliver stimulation containing multifractal features, with the specific intent of enhancing and diversifying the adaptive capacity of a patient's movement system.

To facilitate the discussion of multifractal concepts and their implications for future neurorehabilitation practice, it will be important to consider work occurring in a variety of areas. For example, Cavanaugh et al[14] demonstrated that the temporal sequence of steps taken during customary ambulatory activity in a sample of community dwelling-older adults contained fractal properties. Rand et al[51] recently demonstrated that patterns of support surface translations with temporal characteristics of varying complexity differentially altered the center of pressure signals of healthy adults. In the field of robotics, Wang and Ren[52] recently reported on the development of comfortably wearable, assistive technologies on the basis of multifractal concepts that may dramatically diminish the motor learning curve for movement retraining using prosthetics and orthotics. In our view, such developments have strong potential to expand the array of interventions considered by neurologic physical therapists for building adaptive capacity in their patients.

SUMMARY

Neurologic physical therapists routinely apply concepts of movement variability when considering patients' behavioral goals. Whether constraining variability to promote safety or fostering variability to promote motor skill development, therapists routinely manipulate intervention parameters around variability to optimize patient motor behavior for a given purpose. The short-term effects of such interventions generally are intended to be adapted for use in nonlinear fashion across various future patterns of behavior beyond the clinic spotlight, in potentially unpredictable ways, with varying frequency, and in the context of multiple tasks and environmental conditions. Accordingly, the assessment of adaptability typically centers on the performance of patients attempting to adjust their visible behavior to meet the changing demands of a given task or environment.

The recently identified multifractal fluctuation patterns of human movement show promise for advancing the conceptual basis of neurologic physical therapy in 2 distinct ways. First, the application of multifractal concepts can expand how therapists envision the intended target of their interventions designed to improve adaptability. Rather than targeting visible motor behavior only, multifractal forms of external stimulation also would explicitly target the unseen complex physiologic interactivity occurring *within* the human movement system itself, and therefore, its adaptive *capacity*. In this sense, multifractality expands the concept of “optimizing movement” to more broadly encompass not only external (ie, performance-based) but also internal (ie, capacity-based) forms of interactivity and adaptability.

Second, multifractality adds new insights to the fundamental clinical idea that kinematic patterns of movement occurring over a few seconds potentially can influence motor behavior patterns occurring over weeks, months, and years; and similarly, that motor behavior patterns occurring over relatively longer periods can influence patterns of movement occurring over much shorter periods. The existence of multifractal movement fluctuations indicates that such bidirectional influences themselves are likely to vary, depending on the time scales under consideration. For neurologic physical therapists, the implication of this complex, nonlinear idea is that physiologic adaptive capacity is enhanced when such bidirectional, multiscale influences are robust and diverse. Thus, interventions designed to promote, restore, or preserve multiscale internal interactivity (ie, adaptive capacity) may be more likely than traditional interventions to resonate within the human movement system over the long term.

The multifractality concepts presented in this perspective represent the frontier of a relatively nascent scientific field of study. There remains no strong clinical evidence supporting the hypothesis that restoring healthy levels of multifractality in the movement signatures of patients with neurological health conditions prepares them to cope more effectively with irregularities in the natural environment. Indeed, we have only just begun to understand how multifractal movement features characterize the healthy human movement system and that they can be manipulated experimentally. Furthermore, clinically expedient methods for collecting and analyzing long series of repeated movement observations are not routinely available in contemporary practice settings. Nonetheless, we believe that the science and clinical implications of multifractality, interactivity, and adaptive capacity have evolved sufficiently to warrant consideration for expanding the conceptual basis of neurologic physical therapy. At a broader level, we hope that the ideas presented in this perspective contribute to the ongoing dialog regarding the human movement system as the core construct for the physical therapy profession.[1–3]

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Appendix 1. Selected Evidence Supporting the Existence of Movement System Multifractality

