

Normalising in stability analysis; why (not?)

Sjoerd Bruijn



@sjoerdmmb

Acknowledgements

Jaap van Dieen, Andreas Daffertshofer, Onno Meijer, Peter Beek, Jaak Duysens, Stephan Swinnen, Steve Collins, Kim van Schooten, Sietse Rispens, Mirjam Pijnappels, Martijn Wisse, Warner ten Kate, Gert Faber, and many more.

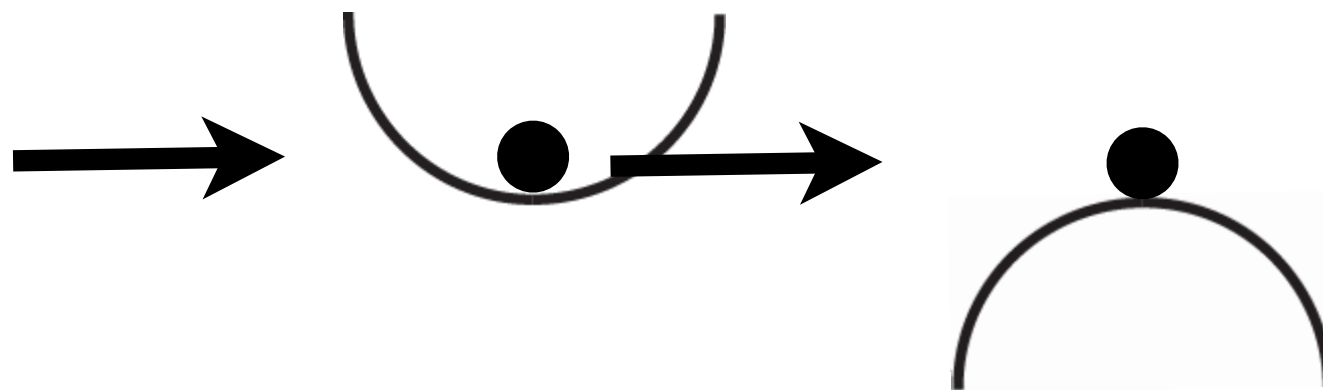
And of course Deepak, for organising, and inviting me.

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- Recap: local divergence exponents
- Effects of time series length
- Effect of normalising time
- Effects of calculating $\log(\text{div})/s$ vs. $\log(\text{div})/\text{stride}$

Recap: Local divergence exponents

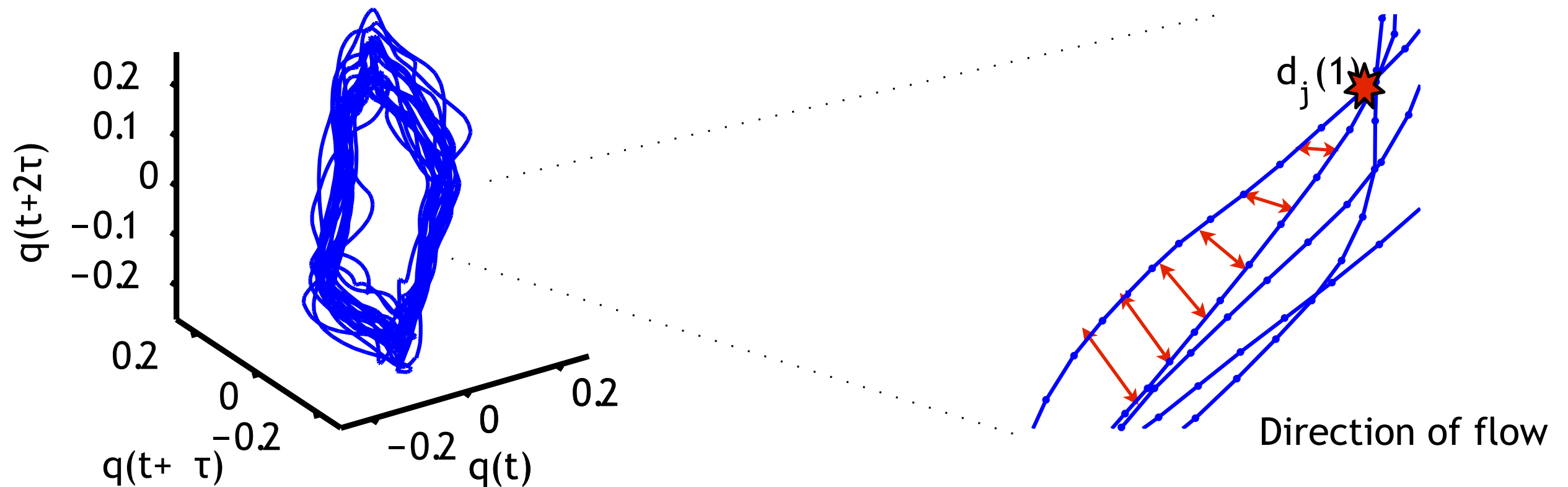
Which one is (more) stable?



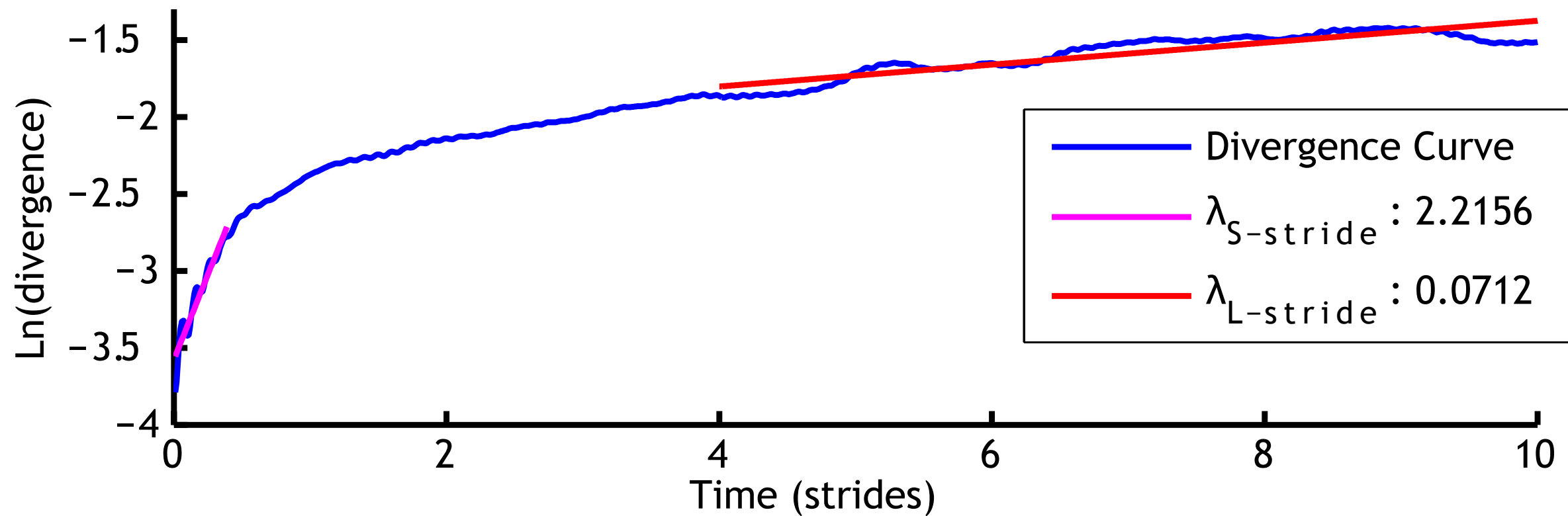
Recap: Local divergence exponents

- the small variations in gait can of course be regarded as small perturbations
- in which case it would be interesting to see what happens to these small perturbations over time
- this is exactly what maximum Lyapunov exponents do

