CENTER FOR RESEARCH IN HUMAN MOVEMENT VARIABLITY
NONLINEAR ANALYSIS CORE

Overview of Fractals in Movement Science

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Overview

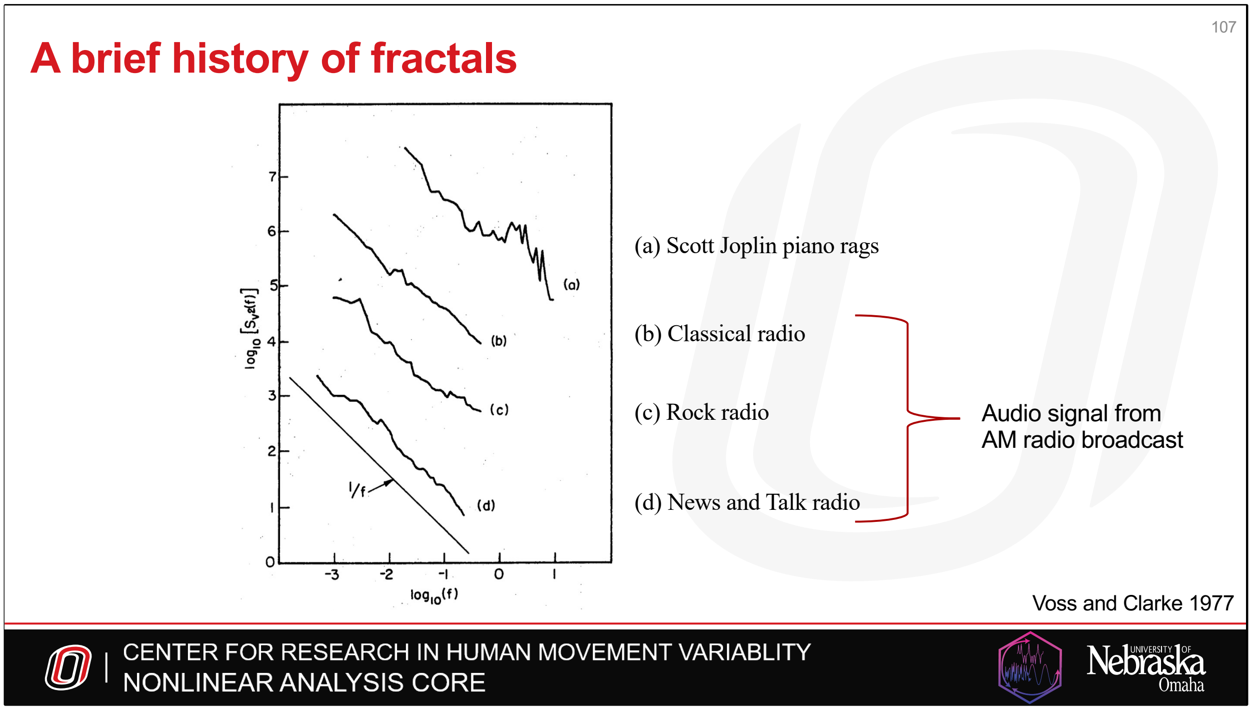
- A brief history of fractals (besides Biomechanics)
- Literature review on how fractal analysis (with a focus on DFA) has been used to measure fractals in movement science
- Summary of fractal analysis in different populations
- Summary of fractal analysis in different physiological data
- Methodological considerations for fractal analysis

A brief history of fractals

1/f noise in music and speech

Voss and Clarke 1977

‘75 ‘95 ‘00 ‘05 ‘10 ‘15 ‘20

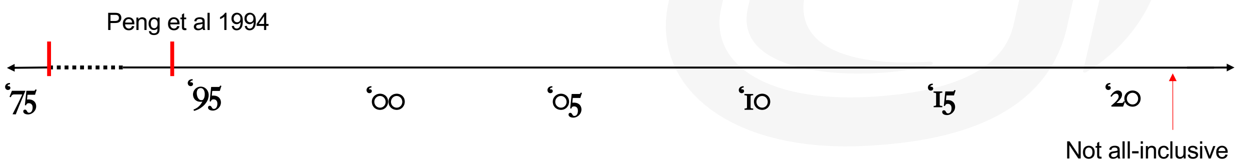


Voss and Clarke wondered how loudness varies across different frequencies so they analyzed the loudness fluctuation spectra of:
a piano track from American composer Scott Joplin (line a), and then the broadcast of different radio stations such as classic, rock and a news n talk radio.

The spectrums exhibits an 1/f dependence, suggesting a certain level of self-similarity in the loudness fluctuations across different frequencies.

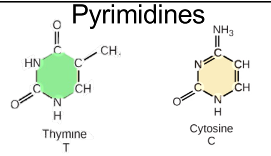
A brief history of fractals in physiology and behavior

Is our own DNA fractal?

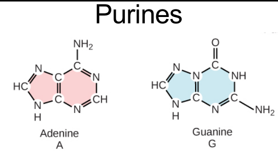


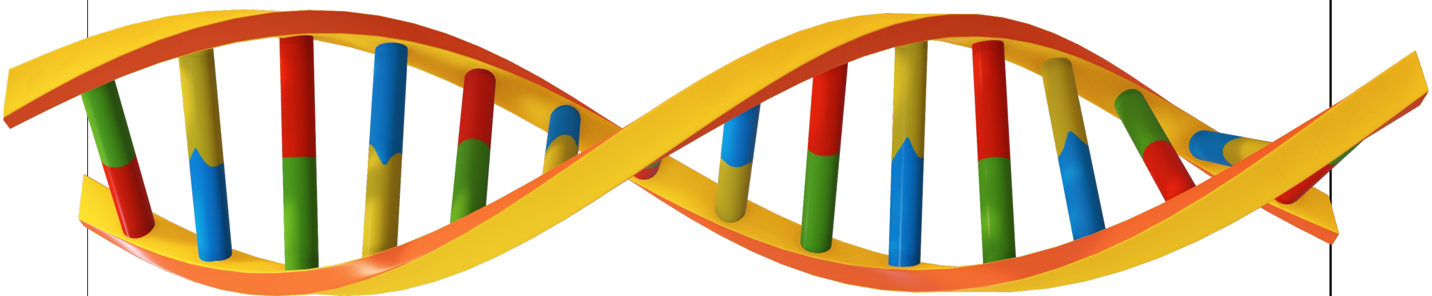
Fractal Analysis – Physiology – DNA

Pyrimidines



Purines

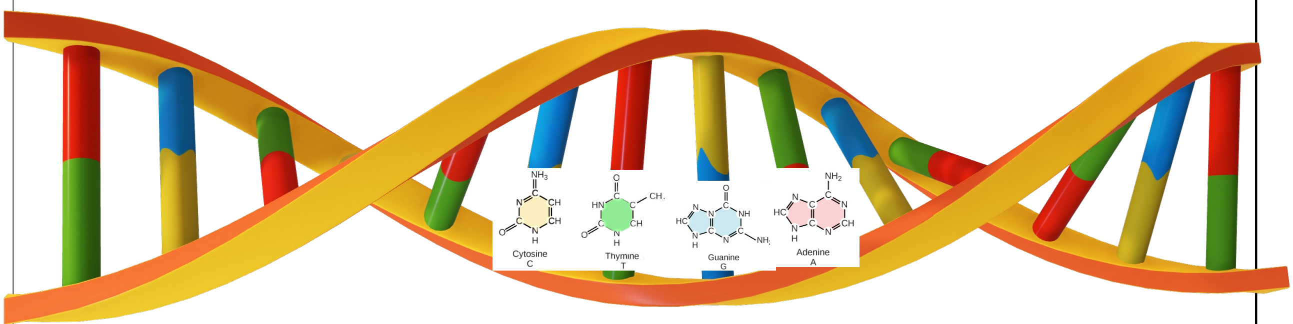




Peng et al. 1994

Fractal Analysis – Physiology – DNA

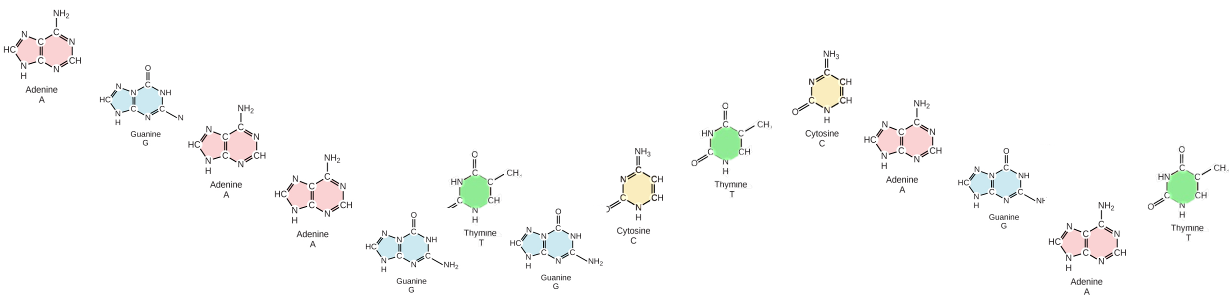
Does patchiness reveal long-range correlations?



Peng et al. 1994

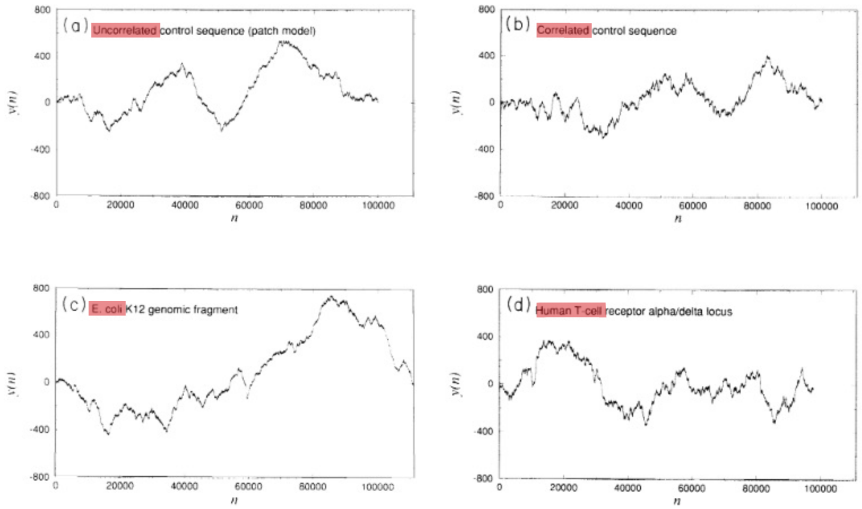
Fractal Analysis – Physiology – DNA

The DNA Walk → **How to do:**
Purine: 1 step down
Pyrimidine: 1 step up



Peng et al. 1994

Fractal Analysis – Physiology – DNA



Peng et al. 1994

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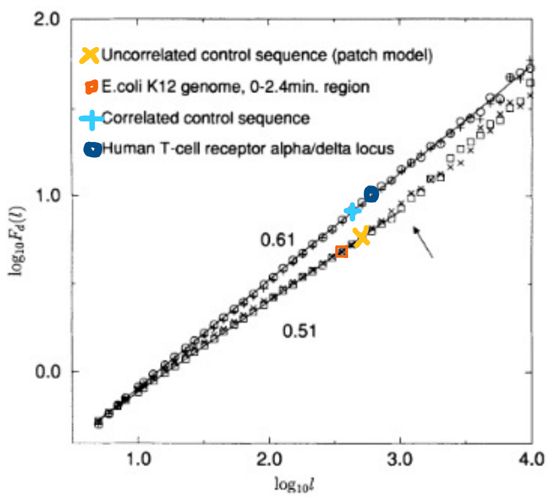
If you followed the sequence just a second ago, we are going to end up getting long DNA sequences like those on the above diffusion plots.

Panels a and b exhibit two generated control sequences where a does not possess long-range power-law correlations, while b does.
Bottom panels , c is viral DNA of E.Coli, and d is a human T cell receptor.

They both seem to have patchiness & There seems to be a trend. So they wanted to examine the underlying structures.

