MOVEMENT DISORDERS

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2. Methods & advanced data processing

multidimensional data analysis,
time series analysis

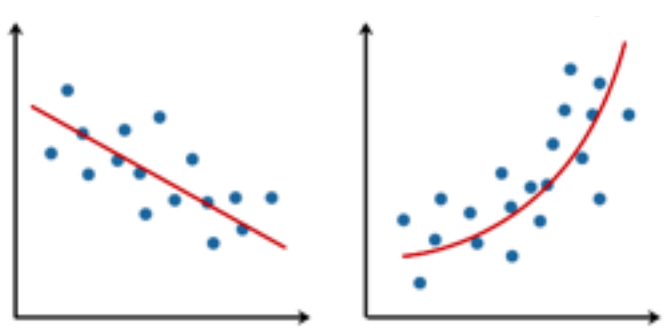
DATA ANALYSIS

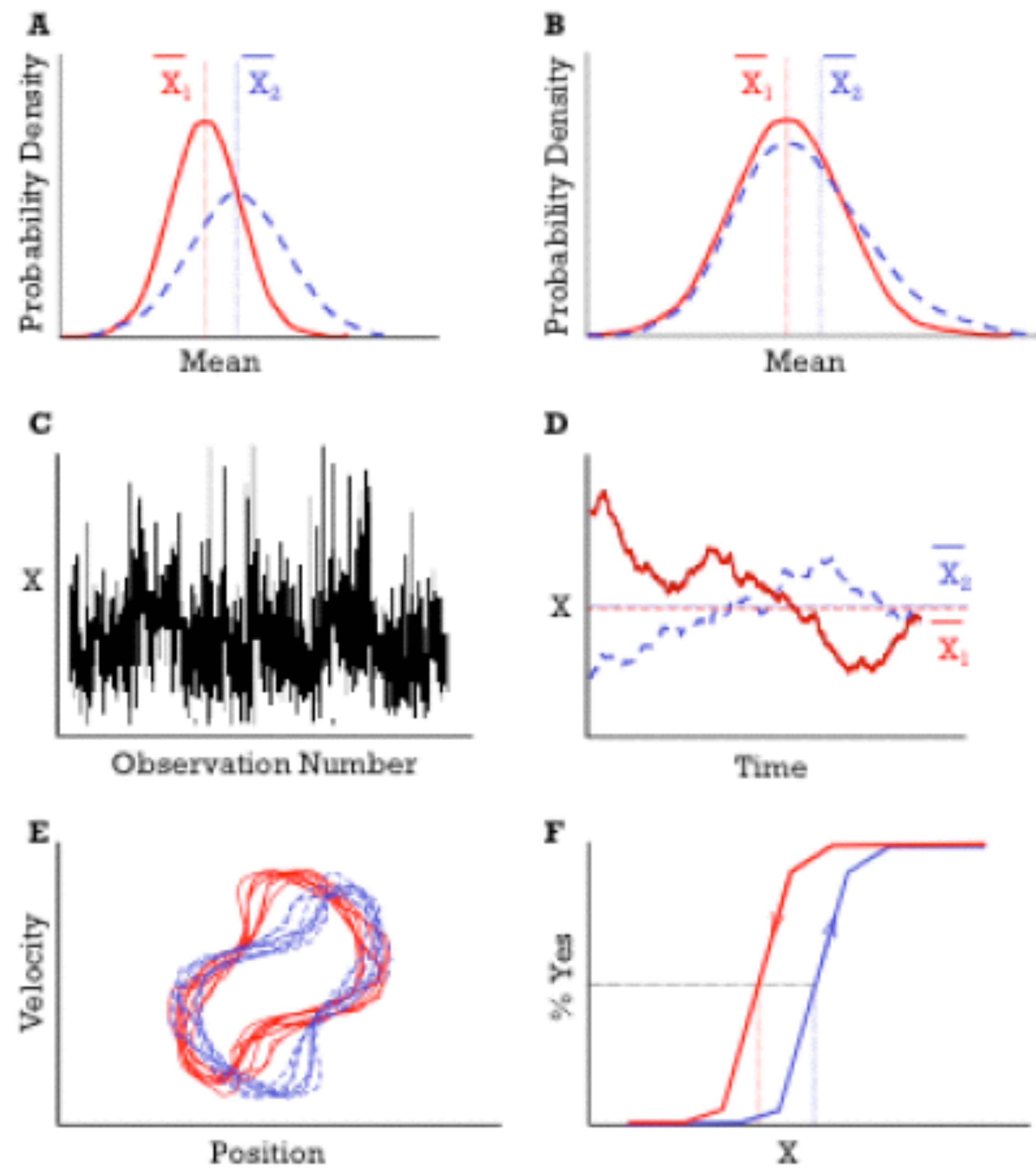
- **Summary statistics**

— comparison of means
— analysis of variance
— regression

- **But**

— structure of variability
— nonstationarity
— multidimensionality





multidimensional data analysis / time series analysis

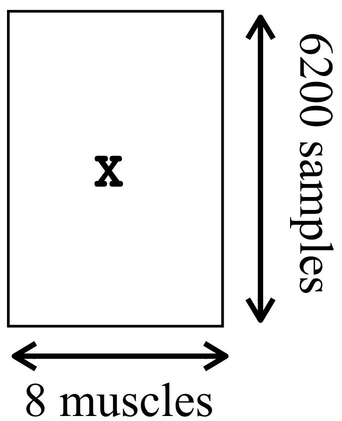
MULTIDIMENSIONAL DATA ANALYSIS

Principal component analysis

from muscle activations to isometric joint torque

`flexion/extension task`

`EMG data` `— 8 muscles, 6.2 s, 1 kHz`



$\mathbf{V} = \mathbf{X}'\mathbf{X}$ covariance matrix

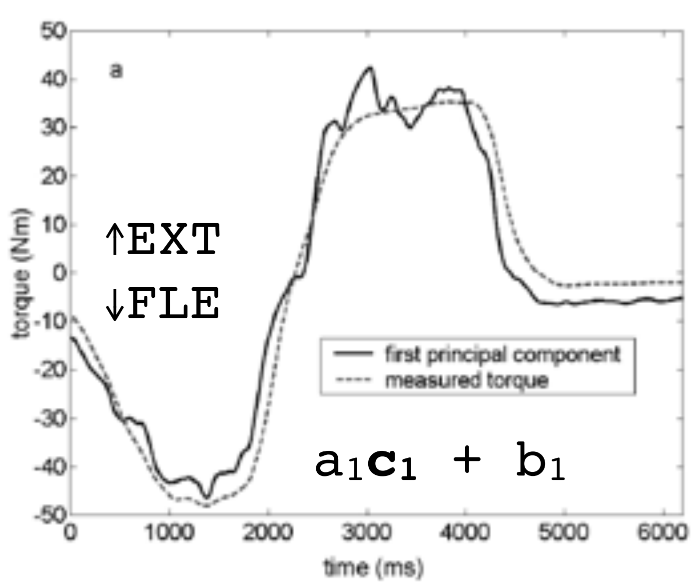
$\mathbf{e}_k \;/\; \mathbf{V}\mathbf{e}_k = \lambda_k \mathbf{e}_k \quad (k=1\ldots8)$ eigenvectors of **V**