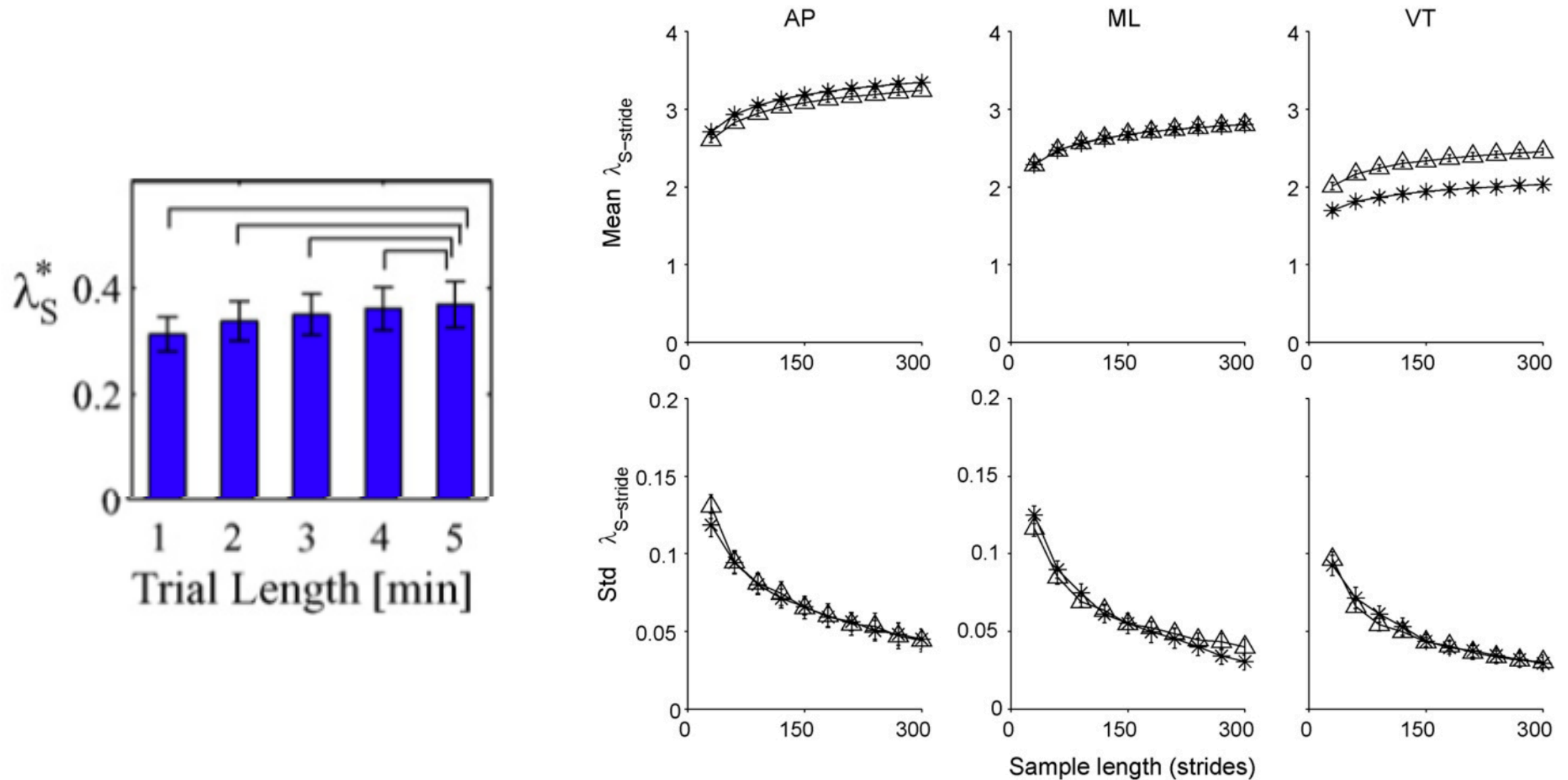
Recap: Local divergence exponents



Recap: Local divergence exponents



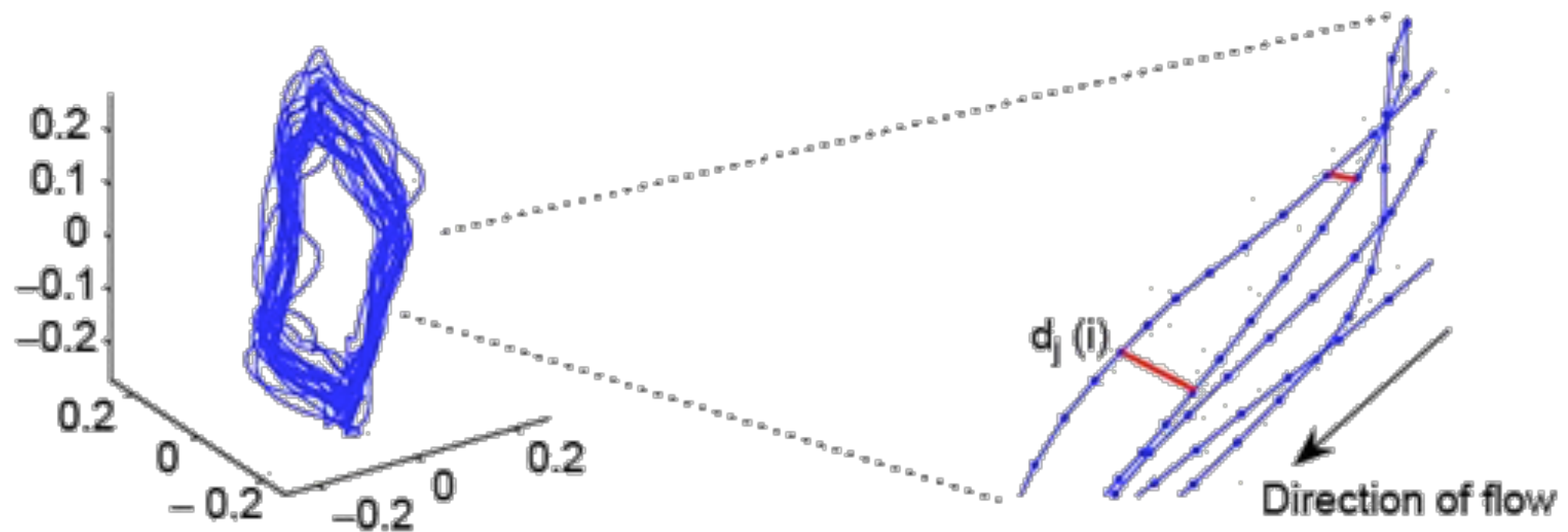
Effects of time series length



Kang et al 2006;Bruijn et al 2010

But why?