Fractal Analysis – Physiology – DNA



DFA algorithm applied to gene sequences

E.coli ~ Uncorrelated
Human T cell ~ Correlated

Peng et al. 1994

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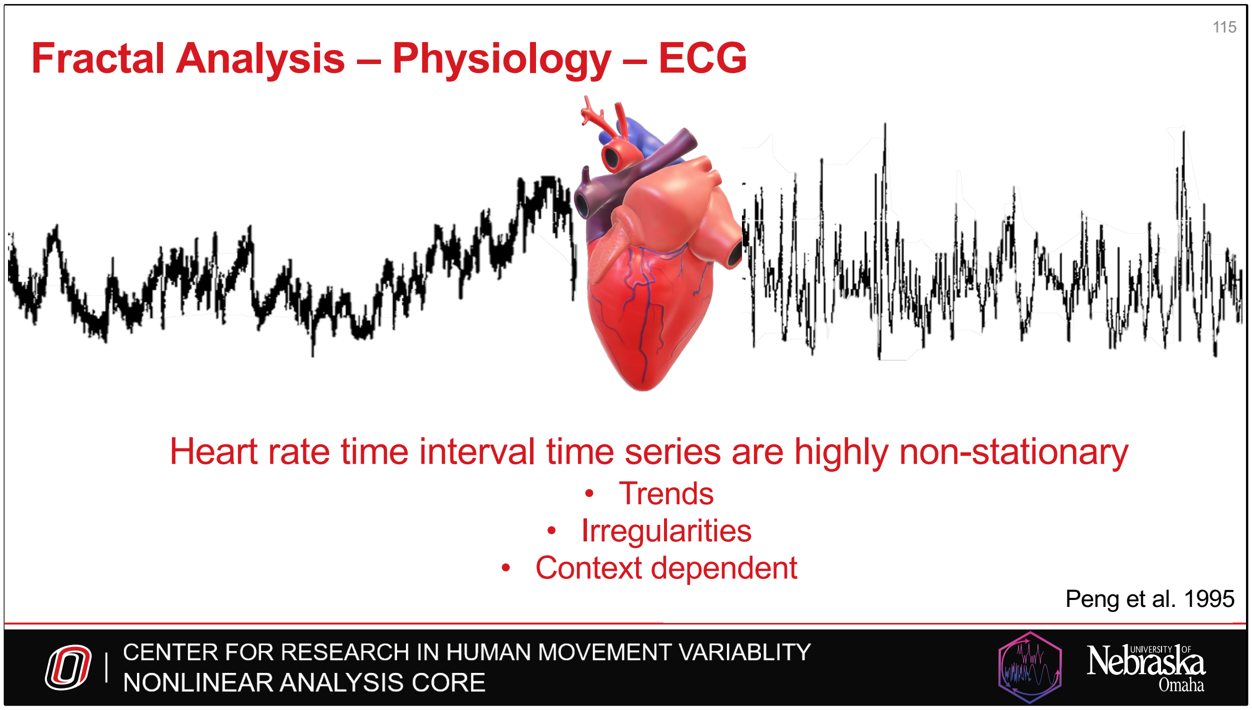
patchiness seems to be an issue in the case of the e.coli virus where alpha value changes right at where the arrow points. So patchiness cannot account for long range correlations.

Fractal Analysis – Physiology – ECG

Does the human heartbeat demonstrate long range correlations?

More related to ASB



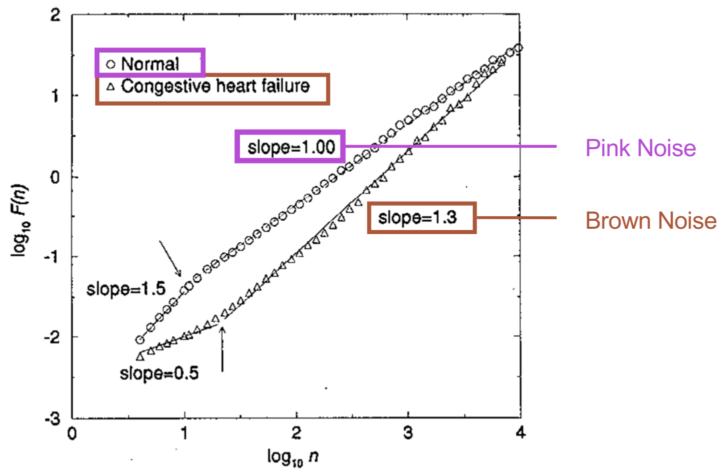
Electrocardiograms of beat-to-beat heart rate intervals – measured

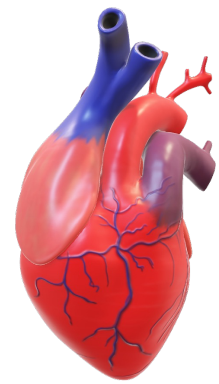
Trend & Irregularities - look at left and right of heart differences - patterns, high and lows etc

Context dependent - going for a run ECG faster than sitting on a chair listening to this workshop (hopefully)

Fractal Analysis – Physiology – ECG

24-hour interbeat interval time series





Peng et al. 1995

For normal healthy: heartrate exhibited pattern of long range correlations where the congested heart failure group deviates from that pattern as we can see from the alpha values on the fluctuation plot

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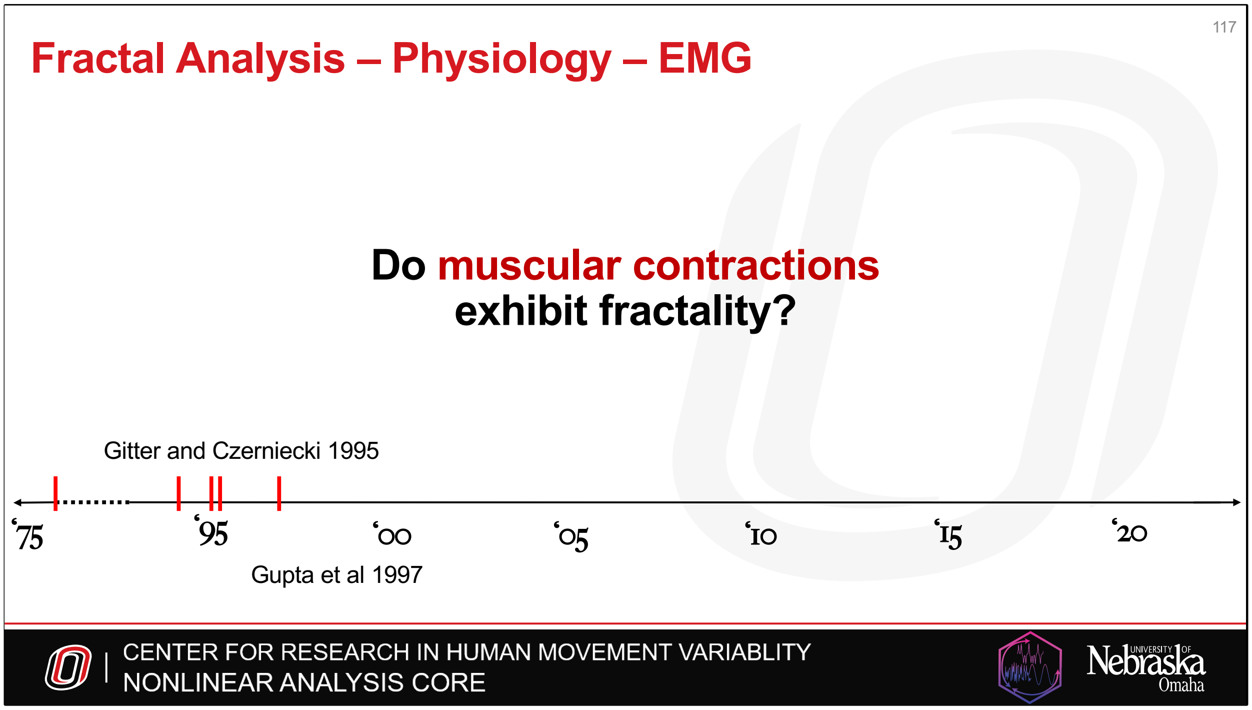
Congestive heart failure: abnormalities in both the sympathetic and parasympathetic control mechanisms

1 subject per group on graph

12 healthy adults and 15 congestive heart failure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Fractal Analysis – Physiology – EMG
Do muscular contractions exhibit fractality?
Gitter and Czerniecki 1995
'75
'95
'00
'05
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'15
'20
Gupta et al 1997
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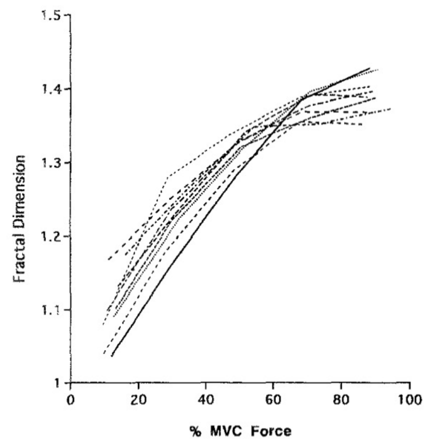
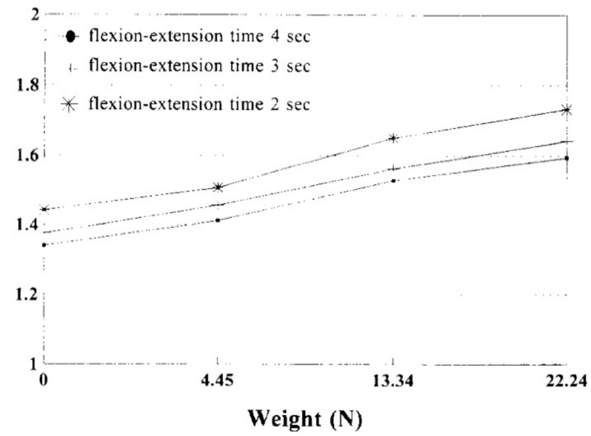
Fractal Analysis – Physiology – EMG





Gitter and Czerniecki 1995

Gupta et al 1997

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When a muscle contracts, motor units are recruited in a specific pattern based on the force required for the task. For low force tasks, a few motor units are activated, while for high force tasks, more motor units are recruited to generate the required strength.

Gitter and Czerniecki: Wanted to determine if the normal EMG interference pattern (IP) has fractal characteristics. – Measured signal of 9 diff bicep muscles when force varied from 10-90% max (x-axis).On the y-axis we have fractal dimension, which also measures fractal characteristics, on a slightly different scale than alpha.
Found that: The EMG interference pattern displays fractal characteristics with a dimension that is highly

correlated with force and ranges from 1.1 to 1.4 as force increases from 10 to 90% MVC.
7 subjects

Gupta: Same paradigm however with different weight force baring (x-axis), not MVC, and for diff speeds rate.(each line)
Results: the fractal dimension of the surface EMG increased with increasing load and increasing flexion- extension speed.
12 young healthy subjects

In summary we can see that fractal dimension changes as a result of muscle force and speed

Fractal Analysis – Physiology – Respiration

Does human respiration demonstrate long range correlations?

Fractal Analysis – Physiology – Respiration

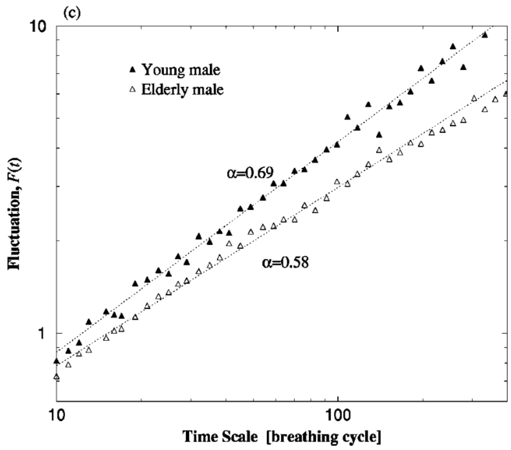


TABLE 2. Individual DFA exponents.

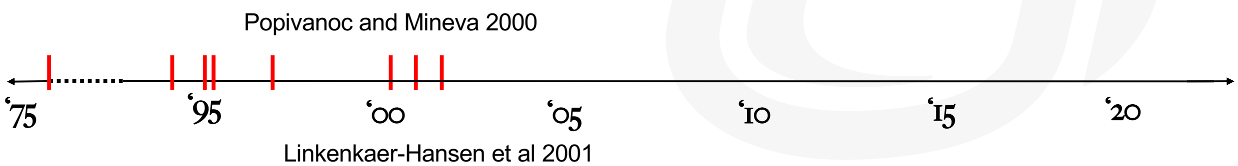
Young female group		Young male group		Elderly female group		Elderly male group	
Age	α	Age	α	Age	α	Age	α
23	0.660	34	0.651	77	0.589	73	0.555
28	0.646	31	0.680	73	0.622	81	0.527
21	0.694	23	0.680	73	0.710	76	0.514
30	0.735	21	0.602	71	0.618	71	0.572
32	0.693	30	0.589	74	0.672	68	0.689
23	0.649	23	0.654	73	0.644	83	0.565
28	0.587	26	0.693	75	0.698	70	0.601
27	0.748	31	0.667	85	0.734	77	0.624
25	0.730	21	0.820	70	0.603	71	0.565
21	0.845	21	0.783	73	0.777	77	0.768
mean ± SD	0.70±0.07		0.68±0.07		0.67±0.06		0.60±0.08

Peng et al. 2002

- <u>They sought</u> to quantify the fractal scaling properties of human respiratory dynamics and determine whether they are altered with healthy aging and gender.
- 2 hours of spontaneous breathing – extracted inter-breath intervals.
- All human breathing cycle dynamics exhibit power law correlations (long yellow highlight values close to 0.7), which in elder groups seems to be degraded but only significantly so in elder men (from 0.68 to 0.6).
-Graph shows the fluctuation plot of 1 subject of each male group summarizing the previous finding.

