Interpreting Dynamical Aspects of Movement Variability: Implications for Rehabilitation Providers

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Introduction

While we may have little knowledge of how nonlinear dynamical measurement procedures are informing rehabilitation practice, it is likely some of our faculty are exploring those concepts. A recent Medline search, for example, indicated the number of publications using the key words "nonlinear dynamics" OR "complexity" OR "fractals" AND "movement" have increased exponentially since Wittman & Phillips[1] published the first paper using "nonlinear dynamics" and "movement" as key words in 1969 (Fig. 1).

In particular, examining nonlinear properties of movement variability (e.g., complexity and fractals) in the context of rehabilitation is emerging as a potentially more informative way to analyze movement tasks that require a complex interaction of body segments than examining traditional linear measurements of those tasks.[2] The movement system is dynamical, one that exhibits fluctuating change over time or over repeated movements, as illustrated in Fig. 2. Linear analyses (mean and SD) may inadequately quantify the fluctuating nature of such signals.

Purpose

To describe how gait variability, analyzed via nonlinear methods, may inform our interpretation of walking capacity. We've examined effects of treadmill ambulation or of using ankle-foot orthoses (AFOs) on gait.

Figure 1

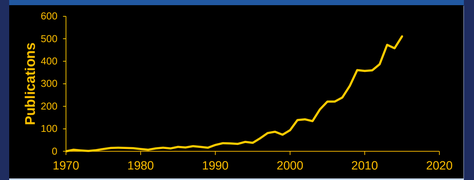

Fig. 1. Number of publications annually using key words ("nonlinear dynamics" OR "complexity" OR "fractals") AND "movement," per a Medline search on 09/18/2017.

Methods

Participants
- Healthy participants (n=20);
- Participants with Parkinsonism (n=6);
- Participants with hemiparesis following stroke (n=13);
- Participant (n=1) with asymmetric lower extremity paresis associated with chronic inflammatory demyelinating polyradiculneuropathy (CIDP).

Instrumentation
- An APDM Movement Monitoring Solutions inertial system (APDM Inc., Portland, OR) with 6 sensors incorporating gyroscopes, magnetometers & triaxial accelerometers was used to capture stride time and stride length data.
- Data were processed with APDM's Mobility Lab software and IWalk plug-in.
- Nonlinear dynamics were analyzed with custom software developed at the Center for Cognition, Action & Perception (University of Cincinnati) and a MATLAB Runtime Version R2014B (8.4) compiler (The MathWorks, Inc., Natick, MA).

Procedures
- Participants completed 6-minute walking trials at preferred walking speeds:
  - Overground along a 30-m path;
  - Healthy volunteers and participants with Parkinsonism additionally completed trials on a motorized treadmill;
  - Paretic participants completed trials while wearing an AFO to compensate for their lower extremity strength deficits.

Figure 2

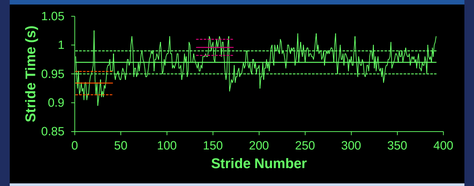

Fig. 2. The mean and standard deviation (SD) across the entire sequence of strides (green) do not capture the fluctuating nature of the stride time signal. The mean and SD from strides 1-20 (orange), for example, differ from the mean and SD of strides 140-160 (magenta).

Methods

Data Processing
- Complexity across trial series data was quantified with sample entropy (SampEn) according to methods described by Richman & Moorman.[3]
- Self-similarities in trial series data were quantified with Hurst (H) exponents via adaptive fractal analysis according to methods described by Riley et al.[4]
  - H = 0.5 →random process, data points uncorrelated.
  - 0.5 < H < 1.0 → persistently correlated process, increases in signal more likely followed by further increases.
  - H < 0.5 → anti-persistent process, increases in signal more likely to be followed by subsequent decreases.

Statistical Analyses
- Linear estimates (means & SDs) were calculated for each gait parameter (stride length and stride time).
- SampEn and H exponents calculated for each gait parameter.
- Where appropriate, dependent t-tests (α = .05) were used to compare data between walking conditions (i.e., overground vs treadmill; without AFO vs with AFO).