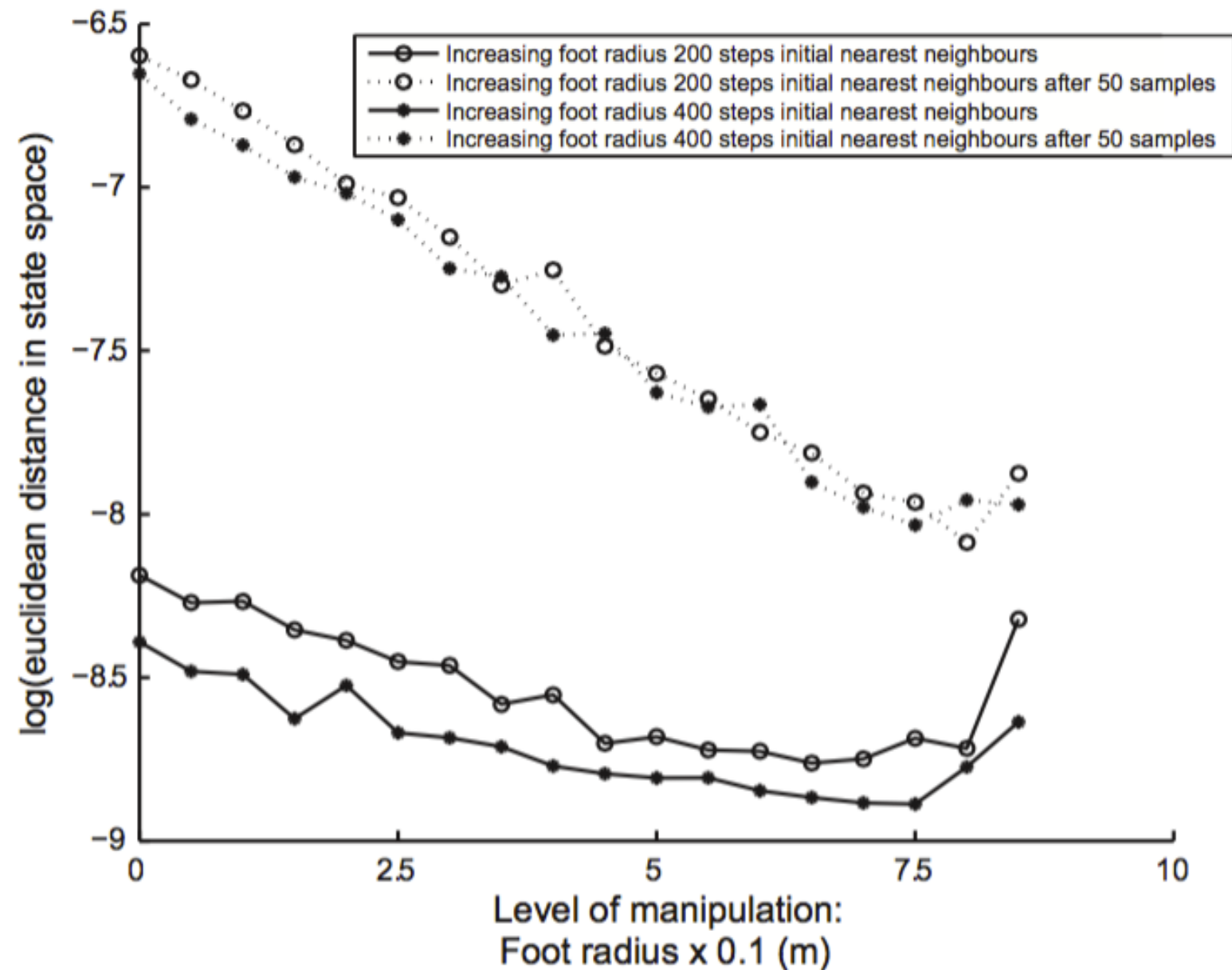
- I have proposed that this could simply be due to an increase in nearest neighbours, increasing the chance that they get closer



Is that really all there is to it?

- long range correlations have been reported in human gait, could these also cause it?
- could yes, but I don't think they do (see later when talking about normalisations)

Is that really all there is to it?



Solutions

- choosing nearest neighbours carefully:

For each point \mathbf{x}_i , consider the shell between two spheres centered at \mathbf{x}_i of radii $r_{\min} < r$, and consider the set of trajectory points \mathbf{x}_j within this i th shell:

$$r_{\min} \leq ||\mathbf{x}_j - \mathbf{x}_i|| = \left[\sum_{l=0}^{k-1} (x_{j+lm} - x_{i+lm})^2 \right]^{1/2} \leq r .$$

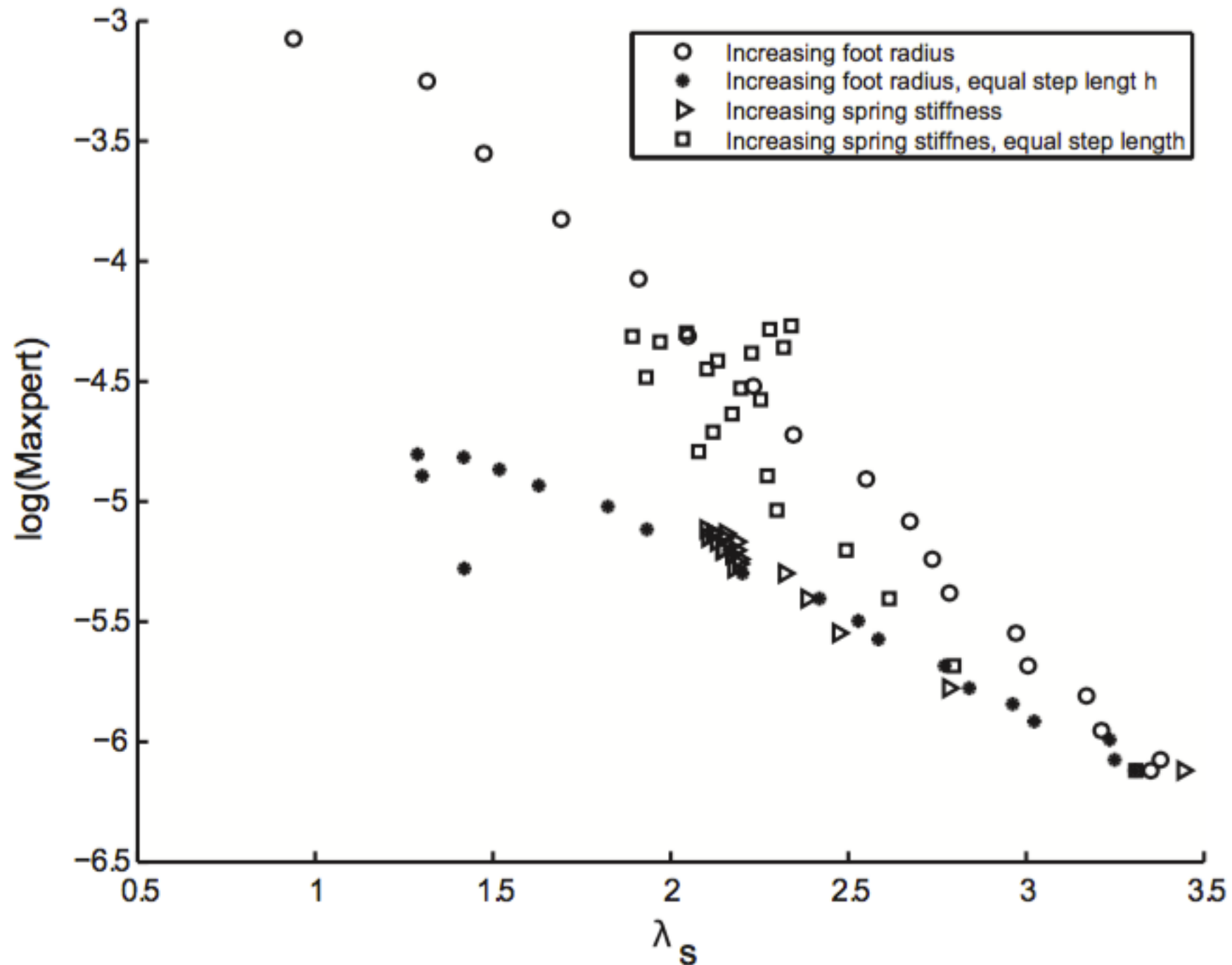
The use of a shell, rather than a ball, is to minimize the effects of noise or measurement error, since these effects are greatest when $||\mathbf{x}_j - \mathbf{x}_i||$ is small. After a time $n\Delta t$,

- but how to determine r_{\min} and r ?