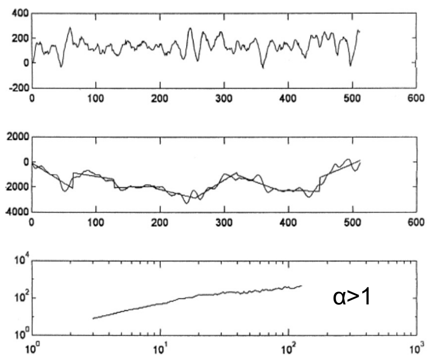
Fractal Analysis – Physiology – EEG/MEG

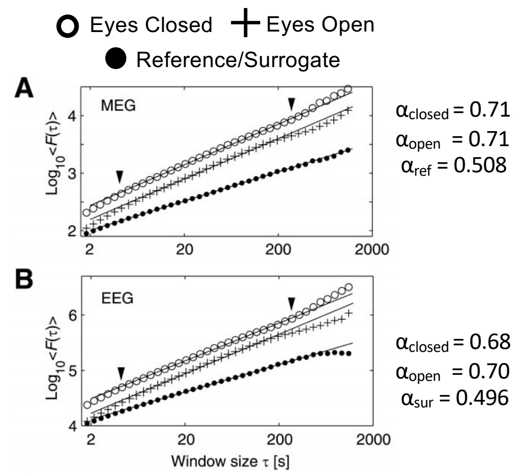
Does brain activity and cognitive load exhibit fractality?



Fractal Analysis – Physiology – EEG/MEG

Mental task performance





Popivanoc and Mineva 2000

Linkenkaer-Hansen et al 2001

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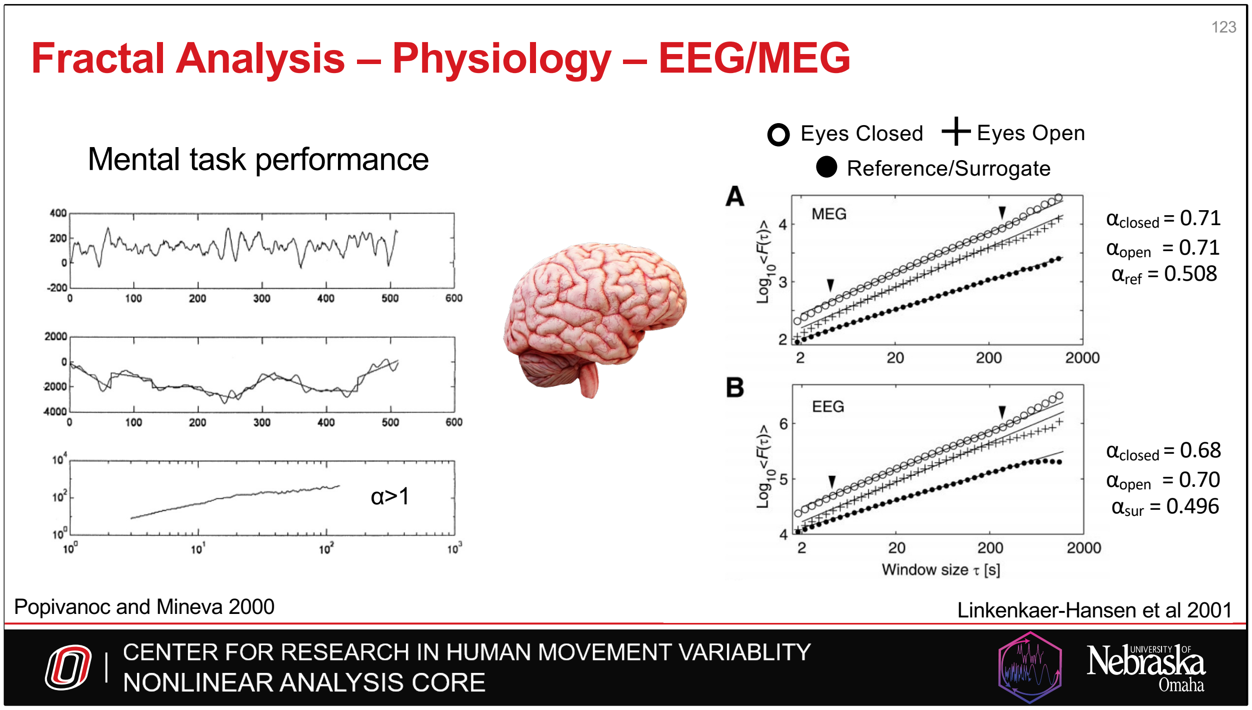
Popivanoc and Mineva:

- Wanted to test DFA method on this signal
- **Task:** (EEG) participant was given a preselected time interval and their goal was to accurately reproduce the time interval between button presses.
- **Results:** The value of alpha of the EEG was above 1.0 which indicates a non-stationary segment. In contrast, during the baseline EEG segments - relaxed sitting - the

alpha values were consistently below 1.0, indicating stationarity.

- **Overall** the study indicates that during the performance of a mental task, the EEG signals change its dynamic behavior exhibiting a fractal structure with long-range correlations, captured by DFA

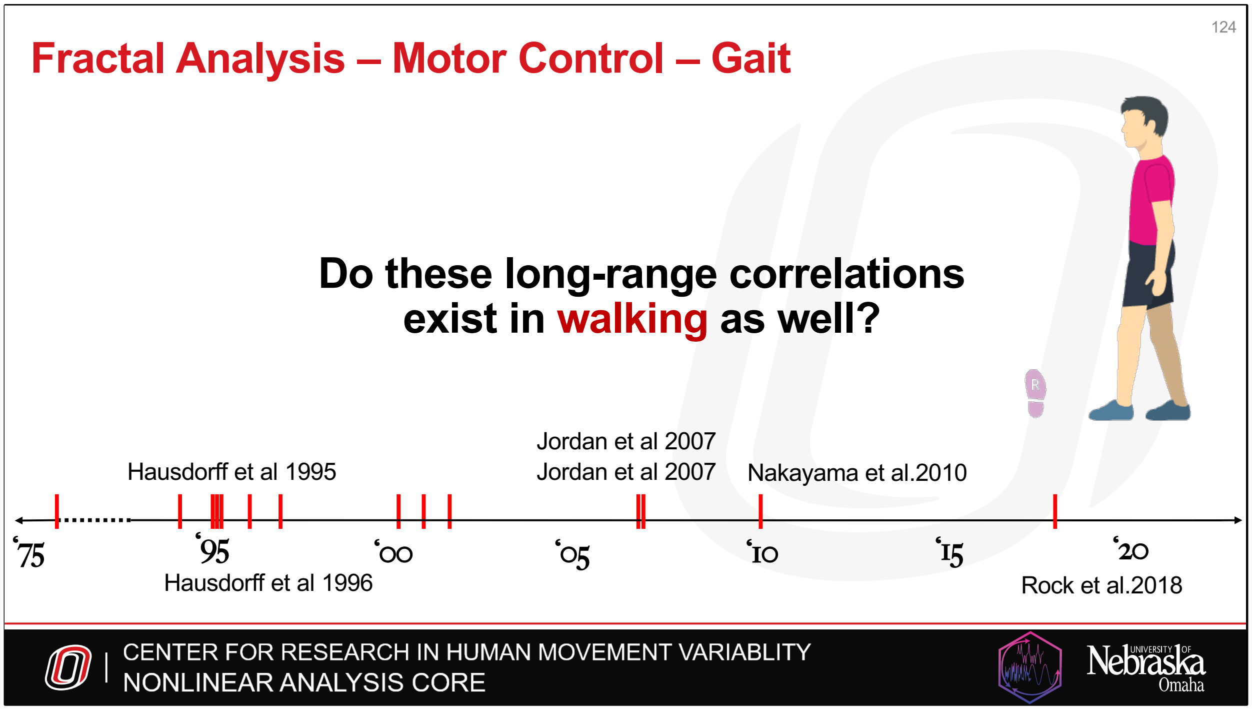


Likenkaer-Hansen:

- **Investigated** the temporal correlations of network oscillations in the normal human brain at ongoing activity during eyes-closed (open circle symbol) and eyes-open (cross symbol) conditions and was recorded with simultaneous magnetoencephalography (A plot) and electroencephalography (B plot).
- **Results:** show that amplitude fluctuations of network oscillations are correlated over thousands of oscillation cycles obeying power law correlation (alphas around 0.7)– however no diff between eyes open or closed

- Surrogation was performed by randomly shuffling the data and repeating the analysis and showing there is a distinct difference

- Subjects: 10 young healthy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Fractal Analysis – Motor Control – Gait
Do these long-range correlations exist in walking as well?
Hausdorff et al 1995
Jordan et al 2007
Jordan et al 2007
Nakayama et al.2010
'75
'95
'00
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'15
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Hausdorff et al 1996
Rock et al.2018
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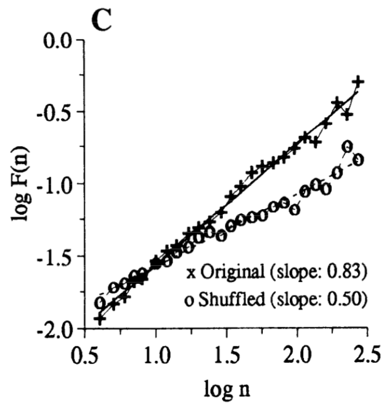
Fractal Analysis – Motor Control – Gait



Hausdorff et al. 1995

Hausdorff et al. 1996

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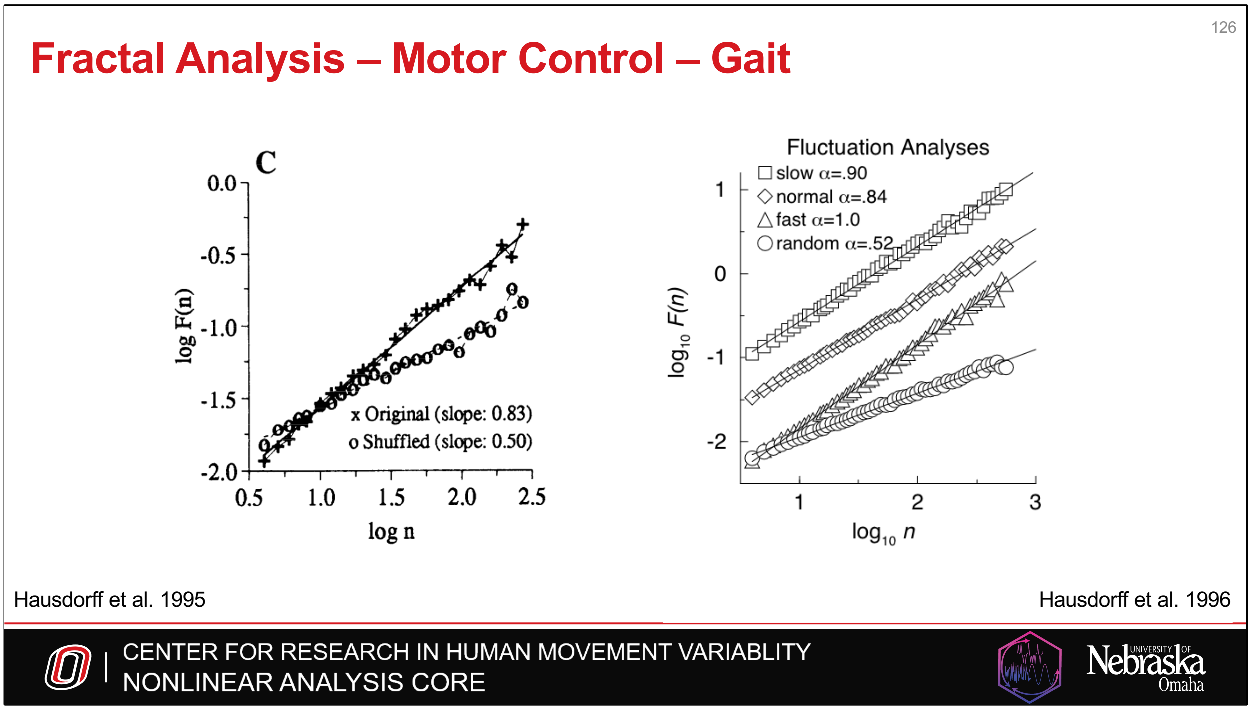
Hausdorff 95: Made Young healthy adults walk for 10min – extracted stride intervals – found strong long range correlation and AGAIN that is verified by randomly shuffling the data and repeating the analysis and showing there is a distinct difference
Documenting the existence of such phenomenon is great, but it also has to respond to experimental manipulations
So a year after that Hausdorff and his colleagues conducted another experiment – (next slide)

Haus 95 – subjects 10 young healthy adults , 9 min walk, self speed, stride intervals



Hausdorff 96: ***Result:*** *"the stride interval time series displayed long-range (fractal-like) correlations over thousands of strides",*
but they do exhibit differences among speeds

So, the patterns we see in gait tend to depend on the speed at which we are locomoting. So more researchers conducted similar studies.