Recent work has examined how healthy adults wield unseen objects by the hand.20 Participants grasp an object behind a curtain only by the object's handle, and they wield it to get a feeling for the object's inertial distribution. This effortful type of touch perception recruits limbs, joints, muscles and tendons, profiting from the hierarchical organization in which each muscle fiber sits within a muscle group, each muscle group encompasses a joint, joints together compose an entire limb, and all is woven together by fascia and skin.17 This hierarchical organization of movement system components requires multifractal modeling for its description generically.17 Measuring wielding movements in terms of their multifractality actually predicts (1) how participants make different use of the same object's inertial distribution to generate judgments of object length, and (2) differences in length judgments over different trials and across different participants. If we provide participants in the wielding study with visual feedback on their judgments, their attention to visual feedback depends on head-sway multifractality; providing visual feedback prompts head-sway multifractality to have a more lasting effect in promoting multifractality in hand wielding.20 The multifractality of wielding simply exemplifies the more general hierarchical organization of movement variability that allows an organism to accumulate and coordinate information for action.

In motor development during infancy, we find a long-standing understanding that infants' spontaneous kicking movements are exploratory.53 Presumably, this exploration entails that spontaneous kicking should carry information from beyond the movement system, from more peripheral degrees of freedom (e.g., the ankle) to more central degrees of freedom (e.g., the hip) closer to the torso. Here again, we can leverage the same usefulness of multifractal measures for indexing the sharing or spread of information across the movement system. Typically-developing infants' spontaneous kicking yields an intermittent series of joint-angle excursions as infants wiggle, squirm, and kick by turn. One study of typically developing infants sampled several minutes of this spontaneous kicking and examined consecutive 30-second segments of joint-angle time series. We used multifractal analysis to assess multifractality in each segment for the hip, knee, and ankles of each infant, and causal modeling provided evidence that joint-angle kinematics exhibited a spreading of multifractality from ankle to knee, and from knee to hip.54 This contingency of multifractality from more peripheral to more central degrees of freedom follows just the sort of flow from periphery to torso that, as noted above, would be consonant with an exploratory role for spontaneous kicking. This example thus used a known exploratory aspect of the movement system to lend further weight to the idea that multifractality is a key feature of exploratory movement variability.

Adults show a similar coordination of multifractal patterning across different muscles participating in the same synergy. Intriguingly, they only show this coordination when their movement is intentional. One study examined EMG signals from muscles in the arm that produce elbow flexion. EMG was collected in under two conditions, one in which elbow flexion was active, i.e., initiated by the participants on their own intention and motive force, and one in which the flexion was passive, i.e., initiated by an experimenter. EMG shows closely coupled multifractal patterns when the movement system is actively flexing the arm, but not when the experimenter provided the motive force behind the flexion movements. Thus, multifractal fluctuations appear to be a specific hallmark of the intentional cooperation of multiple degrees of freedom.55

Neural signals themselves carry multifractal patterns that serve to translate motor command into movement trajectory.18 Even their supporting fascia has been shown to display a multifractal geometry.17 Thus, neural signals contain and are contained by temporal and spatial multifractal structure.

Reference list given in: Cavanaugh J et al. Multifractality, interactivity, and the adaptive capacity of the human movement system: a perspective for advancing the conceptual basis of neurologic physical therapy. J Neurol Phys Ther. 2017; Oct 40 (4)

Appendix 2. A brief introduction to measuring multifractality

Multifractality, as its name suggests, is the case of multiple fractalities. One way to understand fractality is to revisit (briefly!) some fundamental concepts of probability. We begin with a straightforward dice-rolling example to show how standard deviation can reveal temporal correlations, a statistical signature of the echoing across time scales noted above. Temporal correlations exemplify fractality.