Solutions

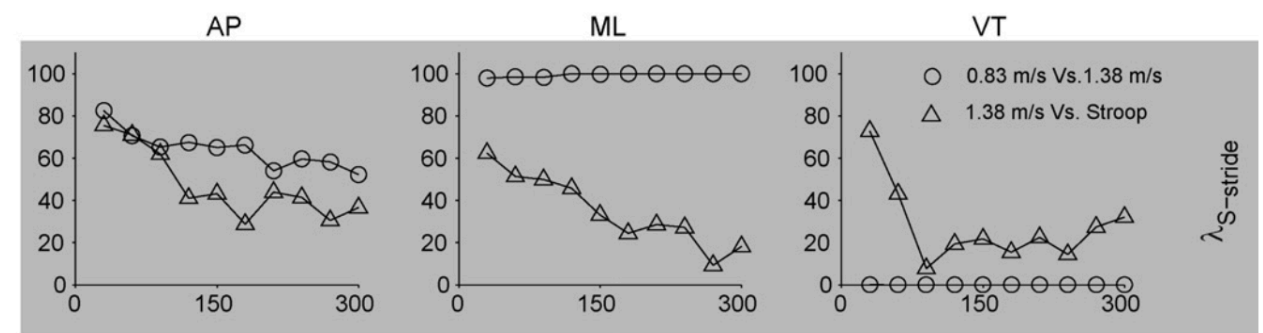
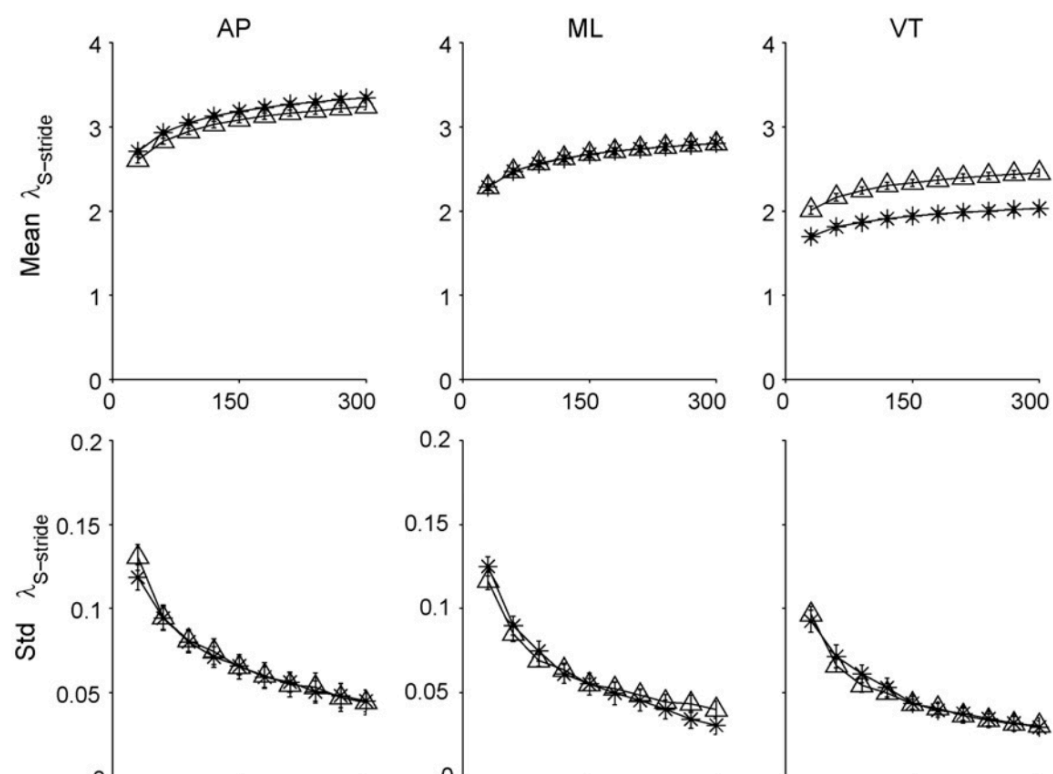
- using equal amount of cycles
- is our usual choice
- and works quite well

Results model



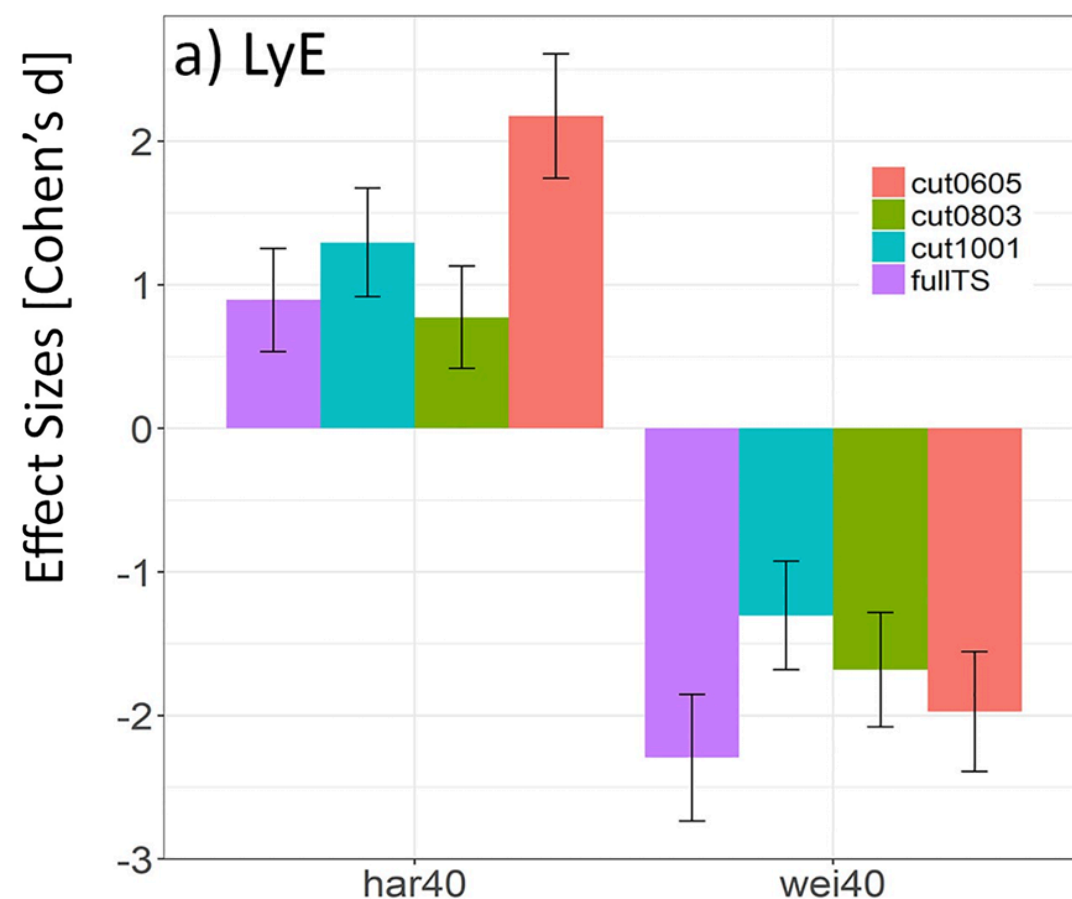
So how long should your data series be?