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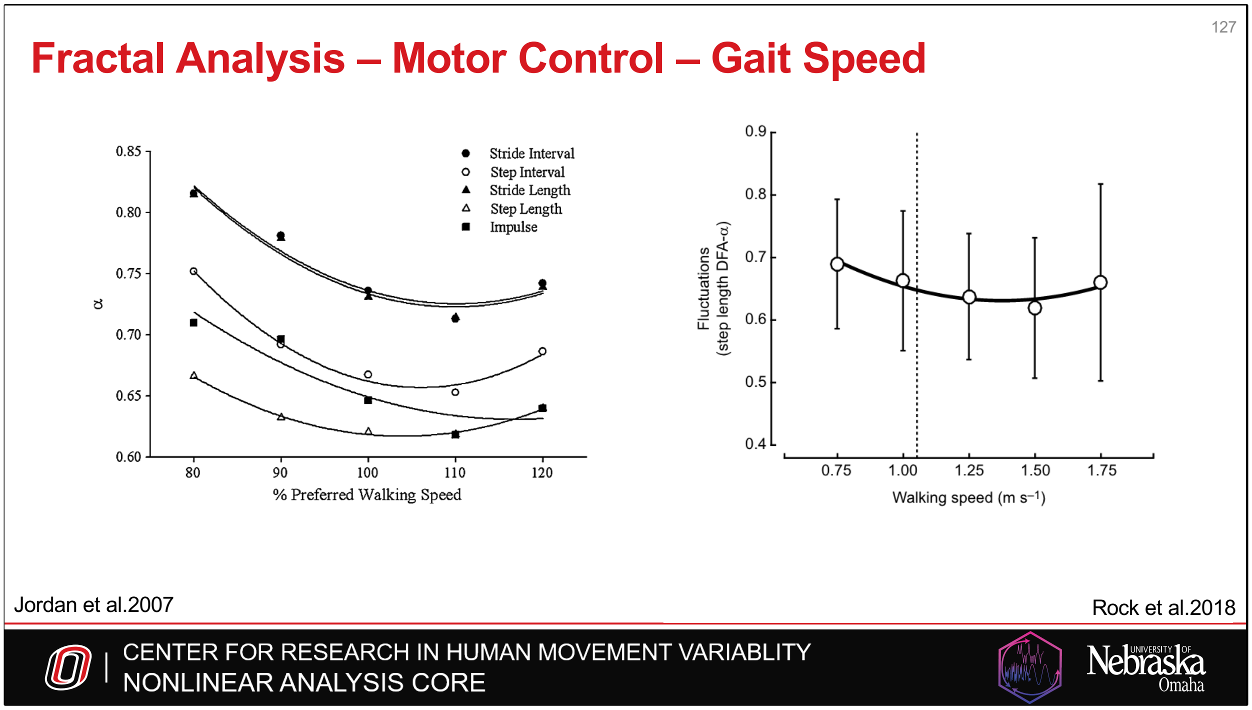
Subjects: 10 young healthy adults, 1h walk, diff speeds, stride intervals

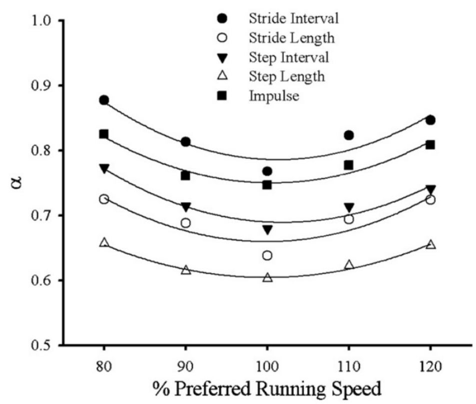


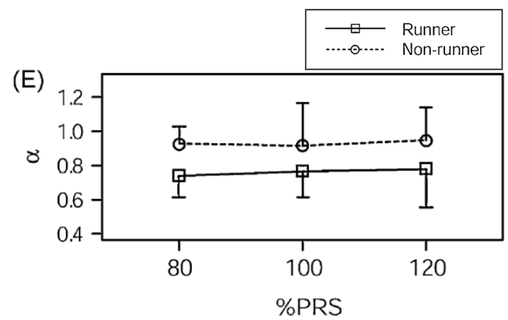
Jordan et al extended Hausdorff's work by having ppl walk at more various yet precise percentages of their preferred speeds (x-axis). for 12min walk
Jordan: signif diff between each pairwise speed combination within each gait parameter represented by each U-line
(650 strides, 11 young healthy)

Rock: a main effect of speed was found on step length variations as well (10 young healthy, 15min walks)

Why the U shape? (if they ask)
- Common thread – all done in a treadmill – curious what it would be OW – contradictory to other gait research

Fractal Analysis – Motor Control – Running Speed





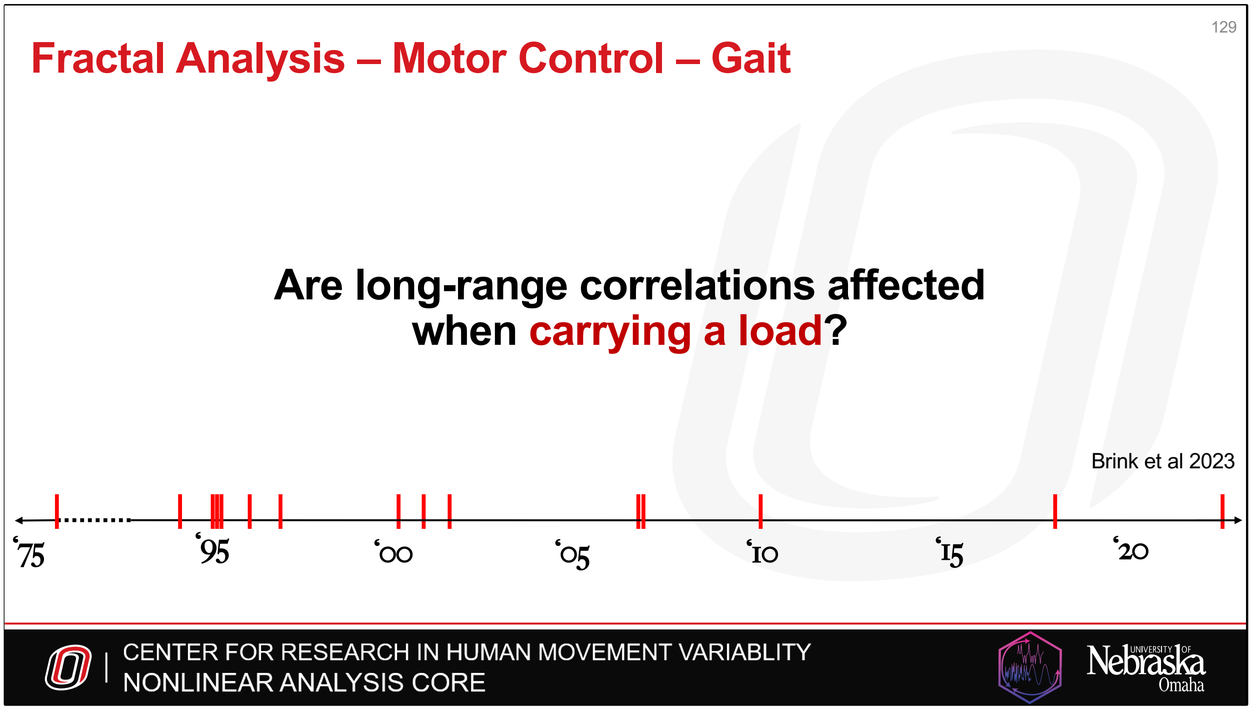
Jordan et al.2007

Nakayama et al.2010

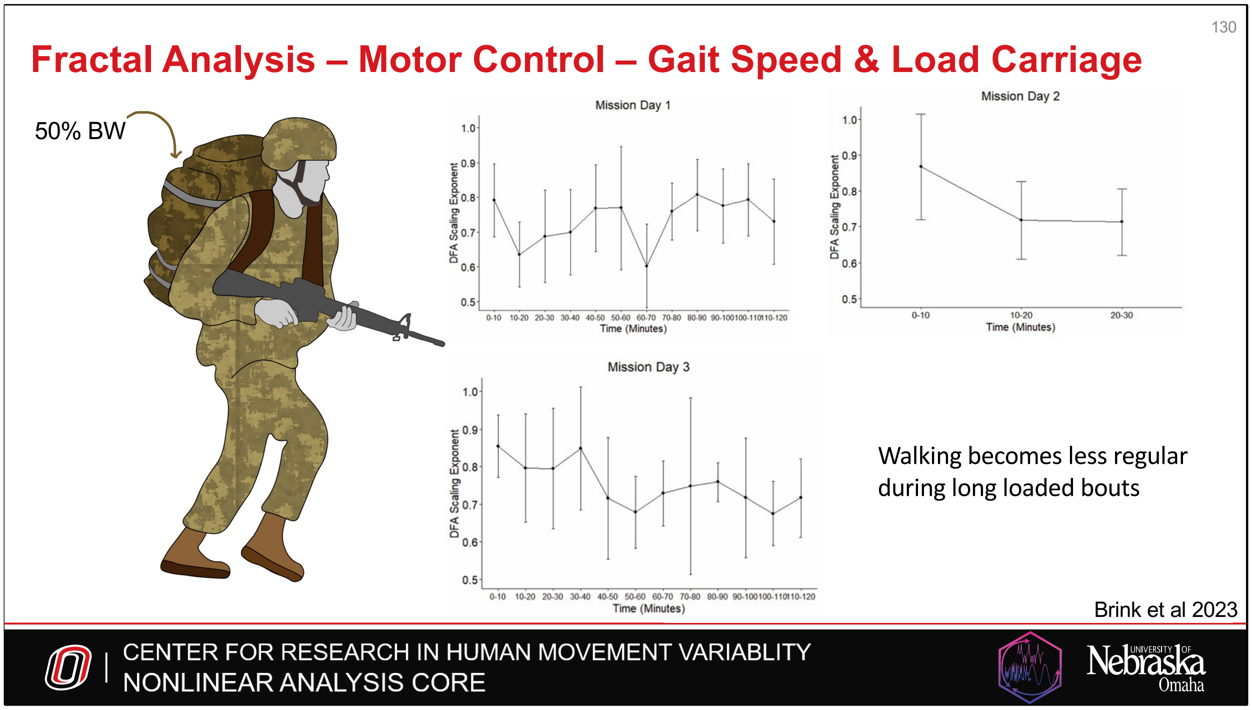
Such patterns are transferrable in another form of locomotion, which is running

Jordan: same

Nakayama: Although significant diff of speed was not observed - hard to observe between so close speed 80-100-120 even in Jordans study, they found significant diff of groups - reliably distinguishing between runners and non-runners



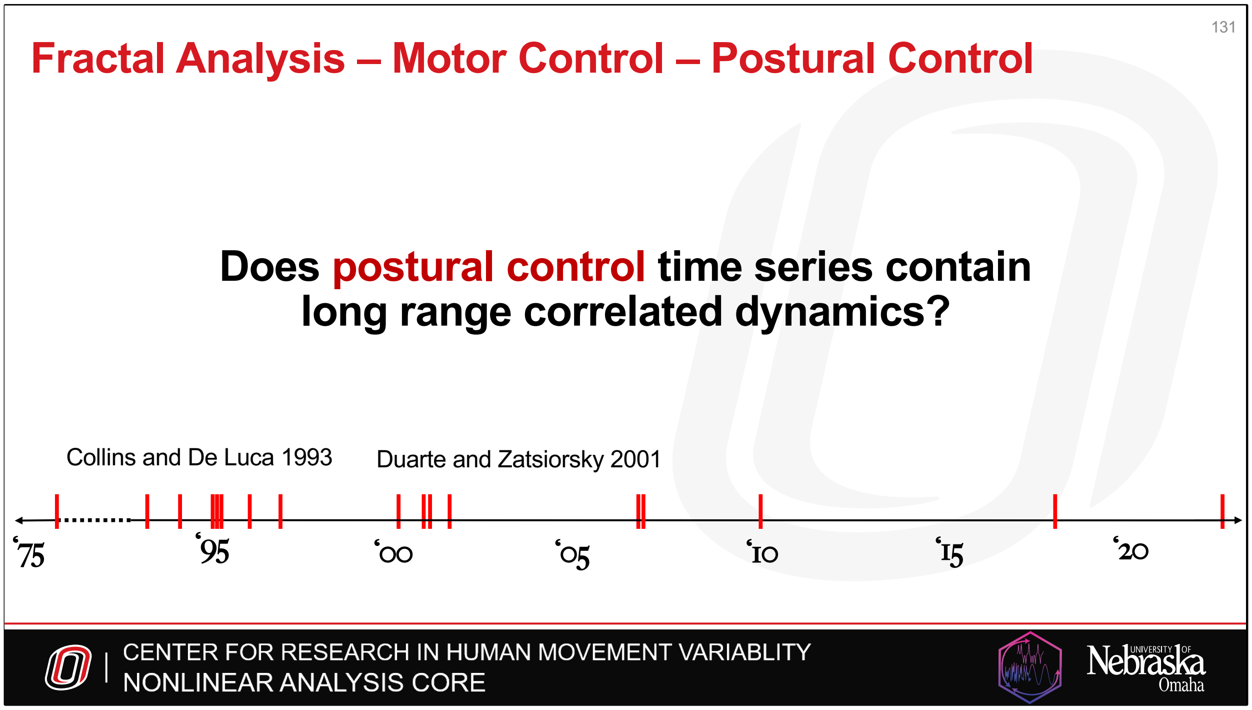
Not only gait is affected when changing speed, but also when carrying a load.