Dice roll example

Let us say that we roll two six-sided dice, over and over again, taking the sum of the two numbers that roll face-up on the dice. Let us assume that the dice are fairly constructed so that, for each die, there is an even probability of each face, that is, for the numbers 1, 2, 3, 4, 5, and 6. As we roll the two dice, pick them up, and roll again, there should be no sequence between the two-dice sum for each roll. If we took note of the sums as we rolled the dice, we might record the following sequence: 4, 7, 9, 3, 7, 10, 8, 6, … and so forth. These values would eventually converge around an average of 6.5, and the standard deviation of the two-dice sums around that mean would converge at some constant value determined by the hands of the dice roller, the edges of the dice, the surface where the tumbling dice roll, etc. By the thousandth or so dice roll, the standard deviation will not budge very much from what it had been after the hundredth or so dice roll.

If we construct what's called a "random walk" from these dice rolls, we get a different result. Random-walk variability grows slowly for independent random events. A random walk is summing up of progressive values of individual measured "steps." In this case, each steps in the random walk will be from each dice roll. So, our random walk for the two dice rolls from above would start out with 4 because that is the first "step." Our random walk would continue with 4+7 = 11, 4+7+9=20, and so forth. The random walk for the first eight dice rolls shown above would be 4, 11, 20, 23, 30, 40, 48, and 54. Because each number on the dice faces is positive, the random walk of the dice-roll sums will always increase, and so, whereas the series of individual dice-roll sums eventually settles on a stable value, the random walk for the dice-roll sums has a standard deviation that always increases. If the dice and the rolls are completely fair, if there's no effect of one dice roll on the next, then we can be fairly sure that, once the series of individual dice-rolls settle on its stable standard deviation, the standard deviation of the random walk will increase slowly, at a rate defined by the square root of roll number. So, for instance, the standard deviation of the random walk at 100 rolls will be double what it was at 25 rolls, and the standard deviation of the random walk at 400 will be double what it was at 100 rolls. That is, for fair dice with fair rolling, when there is no temporal correlation from one dice roll to the next, the standard deviation grows slowly, taking ever more rolls to double.

Faster growth of variability in temporally correlated events

What if your dice are loaded? What if someone has perfected the art of rolling the dice to manipulate the outcome? What if, essentially, there is a distinct relationship across time from one dice roll to the next? In that case, the random walk will grow much more erratically. If the dice-roll sums were temporally correlated, then the random walk would show us a standard deviation increasing much more quickly than before. We might see a standard deviation at 50 rolls double that of what is was at 25 rolls, and again doubling at 100 rolls and once more at 200 rolls. The temporally correlated dice-roll sums would exhibit a random walk with much more rapid growth of variability than we had seen with the random walk of the uncorrelated dice-roll sums. This more rapid growth of variability is often a signature of temporal correlations.

Estimating temporal correlations from standard deviation

Fractal analyses are essentially ways to assess the standard deviation for measured random-walk series. We take a measurement, construct the random walk by taking the cumulative sums as for the dice-rolls. To diagnose a measurement as "fractal," we need to be sure that the fast growth of random-walk standard deviation has to do specifically with temporal correlations. Fast growth of random-walk standard deviation might simply be due to nonstationary (i.e. "explosive") growth: that is, you may have perfected the art of rolling the same number, and as you roll more and more, you might find yourself preferring to roll 12 every time or a 2 every time. Rolling 12 every time and rolling 2 every time would reflect the same temporal correlations, but rolling 12 every time would cause standard deviation to positively explode whereas rolling 2 every time would provide only minimal increase. We want a way to assess temporal correlations, the dependence among consecutive dice-roll sums, without being fooled by trends in the data.

The same physiological, behavioral, and cognitive measurements that inform physical therapy can often be nonstationary. So, judicious use of fractal methods requires adequate removal of trends. Different data may require different methods particularly as different processes as well as different task constraints may produce different trends. 56,57

Reference list given in: Cavanaugh J et al. Multifractality, interactivity, and the adaptive capacity of the human movement system: a perspective for advancing the conceptual basis of neurologic physical therapy. J Neurol Phys Ther. 2017; Oct 40 (4).

Video:

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