- Of course, ideally as long as possible. But if you get fatigue, this also doesn't help you.
- We have (somewhat arbitrarily) suggested 150 strides



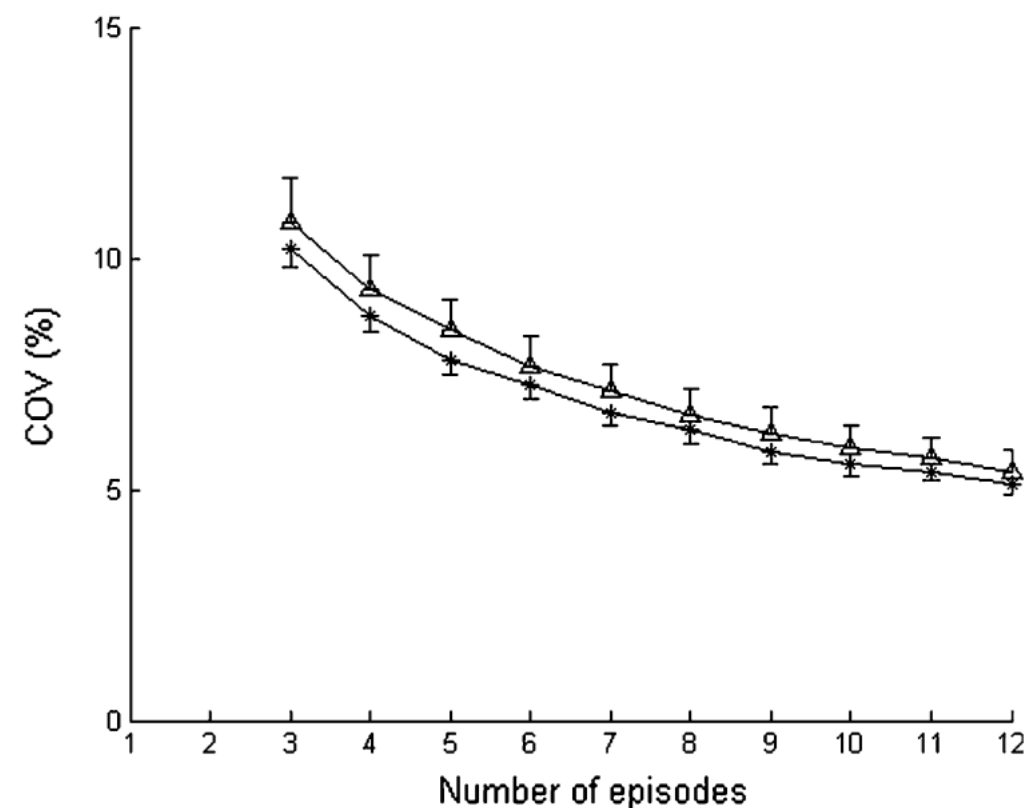
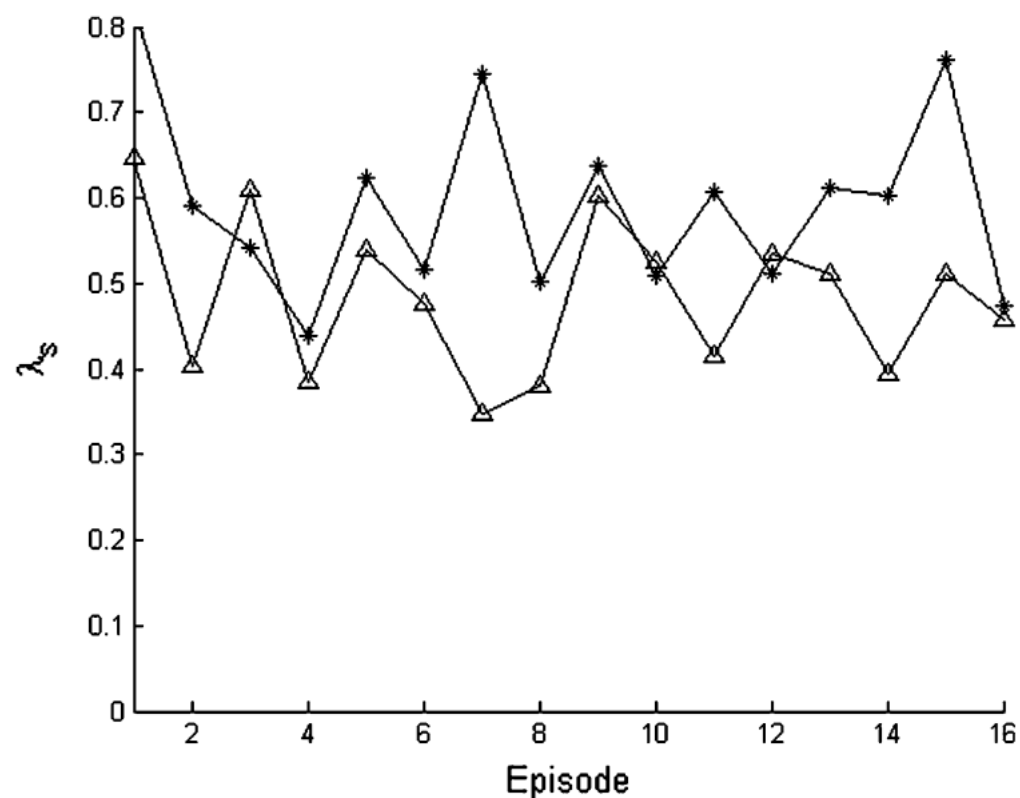
What if you have short time series?

- You can 'stitch' time series together!
- Or averaging over short time series also works!



What if you have short time series?