An organization partically interested in such phenomenon is the military.

Purpose:

lmis1 stayed relatively stable, yet the long range correlations with mis day 2 and 3 diminished as time went on.

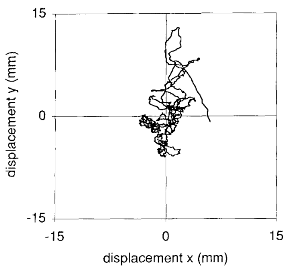


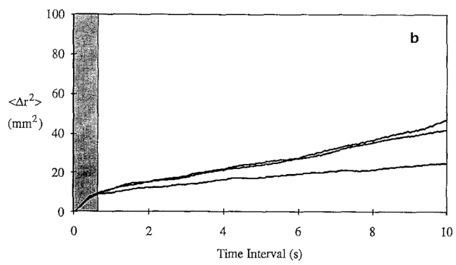
Going beyond manipulations in gait, yet still under the umbrella of motor control, we are going to backtrack in the time line a little bit and discuss postural control

Fractal Analysis – Motor Control – Postural Control

Task: Quiet Stance
Duration: 30 x 30sec

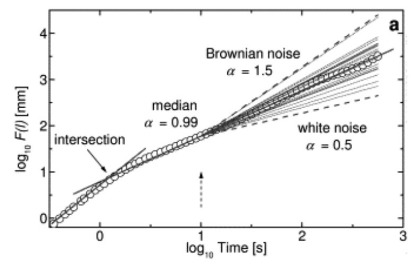
Subject	Mediolateral (x)		Anteroposterior (y)		Planar (r)	
	H_{xs}	H_{xl}	H_{ys}	H_{yl}	H_{rs}	H_{rl}
GM ± SD	0.73 ± 0.07	0.21 ± 0.10	0.77 ± 0.05	0.31 ± 0.12	0.76 ± 0.05	0.28 ± 0.10





Task: Unconstrained standing
Duration: 30min

Mediolateral	Anteroposterior
1.01±0.26	0.98±0.17



Collins and De Luca 1993

Duarte and Zatsiorsky 2001

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Collins and Deluca 1993 –

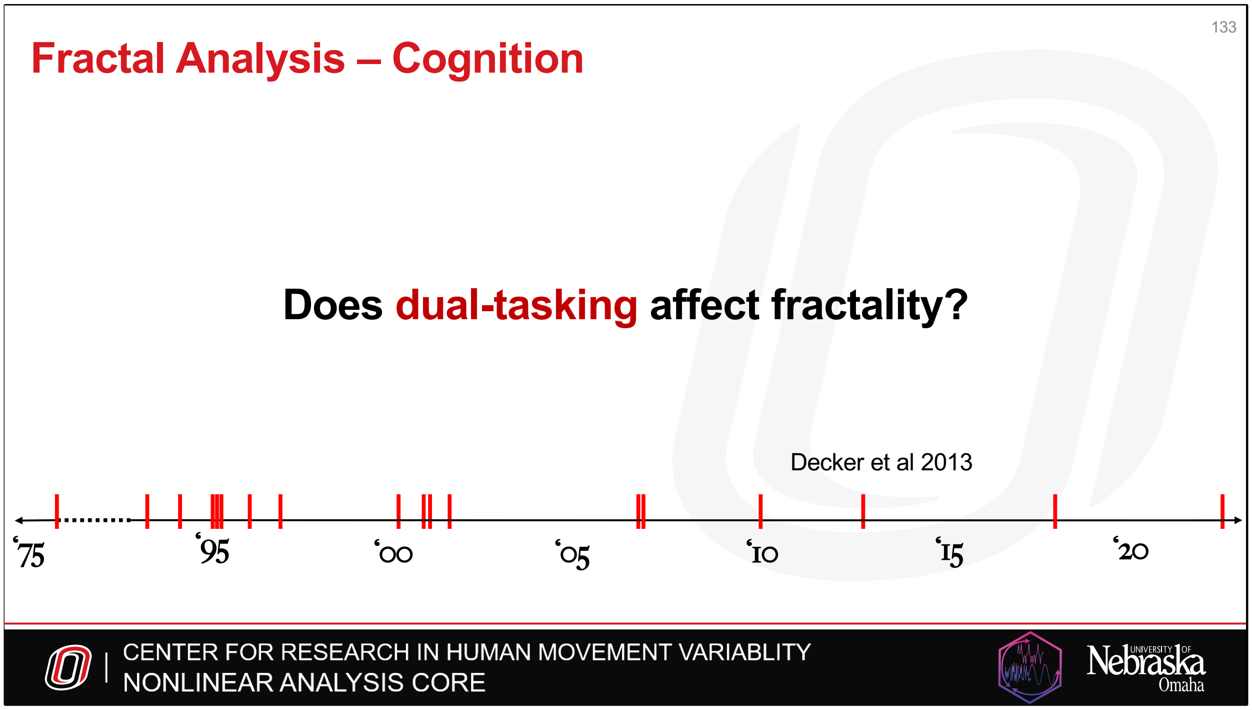
- (27 healthy male subjects)

Duarte and Zatsiorsky 2001 - first to perform DFA on COP trajectories.

Thin lines are the slopes for the ten subjects
Thick line in the middle is the median
White and Brownian are shown for comparison

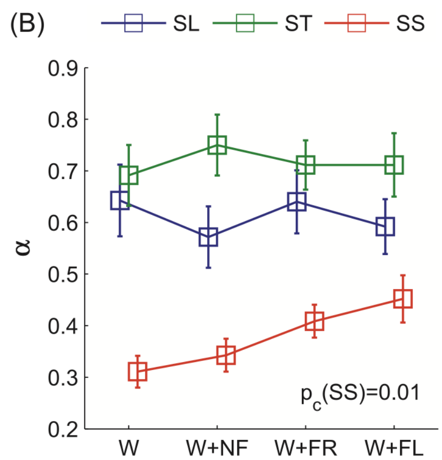
- turn to persistent behavior from 10s up to 10m

(10 healthy subjects) (scaling exponent vary close to 1 (range: 0.68–1.47)) - table



Since we know how fractality is exhibited in physiological signals and motor control, in later years researchers wanted to study how dual tasking during gait affect gait parameters.

Fractal Analysis – Cognition – Dual Tasking



Decker et al 2013

Treadmills impose a speed – which can be achieved with many combinations of stride length and stride time equally, but in order to keep up with that speed humans apply rapidly correcting fluctuations in step speed: SS - an anti-persistent behavior

Decker: Examined whether the regulation of fluctuations in SS <u>and not in ST and SL</u> depends on high-level executive function processes
Task: Young adults walked on a treadmill without a cognitive requirement and while performing a cognitive task of dichotic listening.

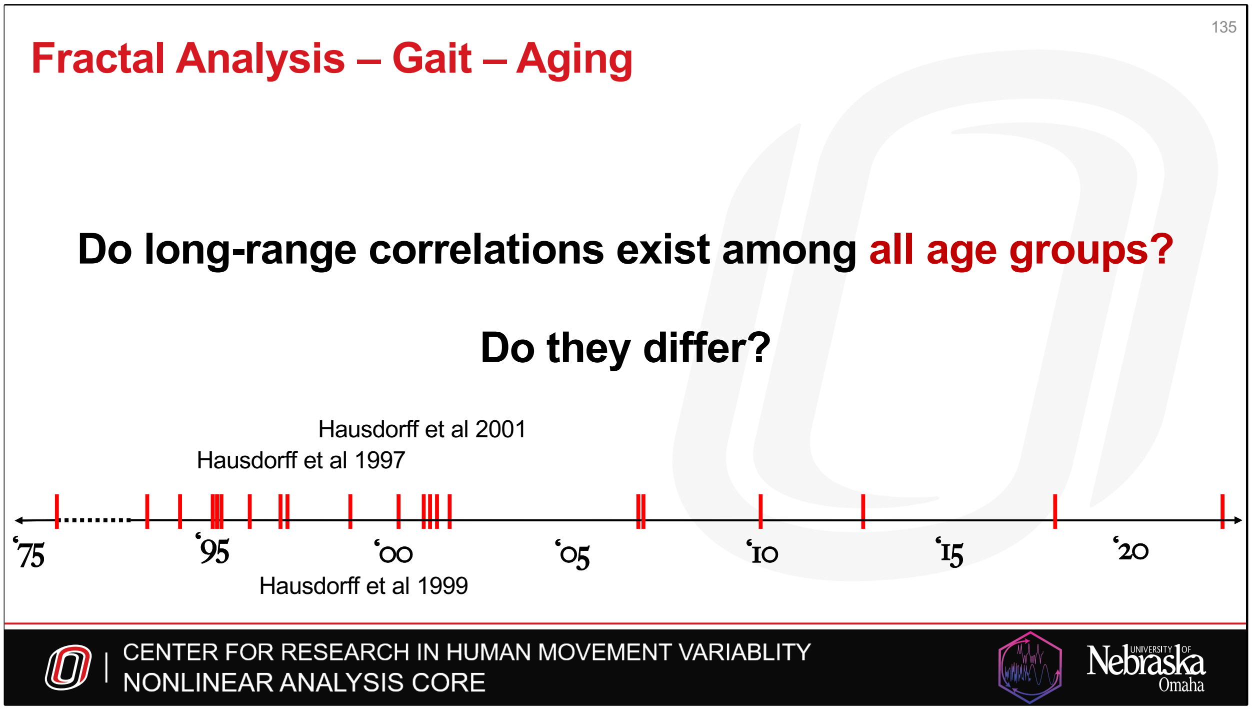
Always heard 2 syllables on each ear, but on:
NF: non-forced (report syllables coming on both left and right ears)
FR: report only right ear syllable, FL – only left

Result: SS fluctuations became less anti-persistent when performing dichotic listening and even more so during single ear reporting, meaning that taxing executive function impaired the ability to rapidly correct speed deviations on subsequent steps.
Dichotic listening had no effect on SL and ST persistent fluctuations

W + FL (a=0.45)

W + NF (a = 0.34).

W (a=0.31)

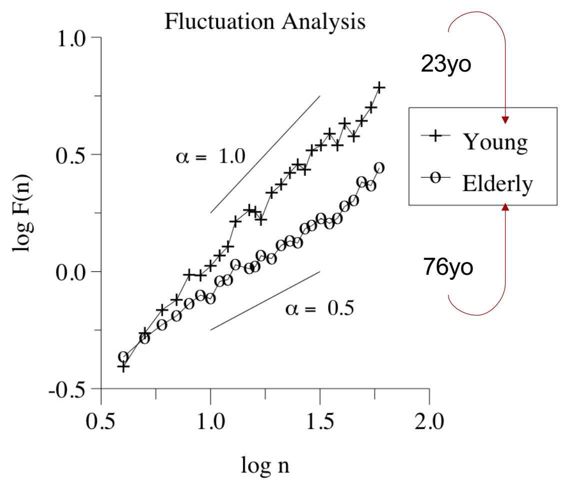


fractal analysis has been used for comparisons among different age groups.

Fractal Analysis – Gait – Aging

All subjects:

	Young	Elderly
DFA α	0.87 ± 0.15	0.68 ± 0.14
Average Stride Interval	1.05 ± 0.07 s	1.05 ± 0.10 s
Stride Interval Coefficient Of Variation	1.9 ± 0.4%	2.0 ± 0.7%



Hausdorff et al 1997

Hausdorff after confirming fractal behavior in walking, and in speed and distance manipulations, he recruited older adults and did another simple walking study.