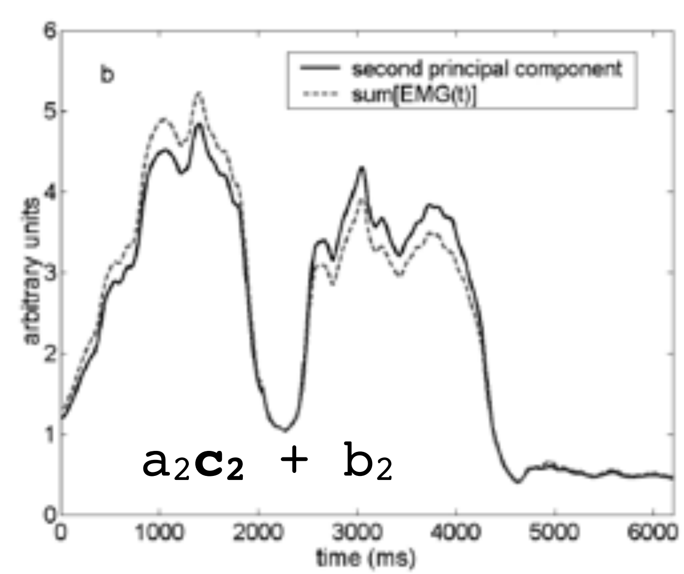
$\mathbf{c}_k = \mathbf{X}\mathbf{e}_k \quad (k=1\ldots8)$ principal components

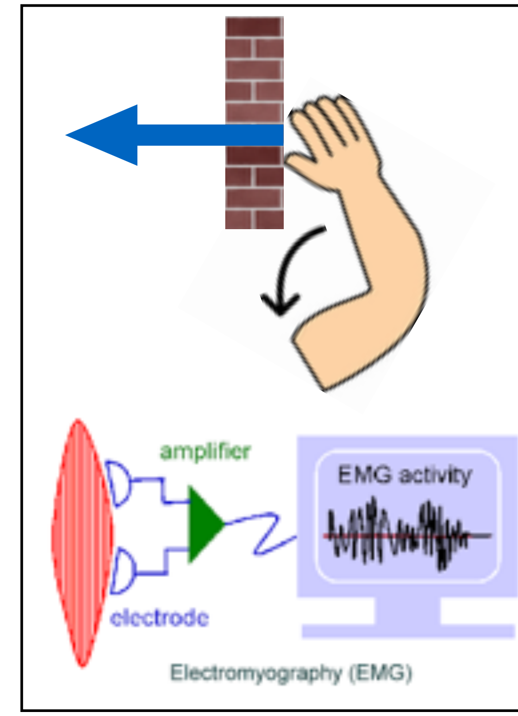
$\dim(\mathbf{e}_k)=8$

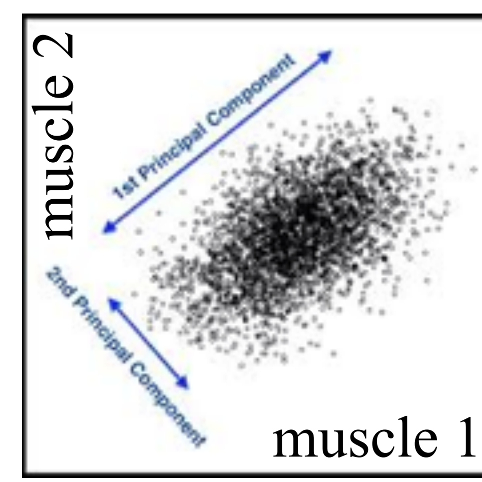
$\dim(\mathbf{c}_k)=6200$

98% of variance explained by 2 PCs









— Kutch and Buchanan, 2001, *Neurosci Lett* 311:97

MULTIDIMENSIONAL DATA ANALYSIS

Nonnegative matrix factorization

dimensionality reduction

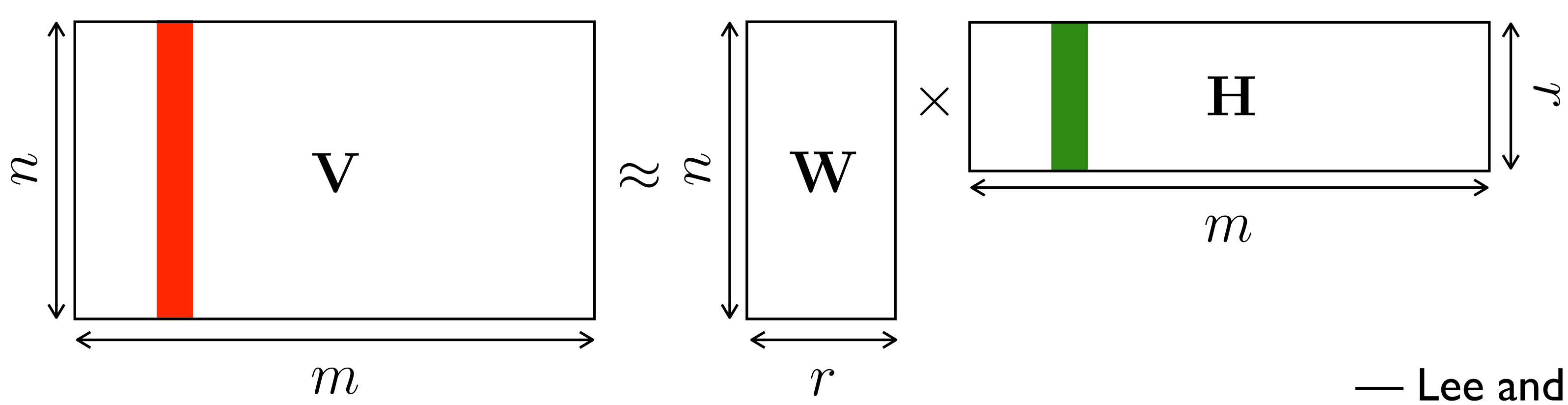
$$\mathbf{V} \approx \mathbf{WH}$$

$\mathbf{V}$	image database	$(\dim n \times m)$
$\mathbf{W}$	basis of images	$(\dim n \times r)$
$\mathbf{H}$	encoded images	$(\dim r \times m)$