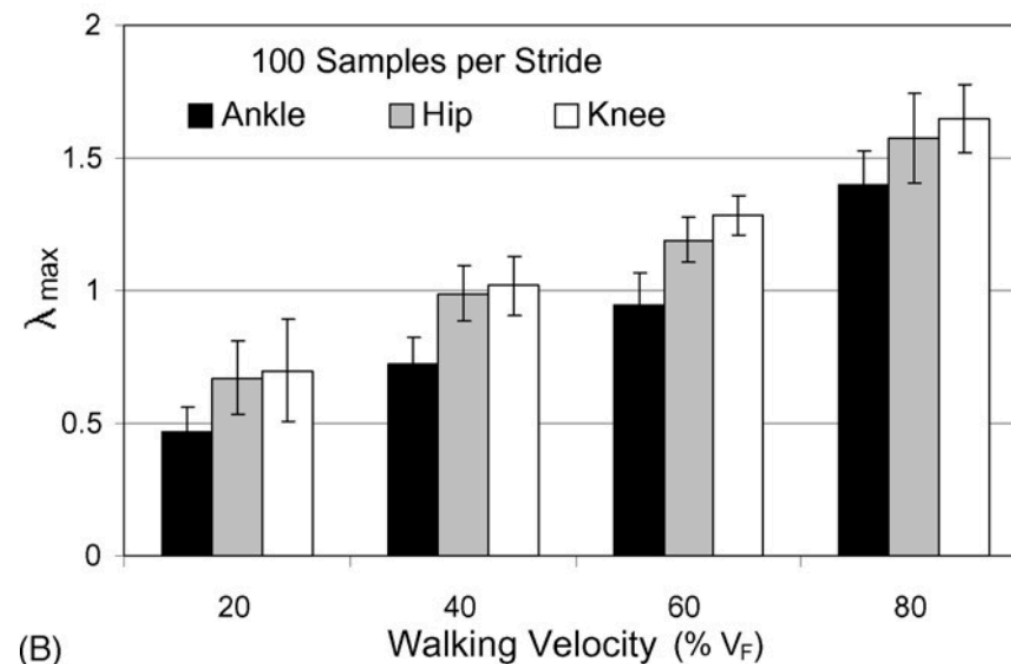
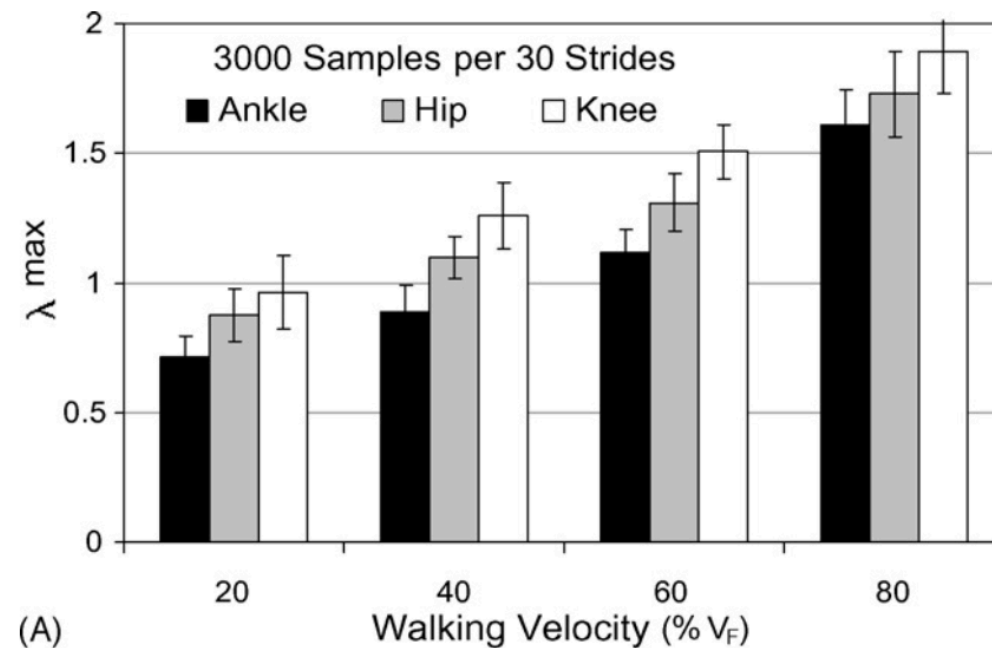
- You can 'stitch' time series together!
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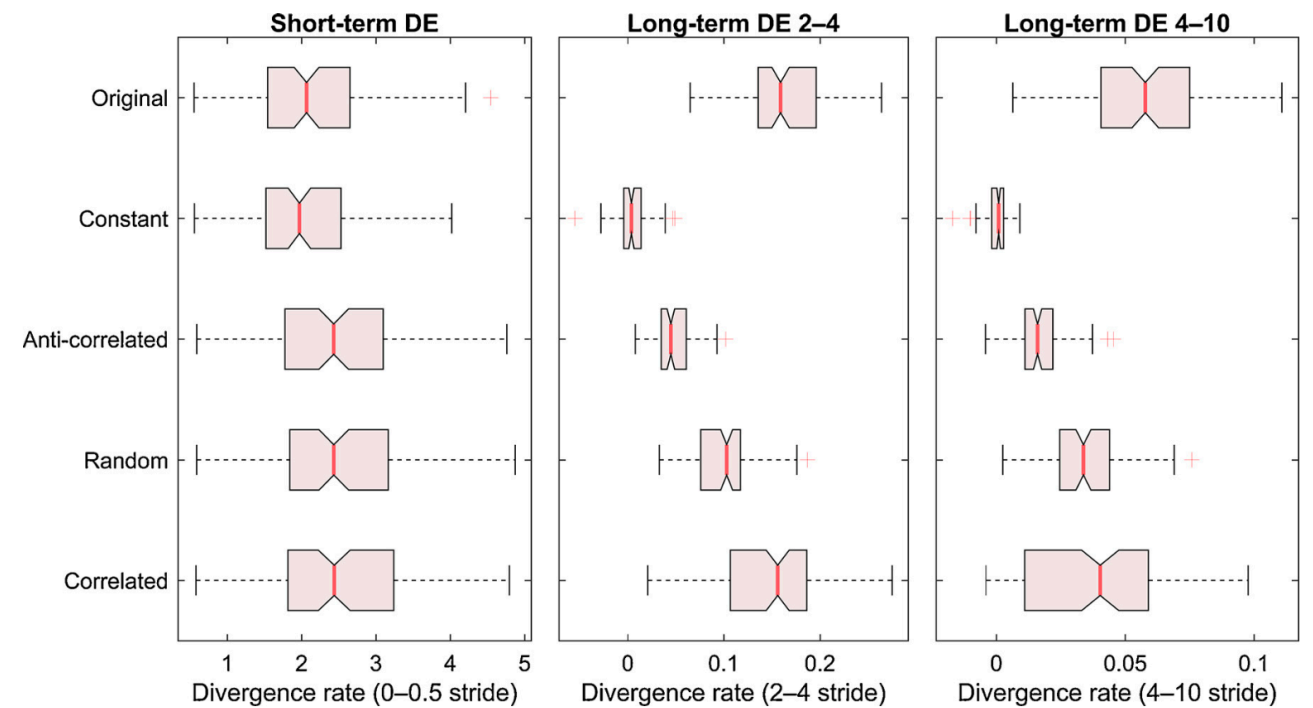
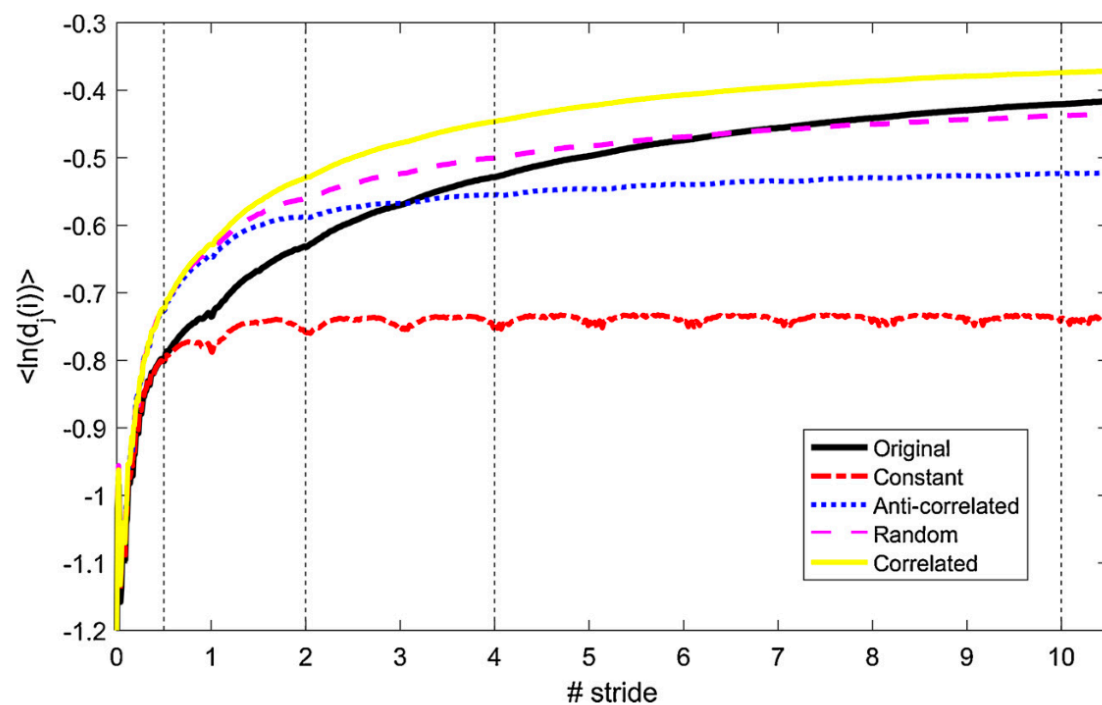
Effect of normalising time