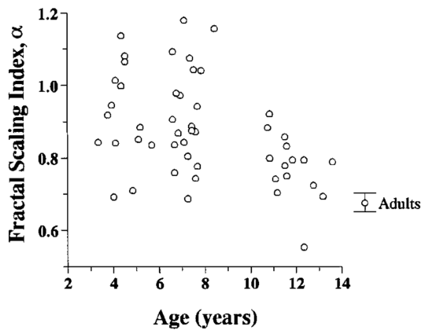
He found: that the stride interval fluctuations are more random and less correlated for the elderly subjects

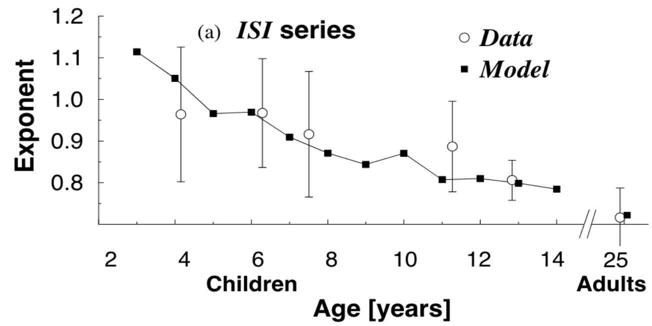
Plot - 1 subject of each group on the fluctuation plot

STD and COV: SAME

- 5-6 minutes walks

Fractal Analysis – Gait – Aging

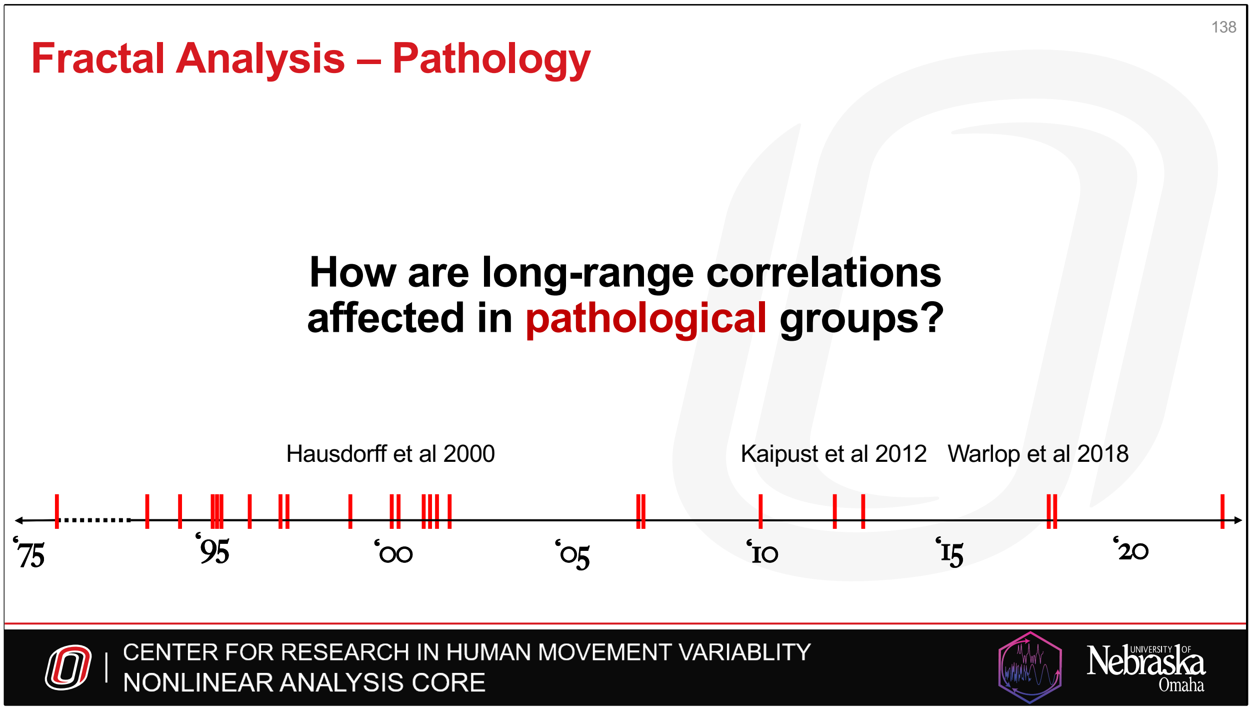




Hausdorff et al 1999

Hausdorff et al 2001

2 years later Hausdorff and his team researched the stride-to-stride variability and temporal correlation in children.
He found: Gait pattern of children is more volatile than the usual walking pattern of healthy, young adults.
He also found that as children mature the scaling exponent comes closer to that seen in young healthy adults



So We clearly see that using fractal analysis it depict differences among age groups, but its also a compelling biomarker to differentiating pathological groups

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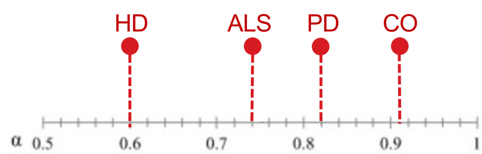
Fractal Analysis – Pathology

Table 1. *Gait rhythm dynamics*

	ALS	HD	PD	CO
Average values				
Stride time, ms	1,370 ± 61	1,138 ± 38†	1,118 ± 30†	1,091 ± 23§
Speed, m/s	1.02 ± 0.07	1.15 ± 0.08	1.00 ± 0.05	1.35 ± 0.04‡
Fluctuation magnitude				
Stride time CV, (%)	4.5 ± 0.6	7.6 ± 1.2	4.4 ± 0.6	2.3 ± 0.1†
Stride time $SD_{detrended}$, ms	65 ± 10	120 ± 25	52 ± 6	27 ± 2‡
Fluctuation dynamics				
α	0.74 ± 0.07	0.60 ± 0.04	0.82 ± 0.06	0.91 ± 0.05
Autocorrelation decay time	4.2 ± 0.6	3.2 ± 0.5	7.2 ± 1.6	5.9 ± 0.4*
Nonstationarity index	0.69 ± 0.05	0.54 ± 0.03*	0.64 ± 0.03	0.67 ± 0.02



Hausdorff et al 2000

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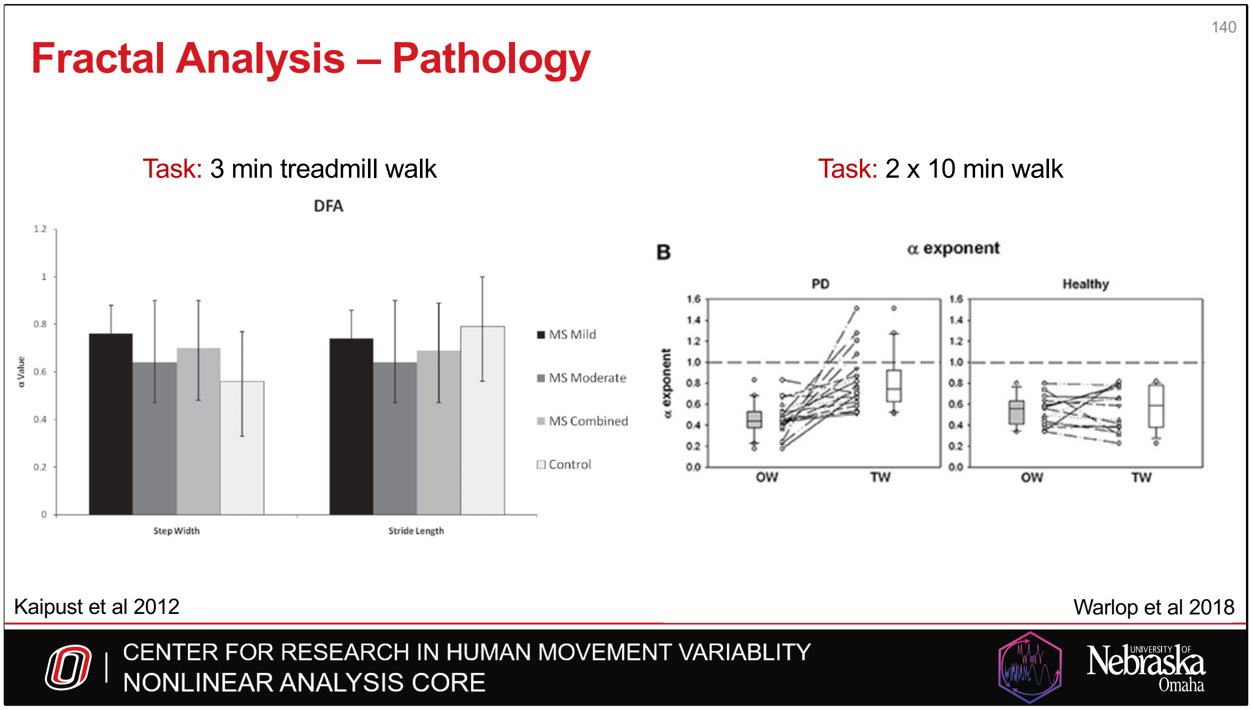
So after Hausdorff and his team looked into the maturation of gait dynamics across ages they sought to understand how such dynamics are affected in different pathologies.

It is clearly seen that each pathology lies on a different scaling exponent distinguishing between each other, however all are below young healthy control at 0.91.

(ALS – amyotrophic lateral sclerosis, affecting the motoneurons of the cerebral cortex, brain stem, and spinal cord – affecting gait)

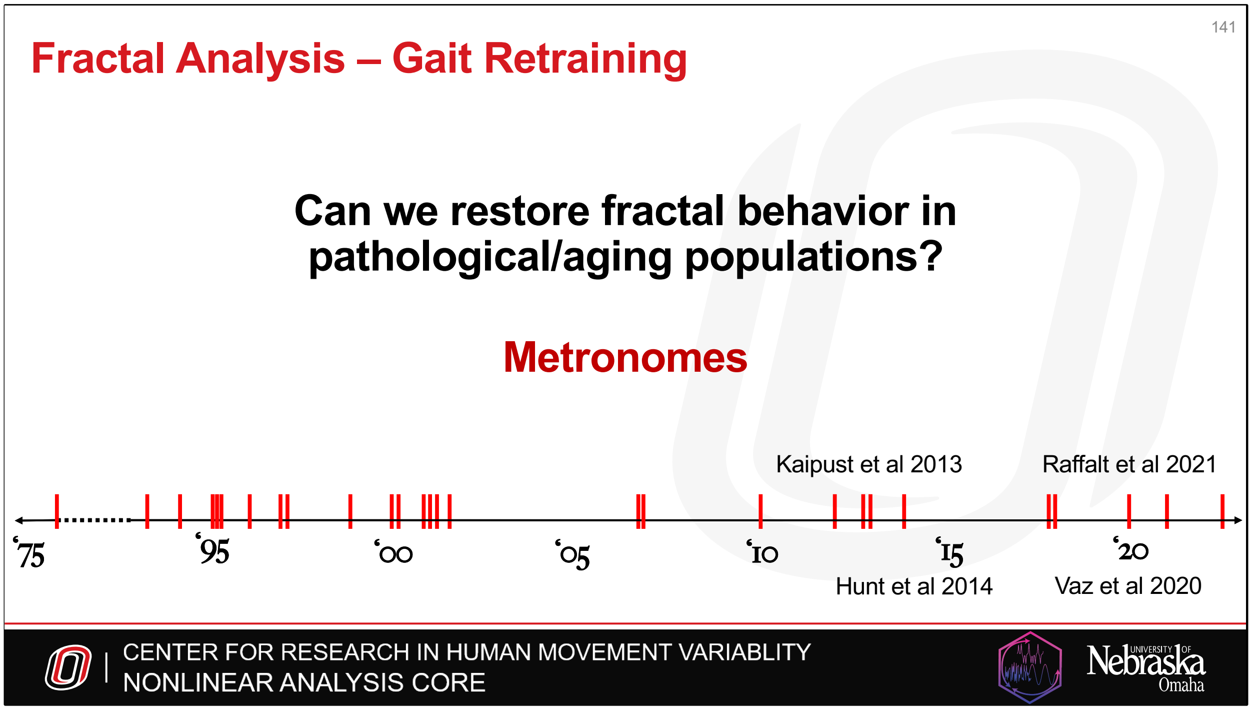


KAIPUST: Studied how gait dynamics of step width and stride length change in the Multiple Sclerosis group **(**MS)-(demyelinating inflammatory disease of the central nervous system) (10 middle aged -10 MS middle subj)