n	number of pixels
m	number of images
r	number of basis images

original image

encoded image



algorithm

Initialise $\mathbf{W}$, $\mathbf{H}$

Iterate

$$W_{ia} \leftarrow W_{ia} \sum_{\mu} \frac{V_{i\mu}}{(WH)_{i\mu}} H_{a\mu}$$

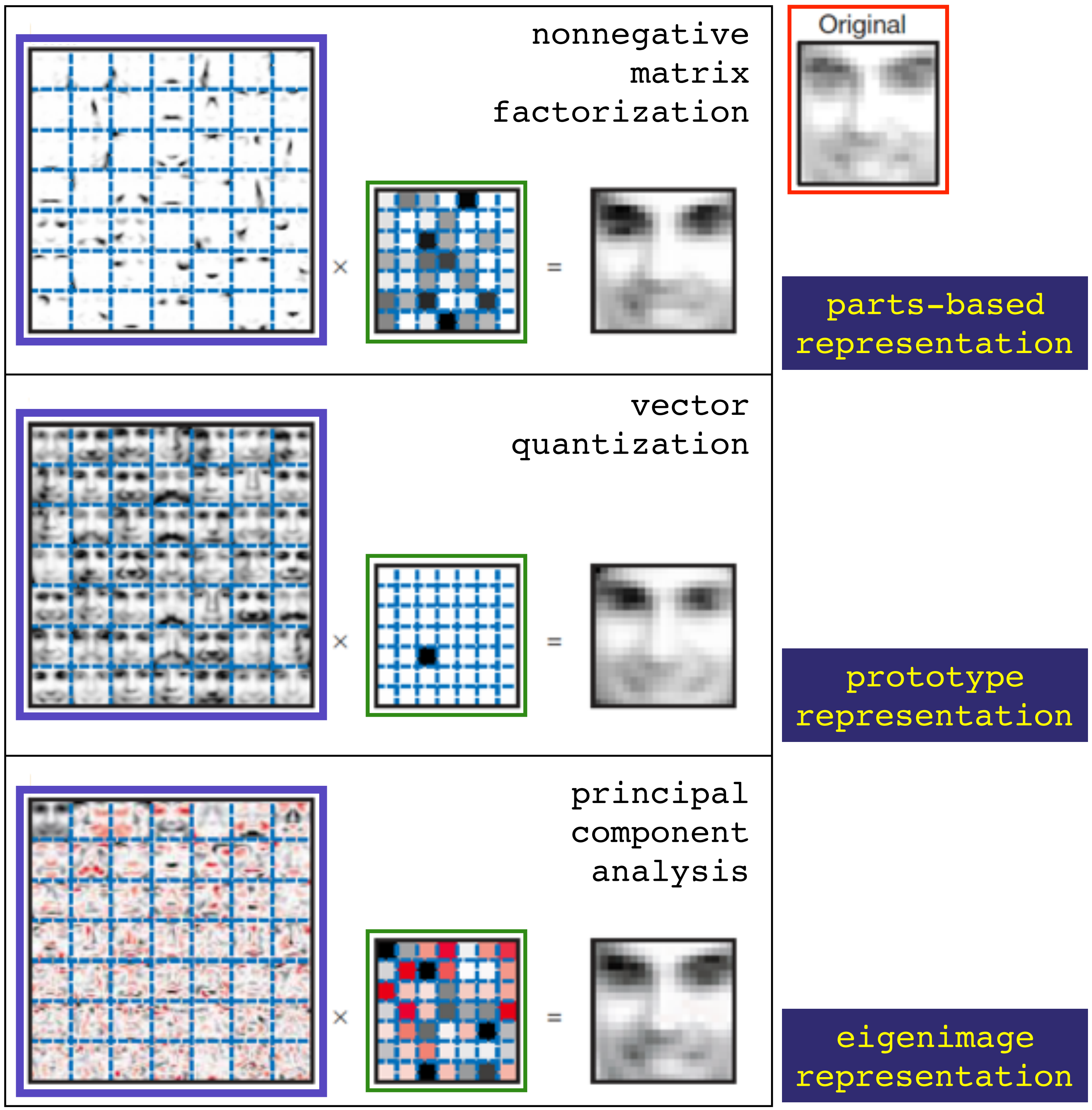
$$W_{ia} \leftarrow \frac{W_{ia}}{\sum_j W_{ja}}$$

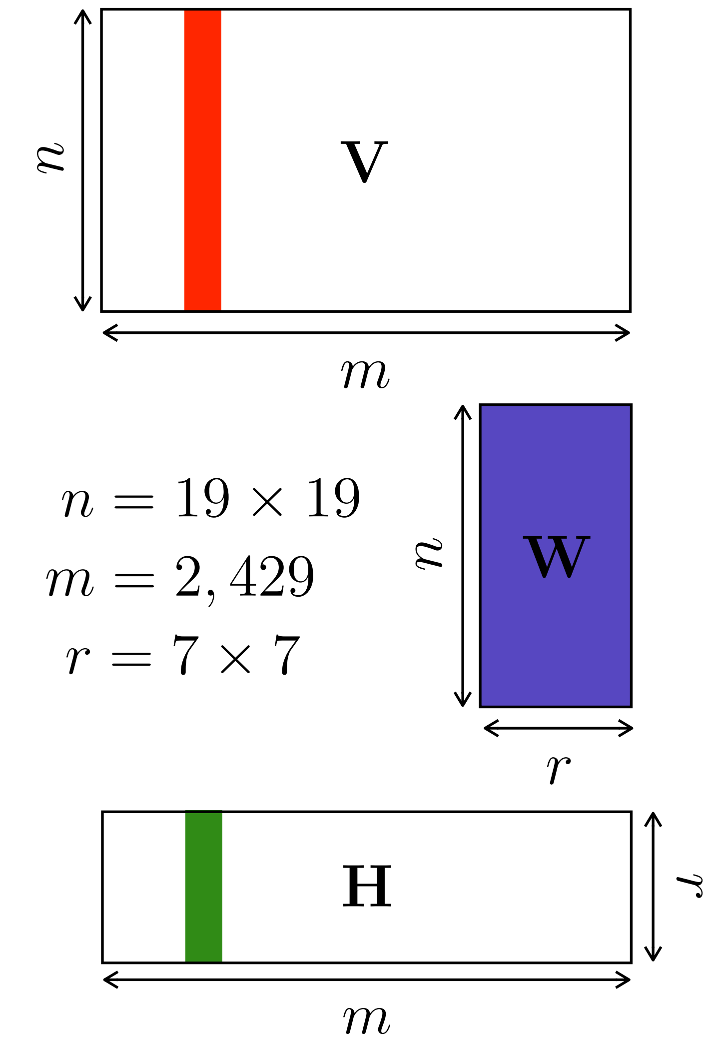
$$H_{a\mu} \leftarrow H_{a\mu} \sum_{i} W_{ia} \frac{V_{i\mu}}{(WH)_{i\mu}}$$

Until stable $\mathbf{W}$, $\mathbf{H}$

— Lee and Seung, 1999, *Nature* 401:788

MULTIDIMENSIONAL DATA ANALYSIS





$$n = 19 \times 19$$
$$m = 2,429$$
$$r = 7 \times 7$$

dim $\mathbf{V}$	$n \times m$	876869
dim $\mathbf{W}$	$n \times r$	17689
dim $\mathbf{H}$	$r \times m$	119021