- why time normalise keeping temporal variability? (Vs. not normalising, or time normalising each cycle)
 - simplifies analysis; in theory, delay should be more or less equal (same main frequency content, i.e. stride time)
 - differences between normalisations seem minor
 - it may affect estimates of long term slope (whatever that may mean)
 - allows checking if state space is correct

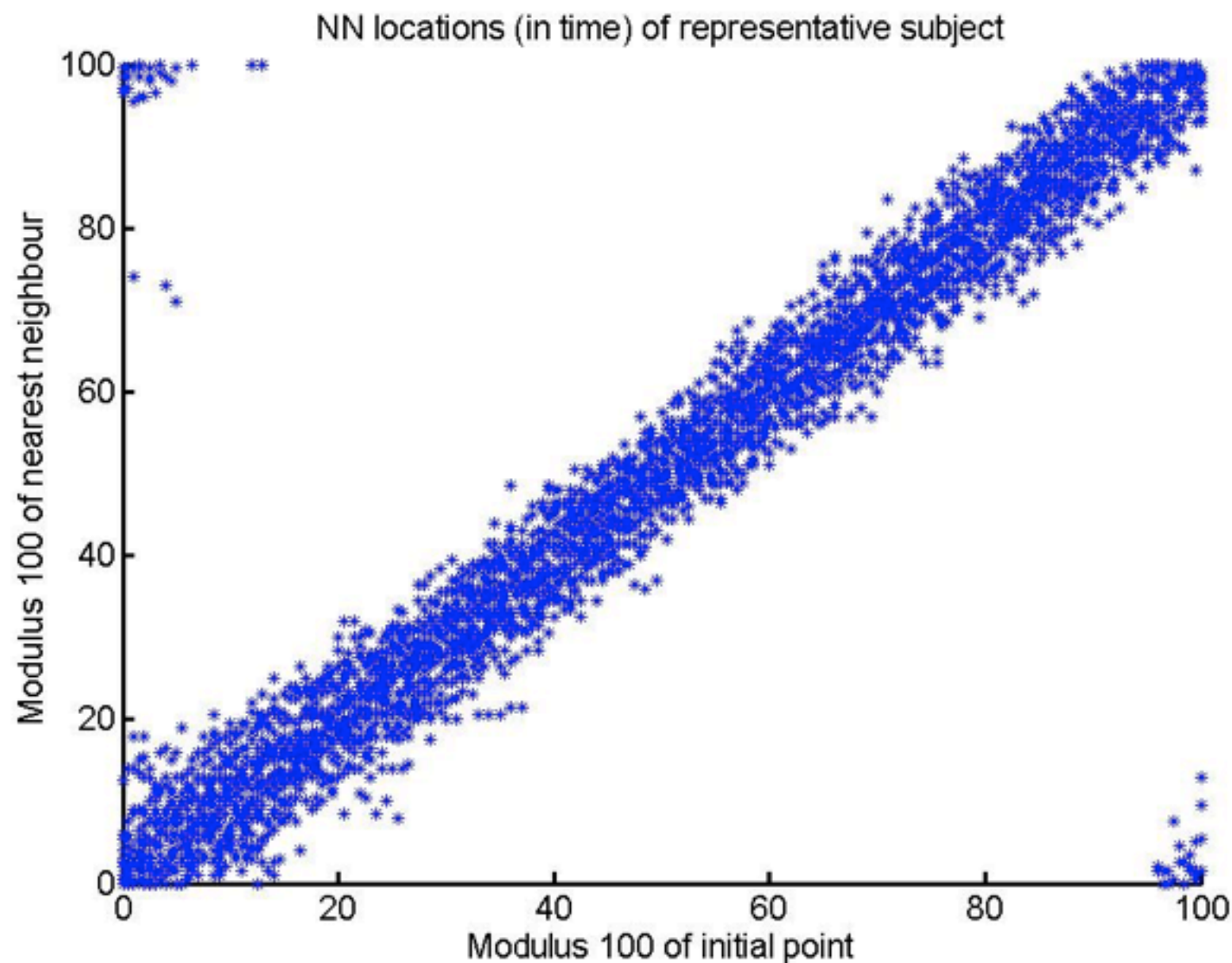
Differences between normalisations seem minor