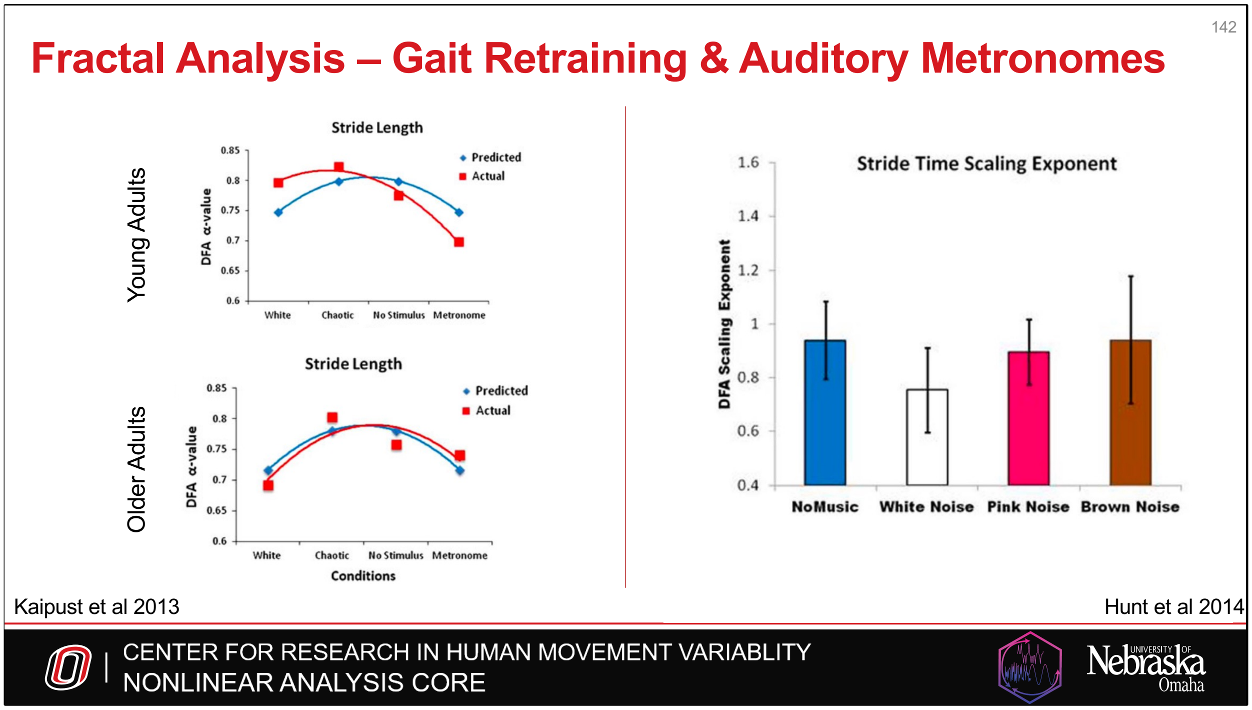
Found: Stride length alpha exponent decrease as disease severity increases while interestingly step width seems to have a higher exponent overall in the MS group - the time duration of 3 minutes while also walking on a treadmill may have affected those results from what would otherwise be expected

WARLOP: Studied gait dynamics in the PD group in the elderly population.
General OW alpha at 0.5-0.6.
PD at TW goes up - may due treadmill acts as pacemaker metronome. , while stays the same for the healthy group

We can see that age, pathology, and equipment can affect gait dynamics



Now we covered how the underlying gait or other physiological signals are affected with age or pathology, so the question is: ..



They used a metronome paradigm – Like we saw in section 2, for the underlying structure of a signal, here the intervals of the pacing signal follows a given noise structure.

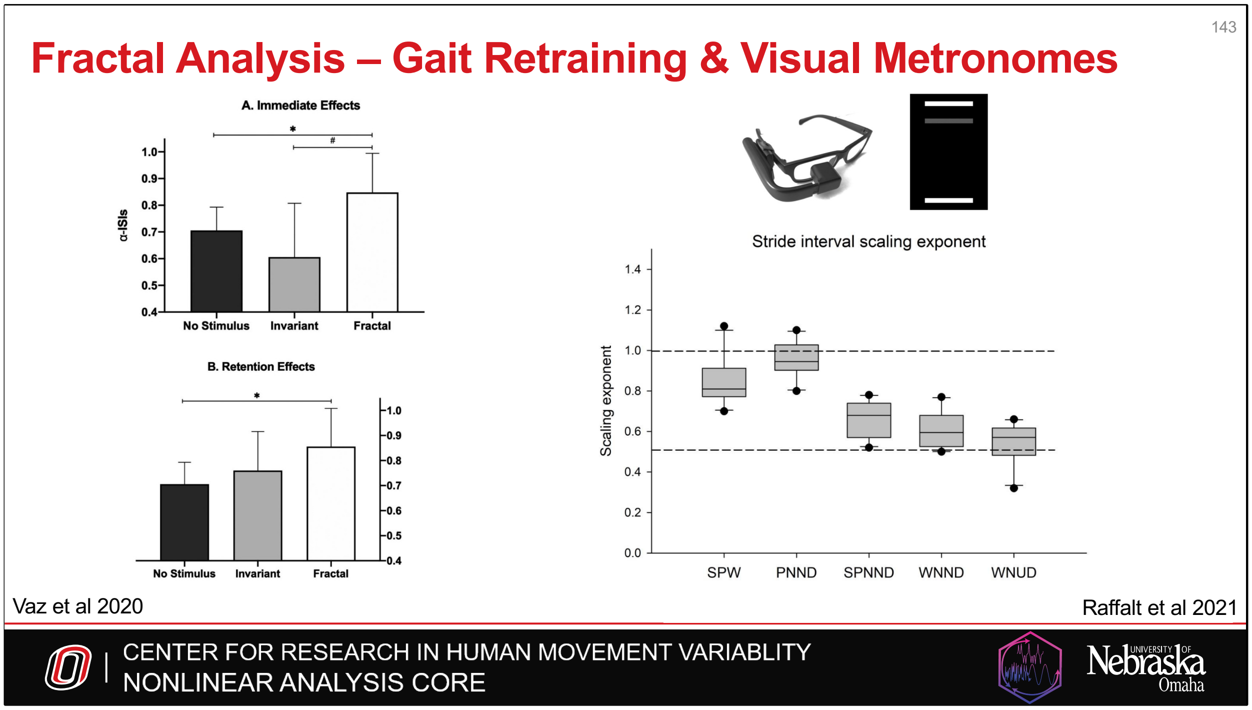
Kaipust: 4 conditions: White, Chaotic (PINK), No Stimulus, Metronome/Iso (same time interval)

- White: old follows as predicted - Young not
- Chaotic metronome produces highest gait variability in both groups.
- No stim: both show a value close to one predicted
- Metronome yielded the lowest alpha in both groups - shows trend towards less complex walking behavior

Overall: This suggests that the younger subjects were not as sensitive to the effect of the auditory stimuli in contrast to the older adults where gait variability is able to be manipulated

Hunt: A year later another member of our department – tested the same concept of gait retraining with variability, and rather than using auditory beeps, he instead embedded those noise structures in music, and saw as expected that pink noise and brown noise walking conditions yielded higher fractal scaling exponents than the white noise condition, mirroring the fractal scaling trends in the actual auditory signals themselves i.e. brown noise higher than pink noise, higher than white noise

Kaipust: The subjects were not explicitly instructed to walk to the beat of the rhythm.



Vaz: 16 elder healthy adults ~ 2x16min walks
Vaz: invariant/isochronous, fractal/pink

Raffalt: they wanted to see how temporal distributions affects alpha
- To Show that not only do the temporal characteristic of a pacing signal mater, but the statistical properties matter as well.

The signals on the x-axis from left to right go from: Most similar to to healthy gait to less similar

-Self-paced walking
-Pink noise normal distribution
-PNND but shuffled to destroy autocorrelation properties
- White signal rand generated – rand time series with normal distribution
- Random time series with a unform distribution

Found that: Clearly evident that the type of pacing signal had an effect on the scaling exponent

Summary of fractal analysis in different populations

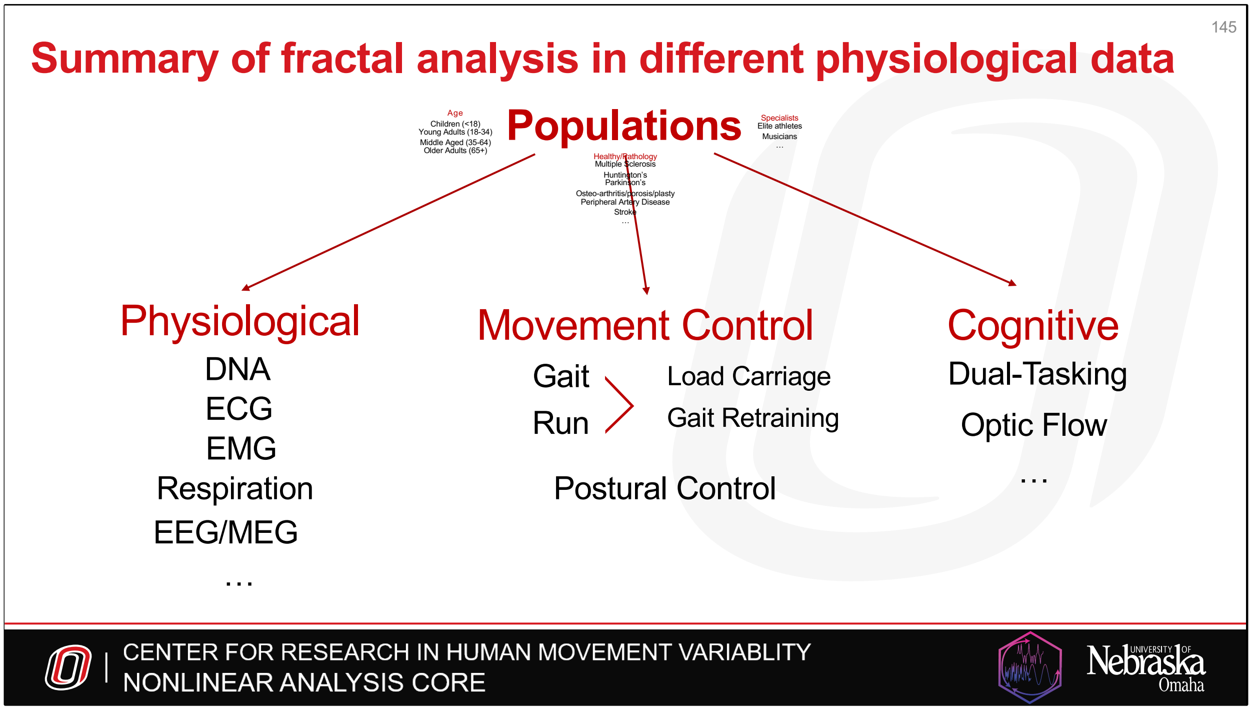
Populations

Age
Children (<18)
Young Adults (18-34)
Middle Aged (35-64)
Older Adults (65+)

Healthy/Pathology
Multiple Sclerosis
Huntington's
Parkinson's
Osteo-arthritis/porosis/plasty
Peripheral Artery Disease
Stroke
…

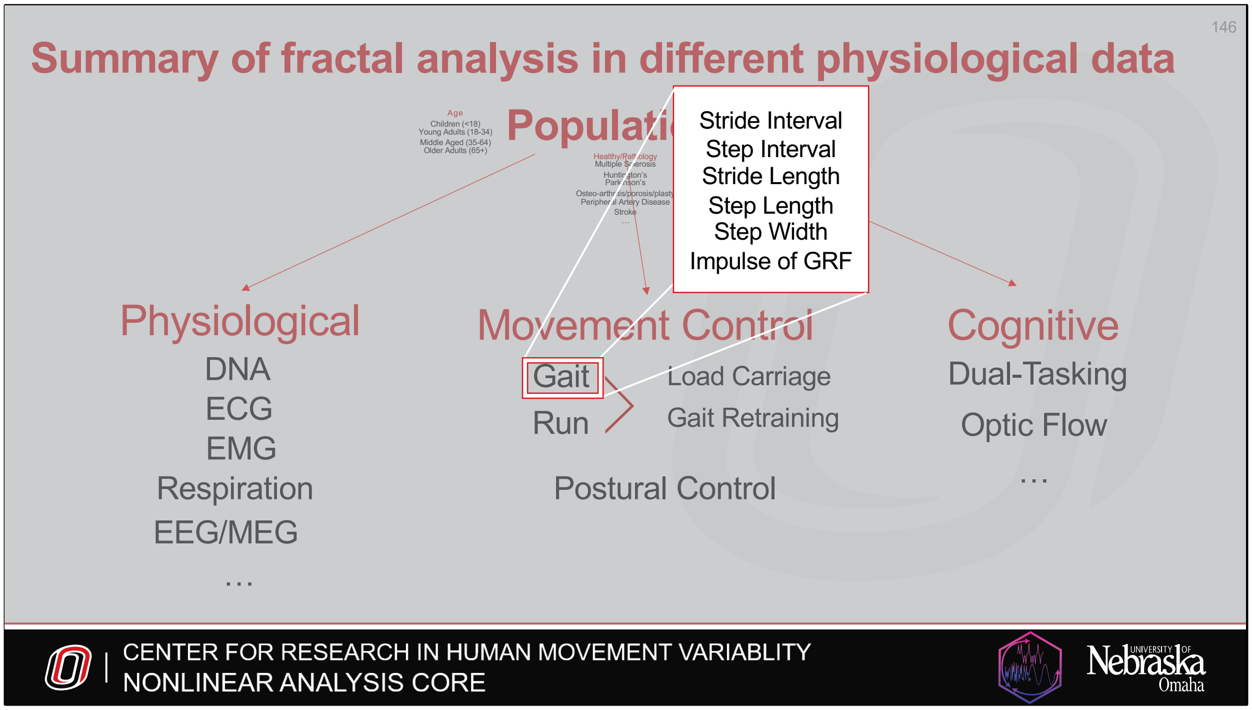
Specialists
Elite athletes
Musicians
…

We saw how the underlying dynamics of an organism change in different age, different health and disease, and specialist non specialist group. Fractal analysis seems to be a potent method to pick up such differences in age groups and pathologies.