THE COORDINATION PROBLEM

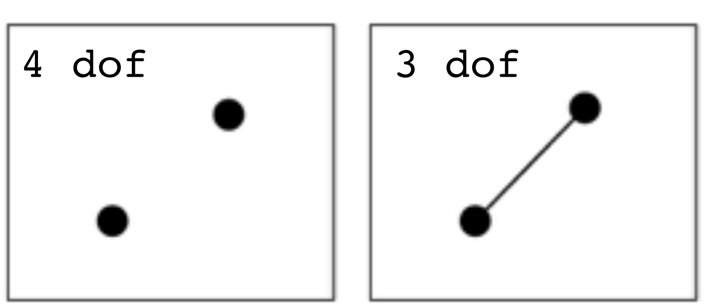
Concepts

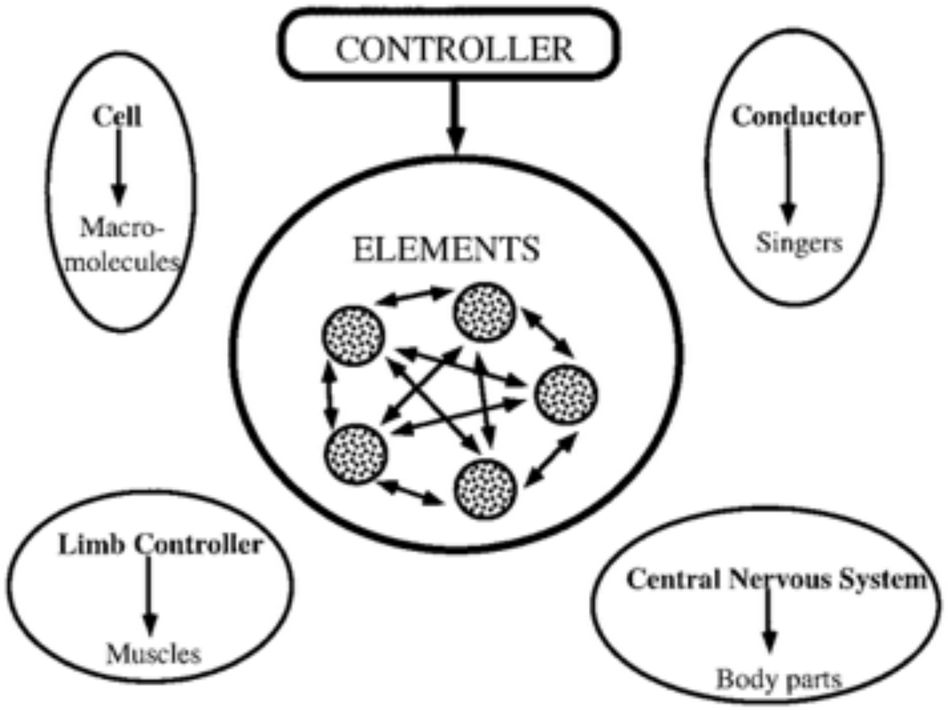
— *Is the CNS concerned with the control of each individual (muscle) or does the CNS simplify control by combining (muscles) into groups and controlling each group, rather than the individual (muscle)?*

— **synergies**, structural units, coordinative structures, ...

```
The controller organizes
relations among elements
at a hierarchically lower
level, and these relations
assure stability of motor
performance with respect
to a particular motor task
```

`dimensionality reduction`





— Latash et al., 2002, *Exerc Sports Sci Rev* 30:26
— Macpherson, 1991, in *Motor Control: Concepts and Issues*, Wiley

SYNERGIES

- **Definition**

— "acting together"
— common source or coincidence
— muscles, joints, multi-segmental / whole-body movements
— anatomical *vs* functional
e.g **muscle synergy** — a set of muscles which act together to produce a desired effect

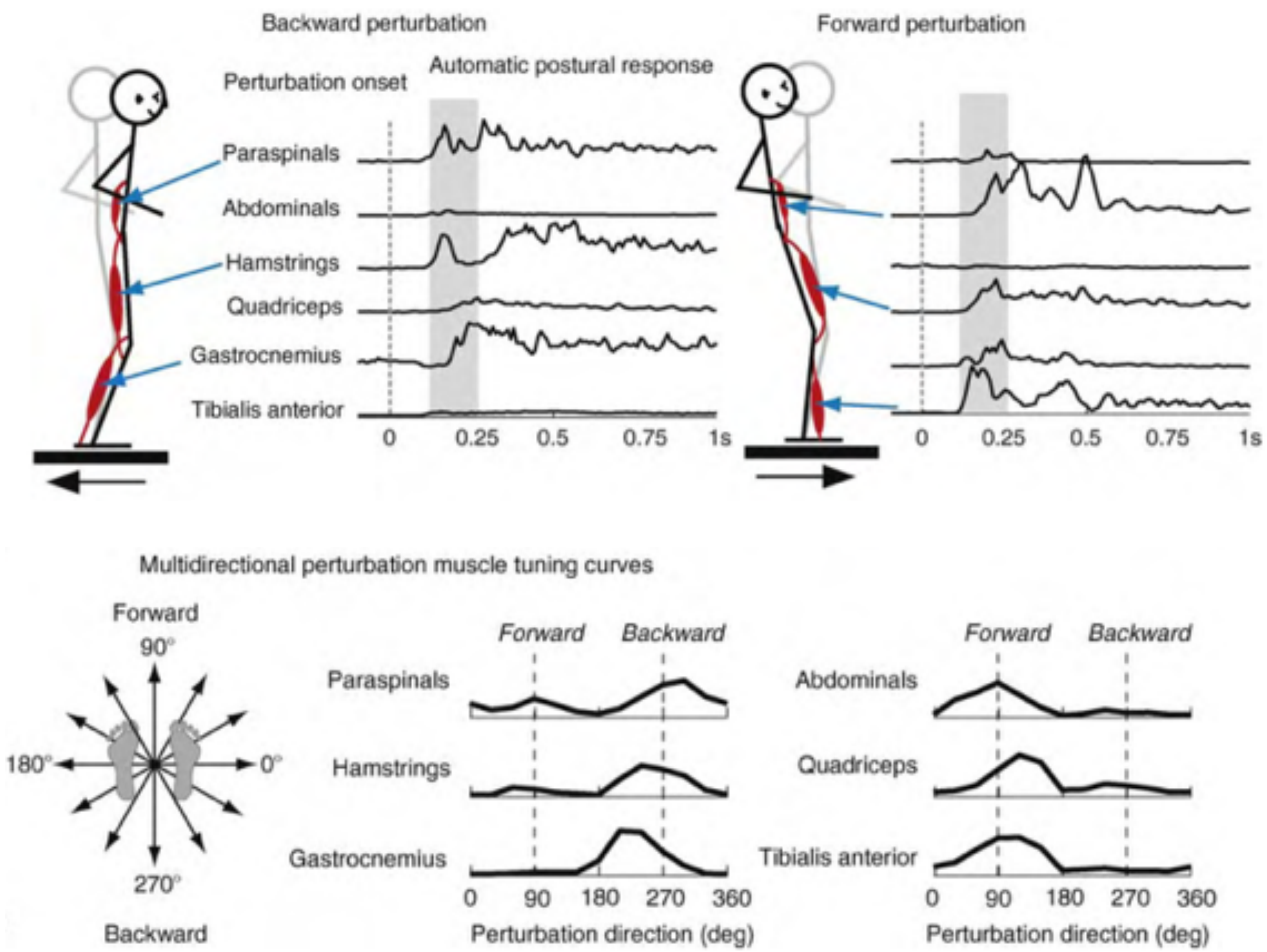
- **Narrow to broad meaning**

— agonist / which acts with the prime mover / synonymous of motor coordination / patterns of activity that occur at the same time
e.g. **locomotion** (Bernstein) — *an extremely widespread synergy incorporating the whole musculature and the entire moving skeleton and bringing into play a large number of areas and conductions pathways of the central nervous system*

POSTURAL SYNERGIES

Theory

— Nashner's «fixed» postural synergies in subjects standing on a moving perturbation platform




```
Postural synergies are
activated in a mutually
exclusive fashion – each
muscle was activated by only
one postural synergy
```

⬇

```
Flexibility in patterns
of muscle activations
(amplitude, prior
experience)
```
e.g. ***ankle/hip strategies***