Figure 3

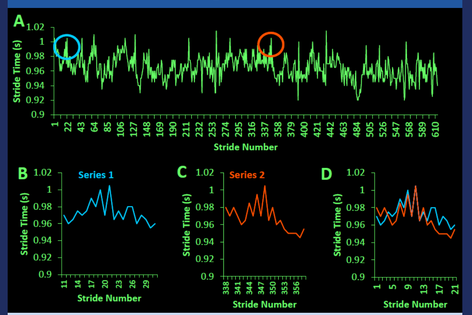

Fig. 3. A trial series illustrates a complex signal with chaotically fluctuating data (A). Data encompassing two series of independent sets of strides are presented (B and C). An overlay plot illustrates repeating 3-point vectors (D). Trial series with lower proportions of repeating vectors have higher sample entropy values.

Results

Treadmill Effects
- In healthy participants (Fig. 4), mean stride times were equivalent in overground (1.03±.05 s) and treadmill (1.03±.05 s) conditions (p=.260), but stride time signals were less complex (overground SampEn 2.20±.15, treadmill SampEn 1.89±.21) and less self-similar (overground H exponent .81±.09, treadmill H exponent .73±.10) on the treadmill.
- Stride time signals in participants with Parkinsonism (Fig. 5), however, were equivalent in complexity (overground SampEn 1.89±.28, treadmill SampEn 1.87±.28) and in fractal self-similarity (overground H exponent .74±.12, treadmill H exponent .78±.06). Mean stride times were also equivalent (1.10±.09 s and 1.12±.14 s, respectively), though they walked more slowly (1.06±.14 m/s vs .90±.14 m/s) on the treadmill with reduced stride lengths (1.15±.08 m vs 1.01±.09 m).

AFO Effects
- In select individuals with asymmetric lower extremity paresis (Fig. 6), sample entropy (e.g., 1.806 and 2.526, respectively) and fractal H exponents (e.g., .57 and .71, respectively) increased when walking with the AFO.

Figure 4

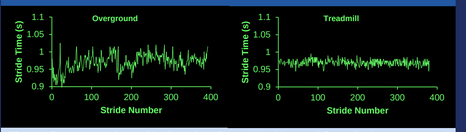

Fig. 4. Representative stride time data from a healthy participant in the overground and treadmill conditions illustrates greater signal complexity overground.

Figure 5

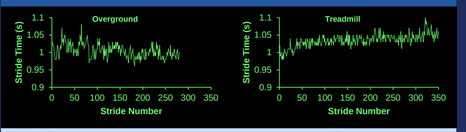

Fig. 5. Representative stride time data from a participant with Parkinsonism in the overground and treadmill conditions illustrates comparable signal complexity.

Figure 6

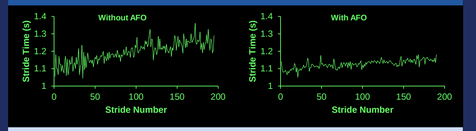

Fig. 6. Trial series for patient's stride time data. Sample entropy = 1.806 and the H exponent = .57 without the AFO; sample entropy = 2.526 and the H exponent = .71 with the AFO.

Discussion & Conclusion

Reduced complexity characterizes biological systems that are rigid, unchanging and predictable.[5] Similarly, fractal H exponents that approach .5 reflect a random, simplistic physiologic system.[6] Increases in complexity and fractal exponents reflect more complex, adaptable, healthy dynamical systems.

Based on our findings, healthy individuals walking on a motorized treadmill produce a less complex stride time signal, suggesting the treadmill system is not sufficiently complex to challenge gait in healthy individuals. Paradoxically, gait dynamics are not altered on a treadmill in individuals with Parkinsonism, suggesting that the consistent pacing produced on a treadmill may provide rehabilitative benefits in that population.[7]

In persons with asymmetric lower extremity paresis, our findings provide some evidence that using an AFO may produce gait signals representing that of a more complex, adaptable and healthy dynamical system.

Interpreting nonlinear gait dynamics may provide more insight about one's walking capacity than is provided through traditional linear measurements of gait parameters.

References

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