We saw fractal behavior occurring within physiological signals, movement control, and cognition..
We also saw how fractal behavior changes in one of these categories and how it may affect another.

Specifically parameters su as .. NEXTT


146
Summary of fractal analysis in different physiological data
Age
Children (<18)
Young Adults (18-34)
Middle Aged (35-64)
Older Adults (65+)
Populati
Healthy/Pathology
Multiple Sclerosis
Huntington's
Parkinson's
Osteo-arthritis/porosis/plasty
Peripheral Artery Disease
Stroke
…
Stride Interval
Step Interval
Stride Length
Step Length
Step Width
Impulse of GRF
Physiological
DNA
ECG
EMG
Respiration
EEG/MEG
…
Movement Control
Gait
Run
Load Carriage
Gait Retraining
Postural Control
Cognitive
Dual-Tasking
Optic Flow
…
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Methodological considerations for fractal analysis

Methodological considerations for fractal analysis

1. Robust to non-stationary time series
2. Use constant sampling rate
3. Data hungry – Long enough to capture the essential dynamics of the system
   - >512 data points for DFA
4. Continuous trial
5. Preferably not cyclic (select correct analysis – not DFA)
6. Be aware of the constraints equipment can place on your data
   - Treadmill versus Overground
7. Surrogate Analysis

1. Bc focuses on the overall structure and scaling properties of the data (such as scale invariance and detrending)
2. For consistent and uniform observations over time
3. -
4. I will make a point about that on the next couple of slides
5. Other fractal analysis for example: LyE or RQA
6. -
7. to assess whether the observed scaling behavior in a time series is genuine

How to address the requirement of >512 continuous datapoints

Multiple short trials

Average α across all trials

Marmelat et al 2018
Pierrynowski et al 2005

How to address the requirement of >512 continuous datapoints

Multiple short trials

~~Average α across all trials~~

Why not?

The accuracy of each estimate using this method could lead to averaging together unreliable scaling exponents and potentially misleading conclusions

Marmelat et al 2018
Pierrynowski et al 2005

How to address the requirement of >512 continuous datapoints

Multiple short trials

The stitching procedure:
Combine consecutive short gait trials to create a longer time series

Marmelat et al 2018
Pierrynowski et al 2005

two different fonts

How to address the requirement of >512 continuous datapoints

Multiple short trials

~~The stitching procedure:~~
~~Combine consecutive short gait trials to create a longer time series~~

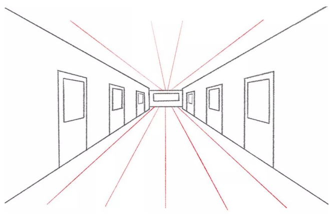
Why not?

estimating *serial* correlations requires continuous recording
&
the stitching procedure creates artificial changes in the scaling exponent α

Marmelat et al 2018
Pierrynowski et al 2005

How to address the requirement of >512 continuous datapoints

Space Constrictions

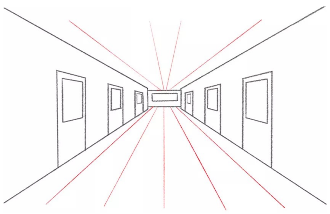


Participants have to walk
back and forth several times

Marmelat et al 2018
Hove et al 2012

How to address the requirement of >512 continuous datapoints

Space Constrictions



~~Participants have to walk back and forth several times~~

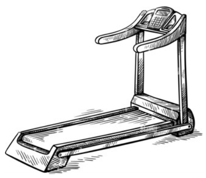
Why not?

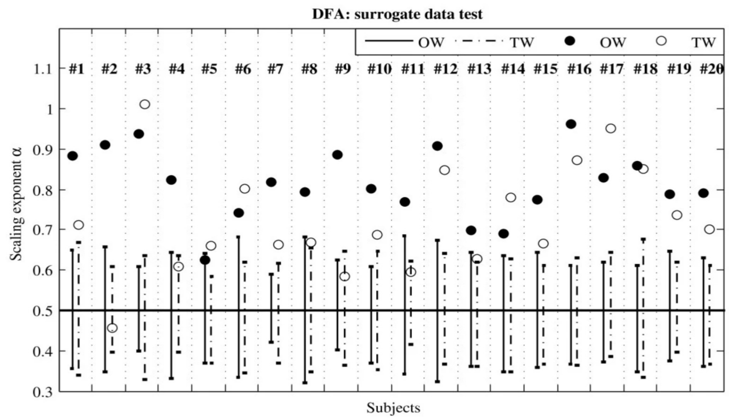
Tight turns introduces artifacts that are inconsistent with fractal analysis assumptions

Marmelat et al 2018
Hove et al 2012

Be aware of the constraints equipment can place on your data

Treadmill VS Overground





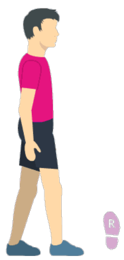
10 min walks

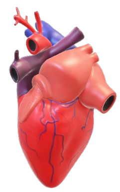
15/20 subjects:
Higher α
OW versus TW

Terrier and Deriaz 2011

Take-Home

Fractal analysis provides a powerful and versatile set of tools to explore and understand the complexity inherent in various natural and experimental phenomena





Thank you!

Questions?

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Using DFA Practically

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Outline of this section

- Review: Fractals in Movement Science
- DFA Checklist
- Bayesian Hurst related to GaitPrint – still unsure about this
- NONAN GaitPrint: An IMU gait database of healthy young adults
- DFA in practice: A MATLAB Tutorial

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Review of Fractals in Movement Science

- Fractals are found in nature
- DFA is one of the common fractal analysis techniques due to its versatility across scientific domains
- Fractal properties are seen in a wide range of signals from radio broadcasts to the intervals between strides and even in the sequences of our DNA
- There is even evidence that it can determine differences between healthy populations and aging or pathological populations
- Interpret the results in the context of the analysis
- **Visualize your data!!!**

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An alpha equal to 1 does not mean healthy and an alpha equal to 0.5 does not mean unhealthy. This is what we see in the literature but there are a lot of factors to consider and as we have seen, things like walking speed can influence this outcome.

Review of Fractals in Movement Science

When performing your own research and analysis:

- Choose suitable fractal analysis methods for your data
- Understand assumptions of each analysis
- Cautiously interpret results

Checklist for DFA

- Is it a continuous trial?
- Did you use a constant sampling rate?
- Does your data appear rough?
- Is it free from any large spikes?
- Are there enough data points?

What is NONAN working on?

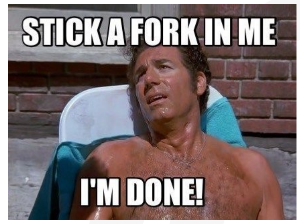
- "Better than DFA?"
- "Optimizing a Bayesian method for estimating the Hurst exponent in behavioral sciences"
- We are working on a MATLAB version of Bayesian Hurst Estimation using the HK Method
  - Simulations are ongoing
  - Results are promising so far, and we expect the function to be released in Fall 2023.

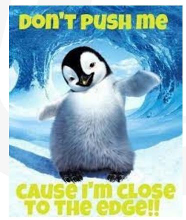
NONAN GaitPrint Database

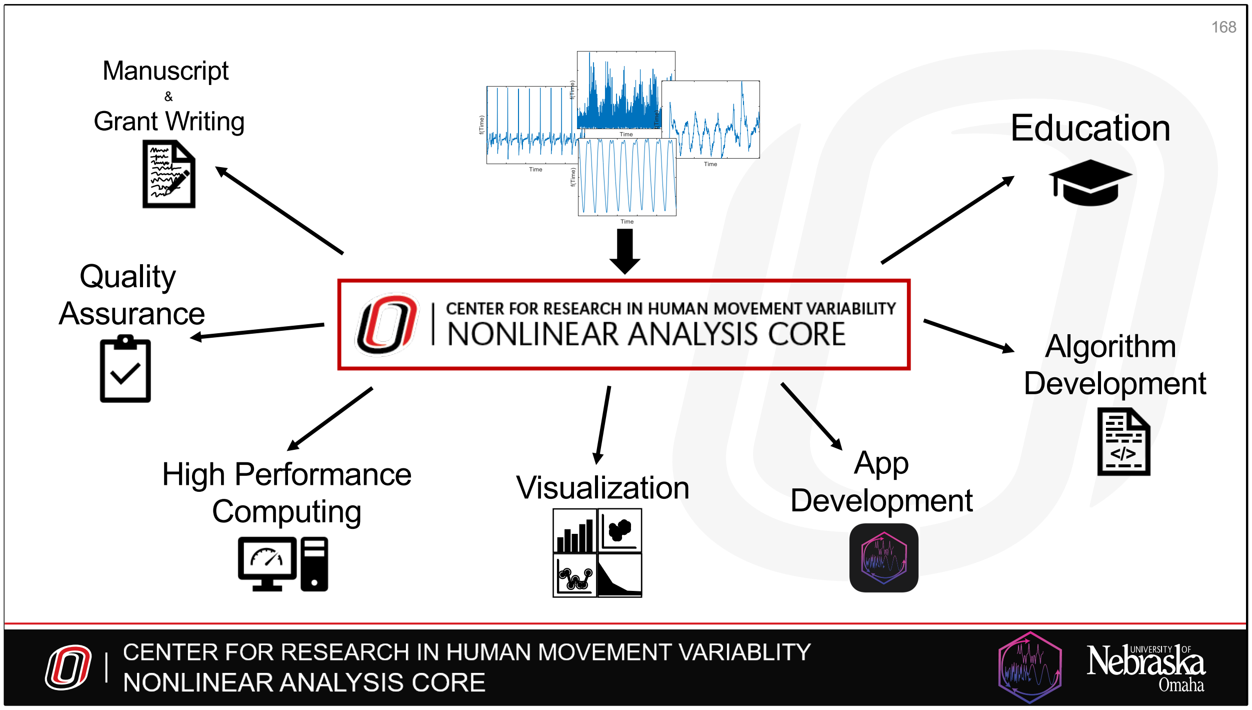
- The Nonlinear Analysis Core has been involved in creating a massive database
  - Spatiotemporal data
  - Pre-calculated nonlinear measures
- Currently only healthy young adults (19-35 years old)
- Working on collecting healthy middle-aged and healthy older adults
- Future plans to include pathological populations
  - Individuals with:
    - Parkinson's Disease
    - Unilateral transtibial amputation
    - Peripheral Arterial Disease
- Database is currently under review at Nature Scientific Data and will be publicly available via FigShare conditional upon acceptance

Switch to MATLAB

- Fork the repo
- Clone the repo/download it
- Don't push to our repo to preserve original code







So, what can you expect from us?..... Well as I mentioned earlier, the Nonlinear Analysis Core provides a number of services to researchers and professionals.
This is a brief overview of the services we offer. As you can see we are very flexible in the needs of our customers and don't only do nonlinear analysis, although that is our expertise. In the last year we have branched out and started doing some app development for iOS and Apple Watch as well as implementing some machine learning as another way to analyse time series data.

Our high performance computing resources consist of two main computers one with 24 cores and ~770GB RAM with a nvidia 3080GPU. Our other PC is built on a threadripper pro platform with a 32 core CPU, 128GB RAM and a RTX 3070 GPU. We also have a Linux PC with 24 cores, 128GB RAM and an RTX 3070 GPU. We also have an M1 MacBook Air which we use for app development.

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