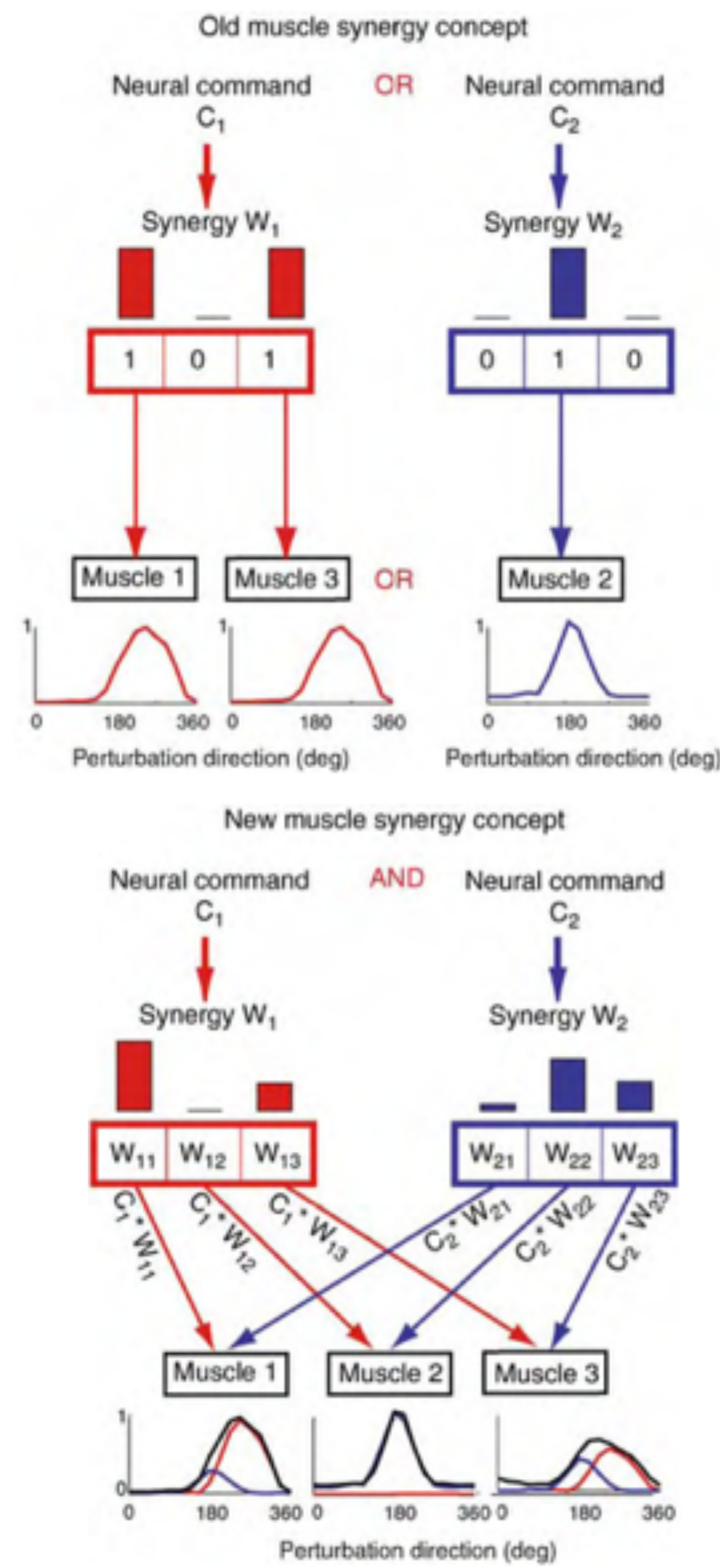
— Nashner, 1977, *Exp Brain Res* 30:13
— Horak & Macpherson, 1996, *in Handbook of Physiology*, OUP

SYNERGY AS COORDINATION

Rejection and new concept

— rejection of the notion of synergy: *too constraining and inflexible for the production of natural movements*

— new concept: *more than one muscle synergy can be activated during a postural response and each muscle can also be activated by more than one synergy. By varying the magnitude of the neural command signals to just a few muscle synergies, many different muscle activation patterns can be generated*



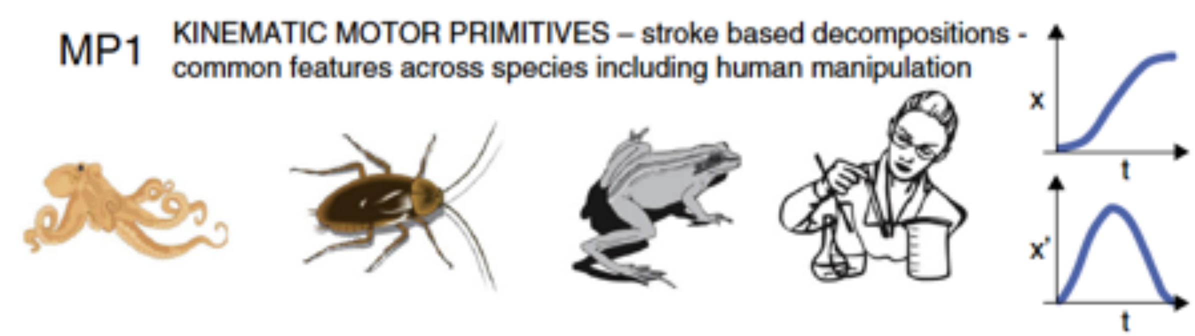
descriptor that indicates some form of motor coordination – no insight into the underlying mechanism of coordination

— Macpherson, 1991, *in Motor Control: Concepts and Issues*, Wiley
— Ting & Macpherson, 2005, *J Neurophysiol* 93:609-613

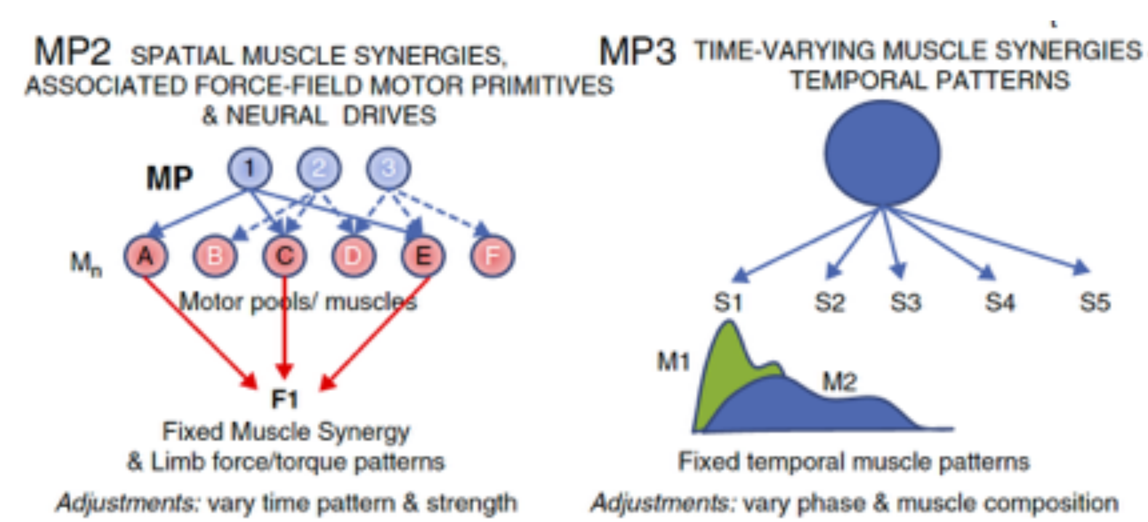
MOTOR PRIMITIVES

- **Compositional elements for movement construction**

- **Kinematic primitives**
segmentation/decomposition



- **Muscle synergies**
— based on EMG signals
— coordinated recruitment of a group of muscles with specific activation balances or specific activation waveforms