But may affect estimates of long term slope



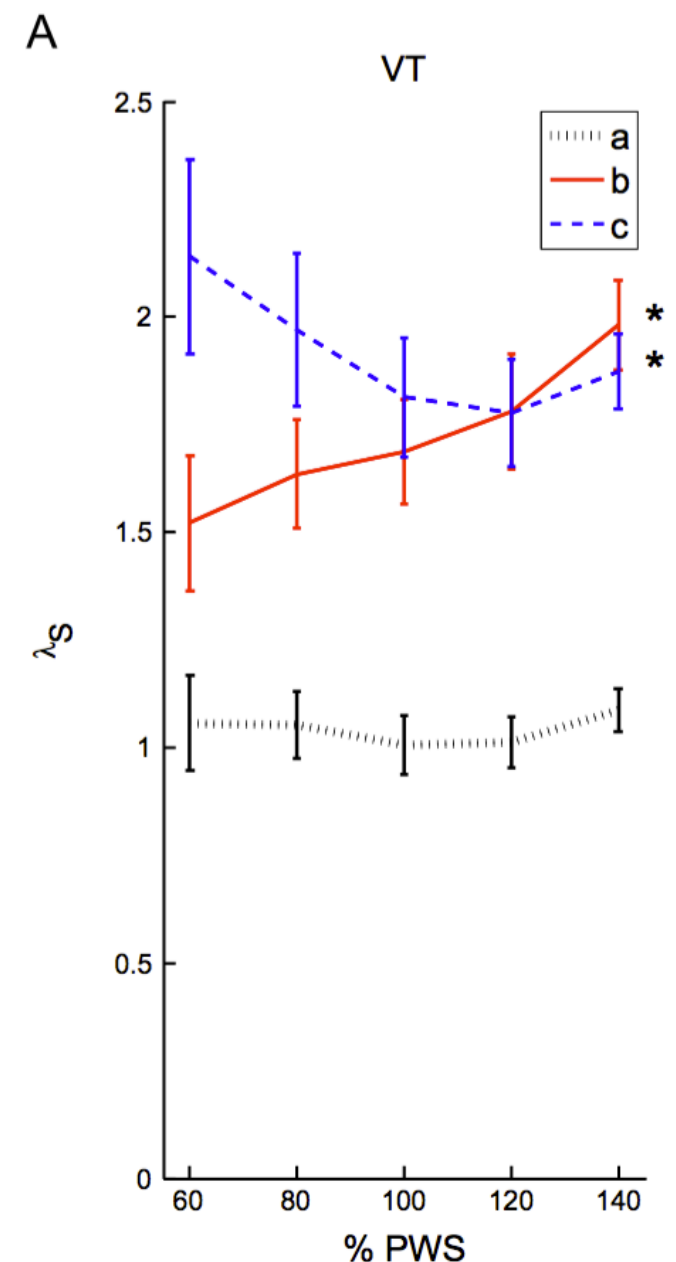
Normalisation allows checking if state space is correct



Unpublished analysis

Effects of calculating $\log(\text{div})/\text{s}$ vs. $\log(\text{div})/\text{stride}$

- usually lambda calculated as div/stride
- **A**: 3 min data for each speed
(more strides per speed!)
 div/stride
- **B**: 115 strides for each speed
 div/second (artificial increase with speed?)
- **C**: 115 strides for each speed
 div/stride



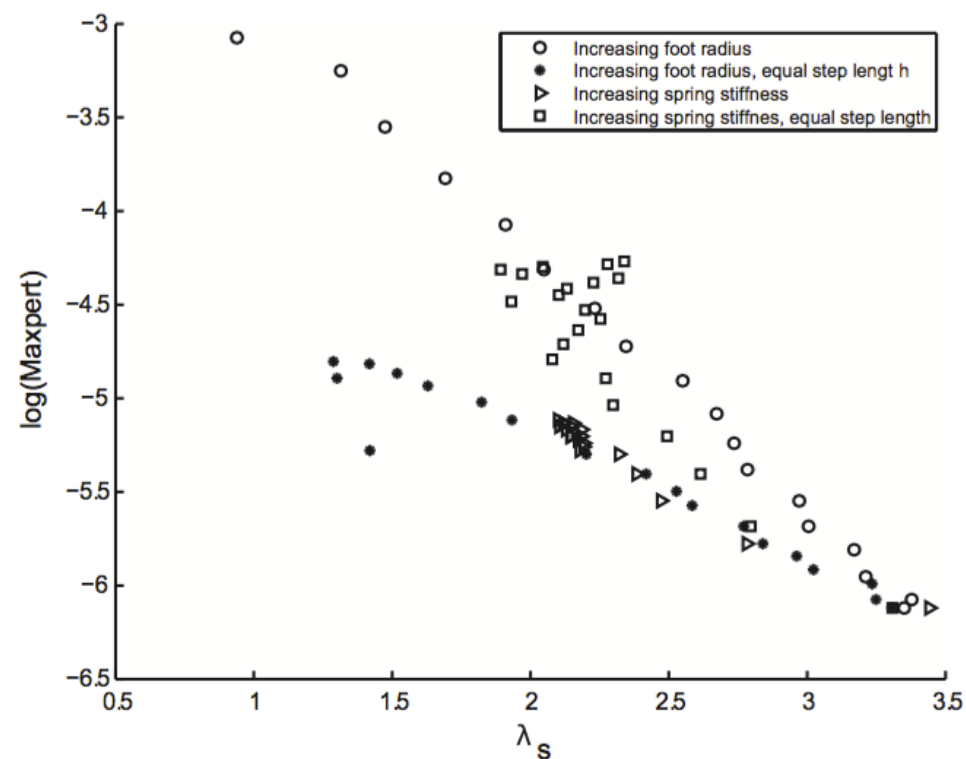
Per stride (vs. Per second)

- Gait happens in steps
- It doesn't matter that much how much you diverge in time, what matters more is how much you diverge per step; that shouldn't be too much

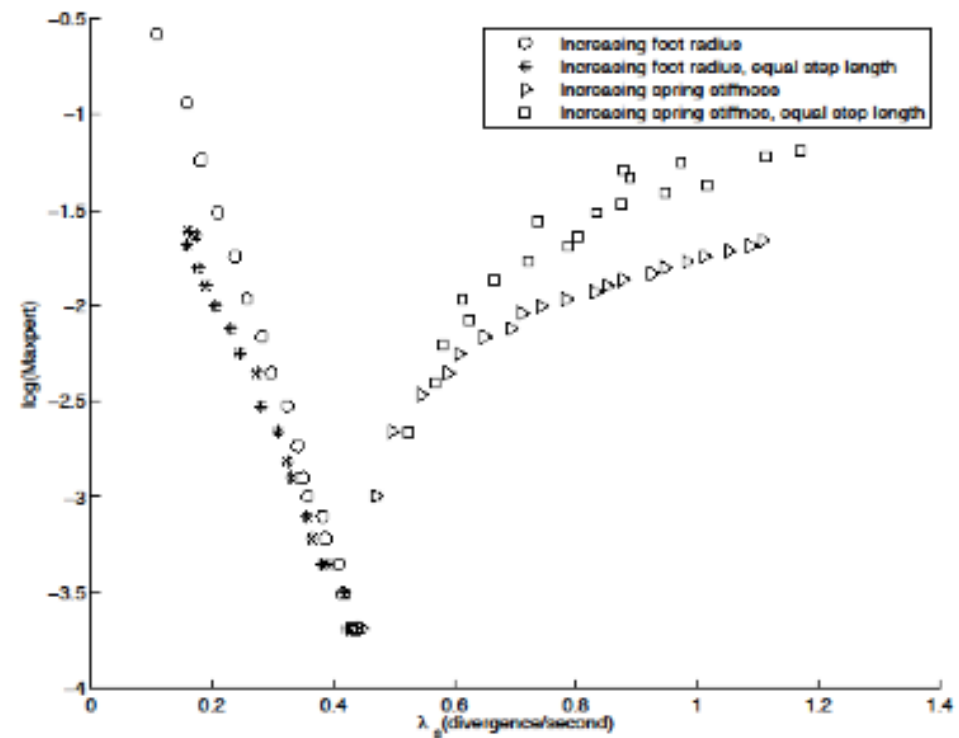
Per stride (vs. Per second)

- but of course, we do not know which one is right....
- so let's turn to our model

log(div)/stride



log(div)/second



Conclusions

- Use equal amounts of strides
- Normalise to a standard time (while keeping between stride variations in stride time intact)
- Express local divergence exponents as $\log(\text{div})/\text{stride}$