MUSCLE SYNERGIES

- **Principle**

dimensionality reduction — mapping simplified by a low-dimensional representation of the motor output: *if all useful muscle patterns can be constructed by the combination of a small number of elements, selecting the appropriate muscle pattern for a goal requires only determining how these elements are combined*

- **Organisation**

— spatial, time-independent synergies
— time-dependent, time-invariant synergies
— time-varying synergies

- **Identification**

multidimensional data analysis

MUSCLE SYNERGY IDENTIFICATION

- **In frogs, cats, humans**

— evidence that the CNS flexibly combines fixed muscle synergies for generating the muscle patterns necessary to perform many motor tasks and behaviors

— a variety of muscle patterns used in different behaviors are generated by the combination of a small number of time-invariant and time-varying synergies

- **Methods**

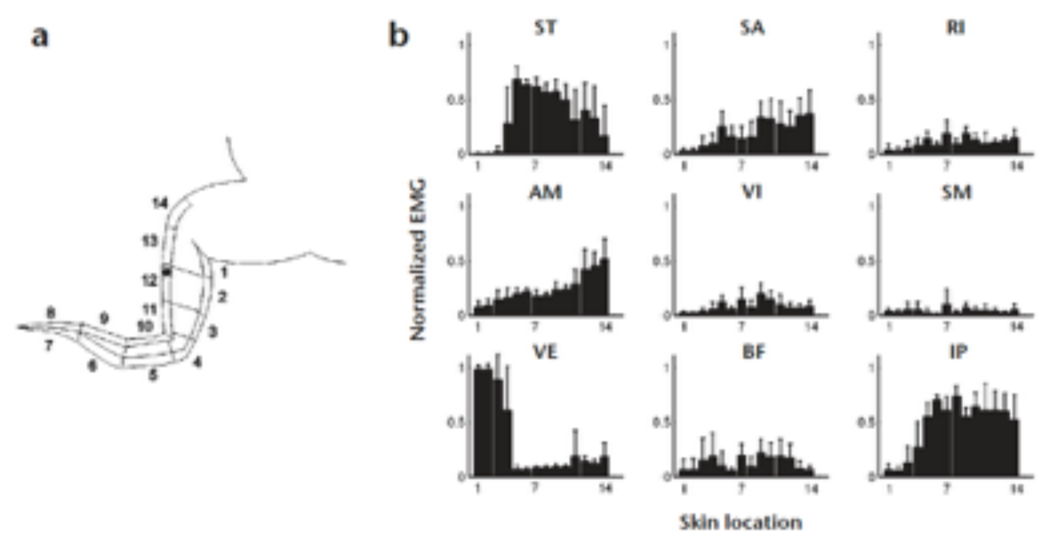
— principal-component analysis (PCA), nonnegative matrix factorization (NMF)

— criterion: variance accounted for (VAF) of the experimental EMG after synergy decomposition

TIME-INVARIANT SYNERGIES

Muscle activation patterns

evoked from cutaneous stimulation of the *spinalized* frog hindlimb



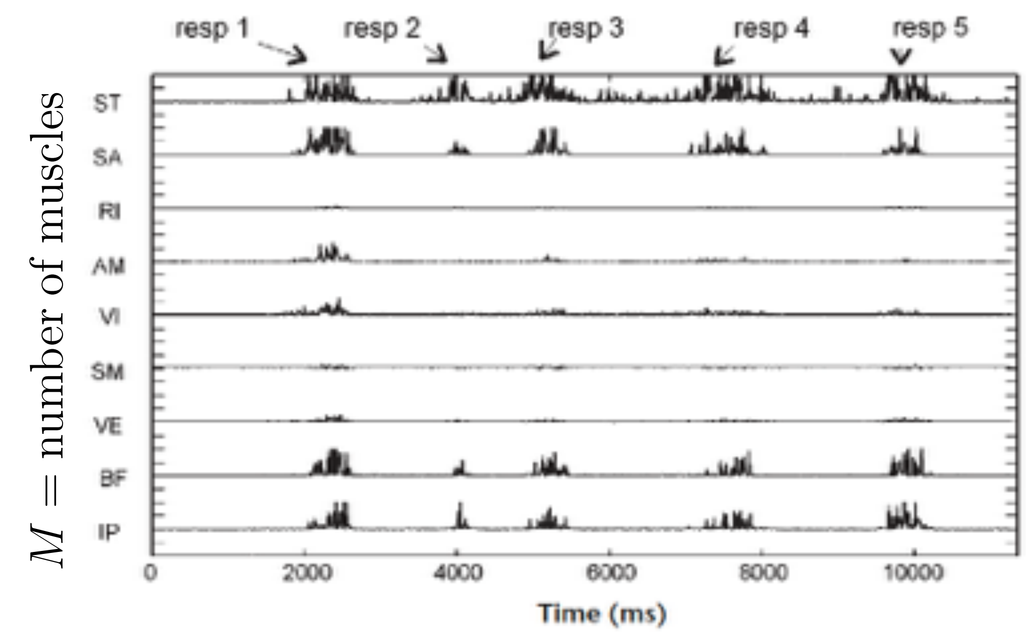
$$\mathbf{m}_j^{\text{obs}} \approx \mathbf{m}_j^{\text{pred}} = \sum_{i=1}^{N} c_{ij}\, g(\mathbf{w}_i) \qquad N = \text{number of synergies}$$

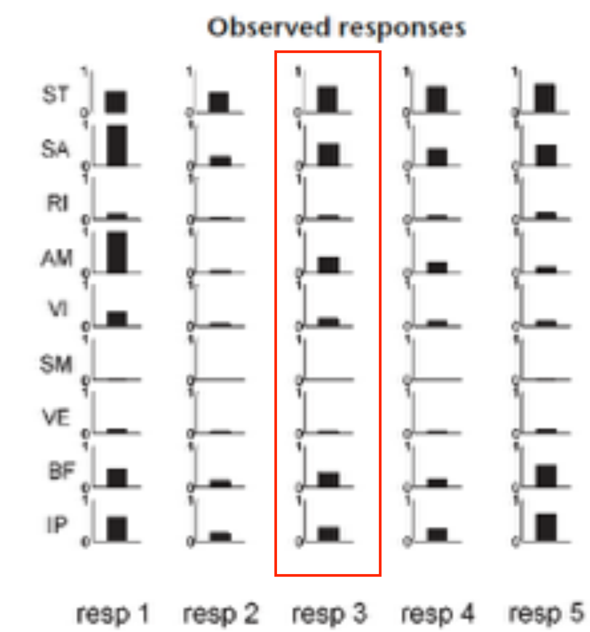
$j = 1 \ldots P$

$\mathbf{m}_j^{\text{obs}}$	observed EMG response	$\dim \mathbf{m}_j^{\text{obs}} = M$
$\mathbf{w}_i$	muscle synergy	$\dim \mathbf{w}_i = M$
c_{ij}	weights	

`method — close to nonnegative matrix factorization`

P = number of observed patterns = 5

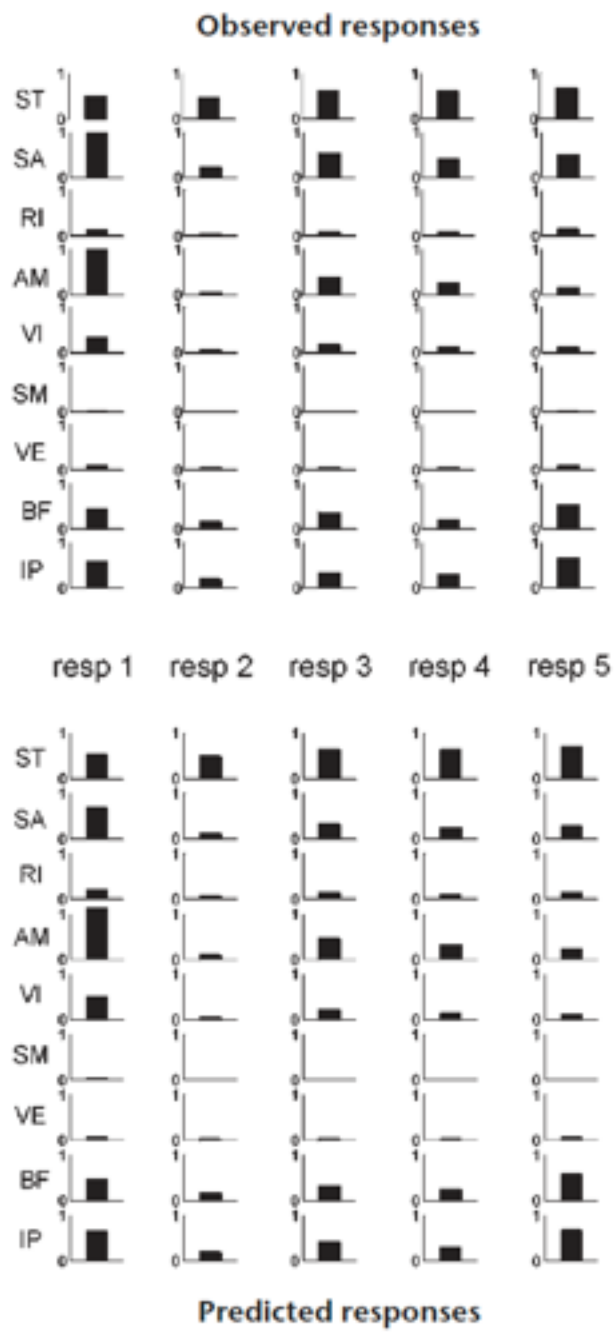




$\mathbf{m}_3^{\text{obs}}$

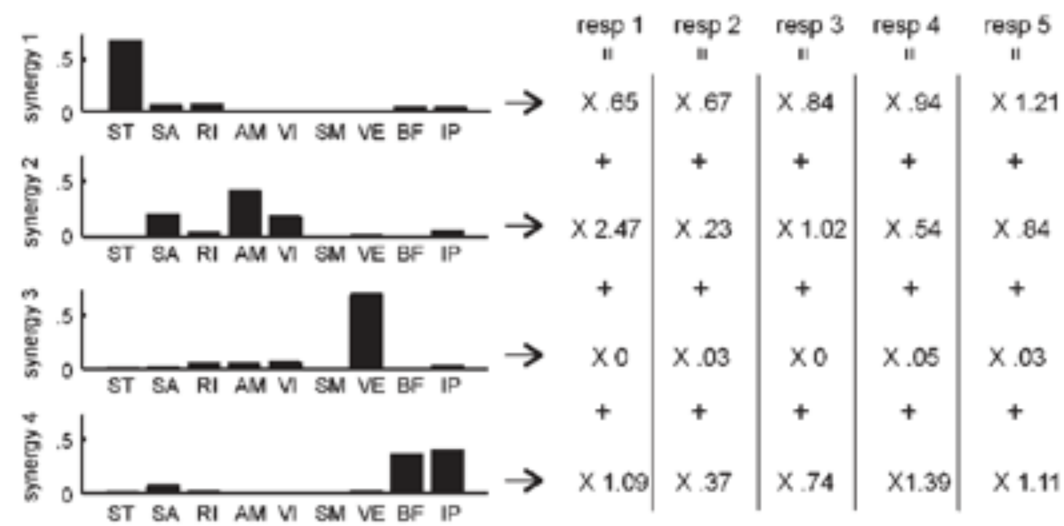
— Tresch et al., 1999, *Nat Neurosci* 2:162

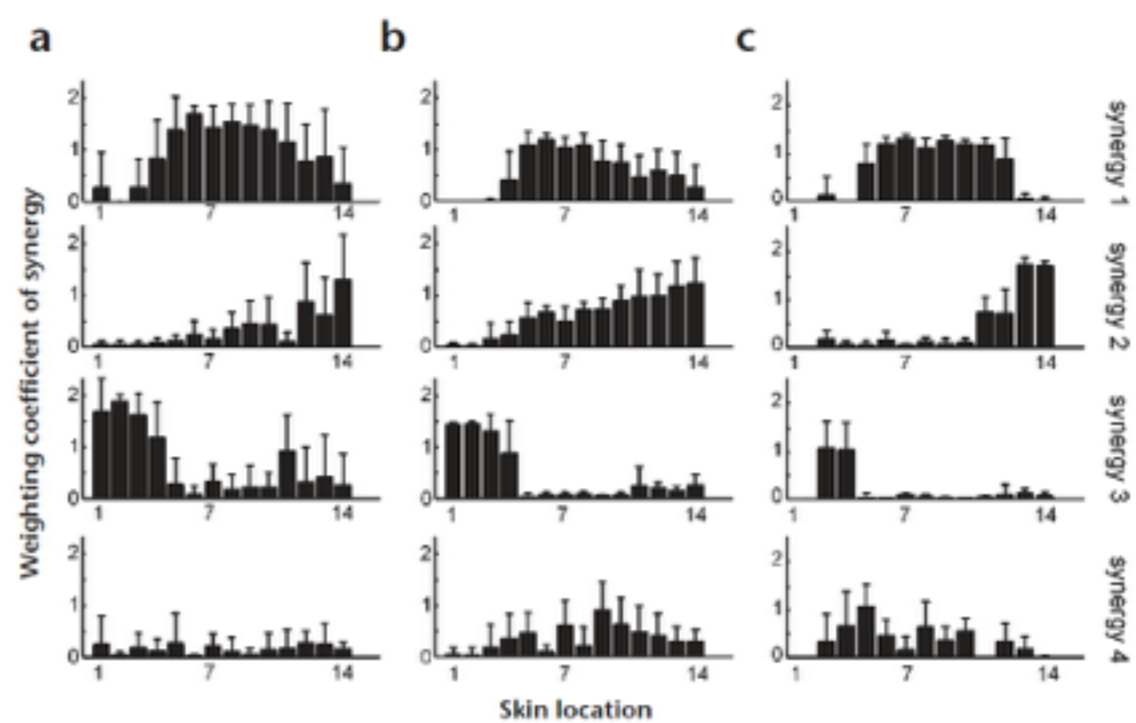
TIME-INVARIANT SYNERGIES



— Tresch et al., 1999, *Nat Neurosci* 2:162

$N = \text{number of synergies discovered} = 4$






```
contribution of each muscle synergy to responses
evoked from different regions of the skin surface
for three different animals (a, b, c)
```

TIME-VARYING SYNERGIES

Muscle activation patterns

during kicking, jumping and walking in unrestrained frogs

`temporal patterns of muscle activation`

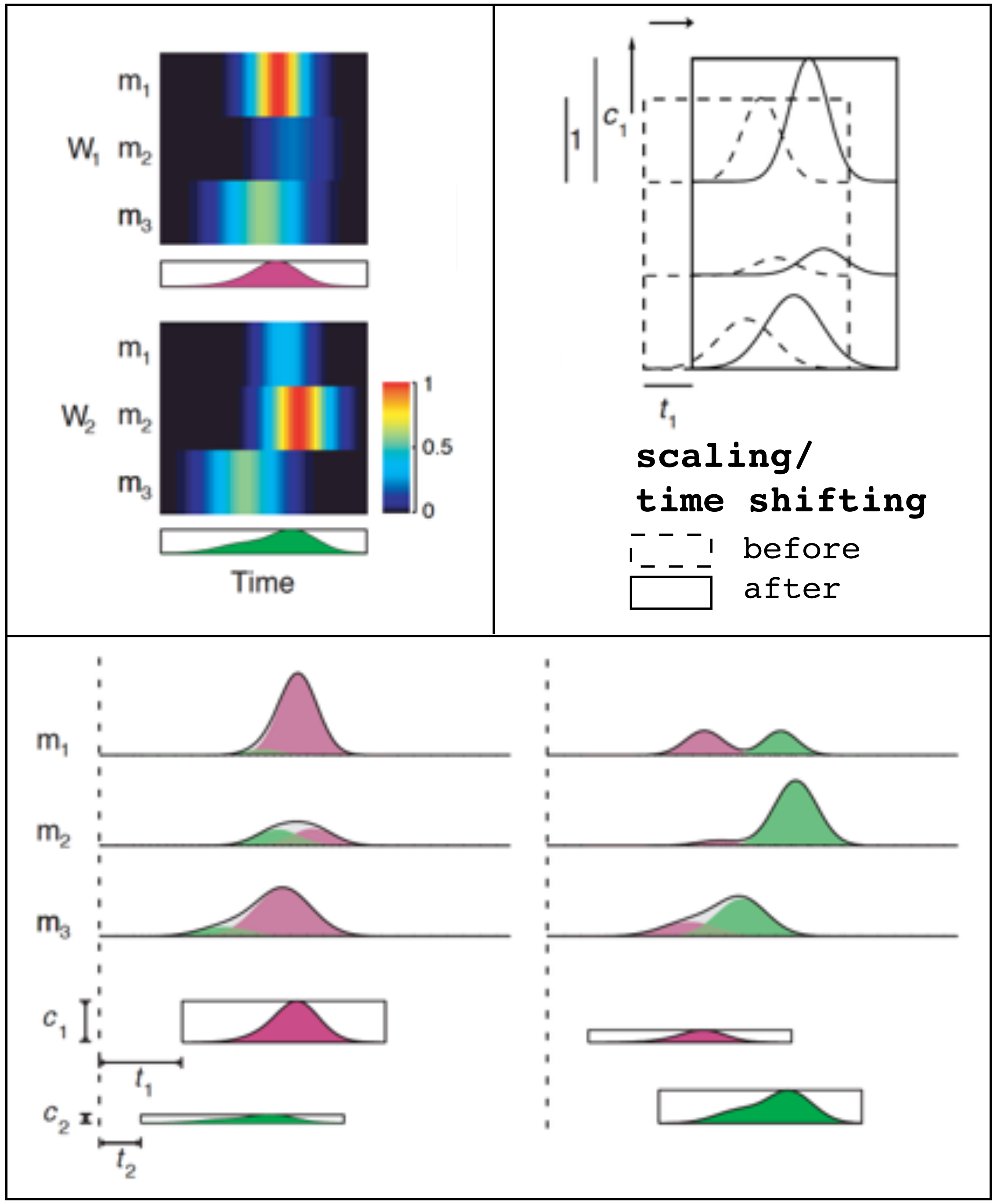
$$\mathbf{m}(t) = \sum_{i=1}^{N} c_i \mathbf{w}_i(t - t_i)$$

$$\dim \mathbf{m}(t) = \dim \mathbf{w}_i(t) = D$$

N	number of synergies
D	number of muscles
J	number of time samples
$\mathbf{w}_i(t)$	time varying synergy
t_i	synergy onset delay

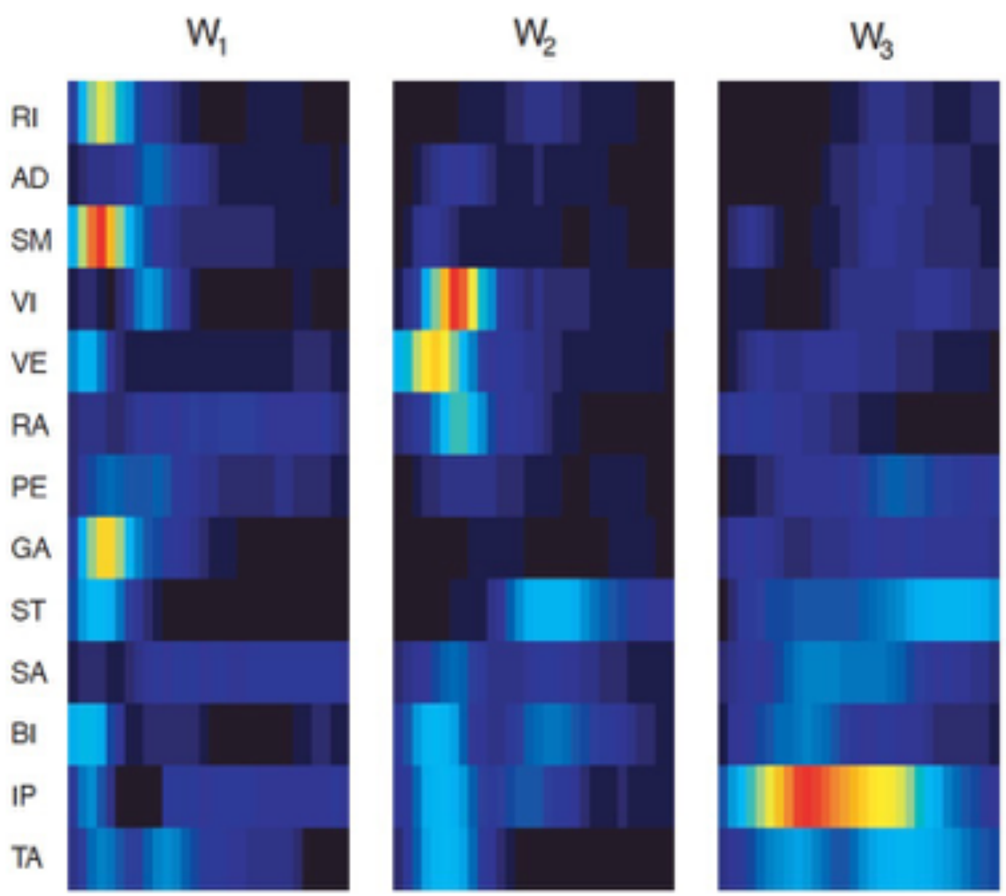
$$\begin{array}{cccc} 0 & \tau_j & T_{\max} & \\ \vdash & + & + \rightarrow & t \\ 1 & j & J & \end{array}$$

$$\mathbf{w}_i(\tau_j) = \begin{cases} 0 & \tau_j < 0 \\ W_j^i & 0 \le \tau_j < T_{\max} \\ 0 & \tau_j \ge T_{\max} \end{cases}$$

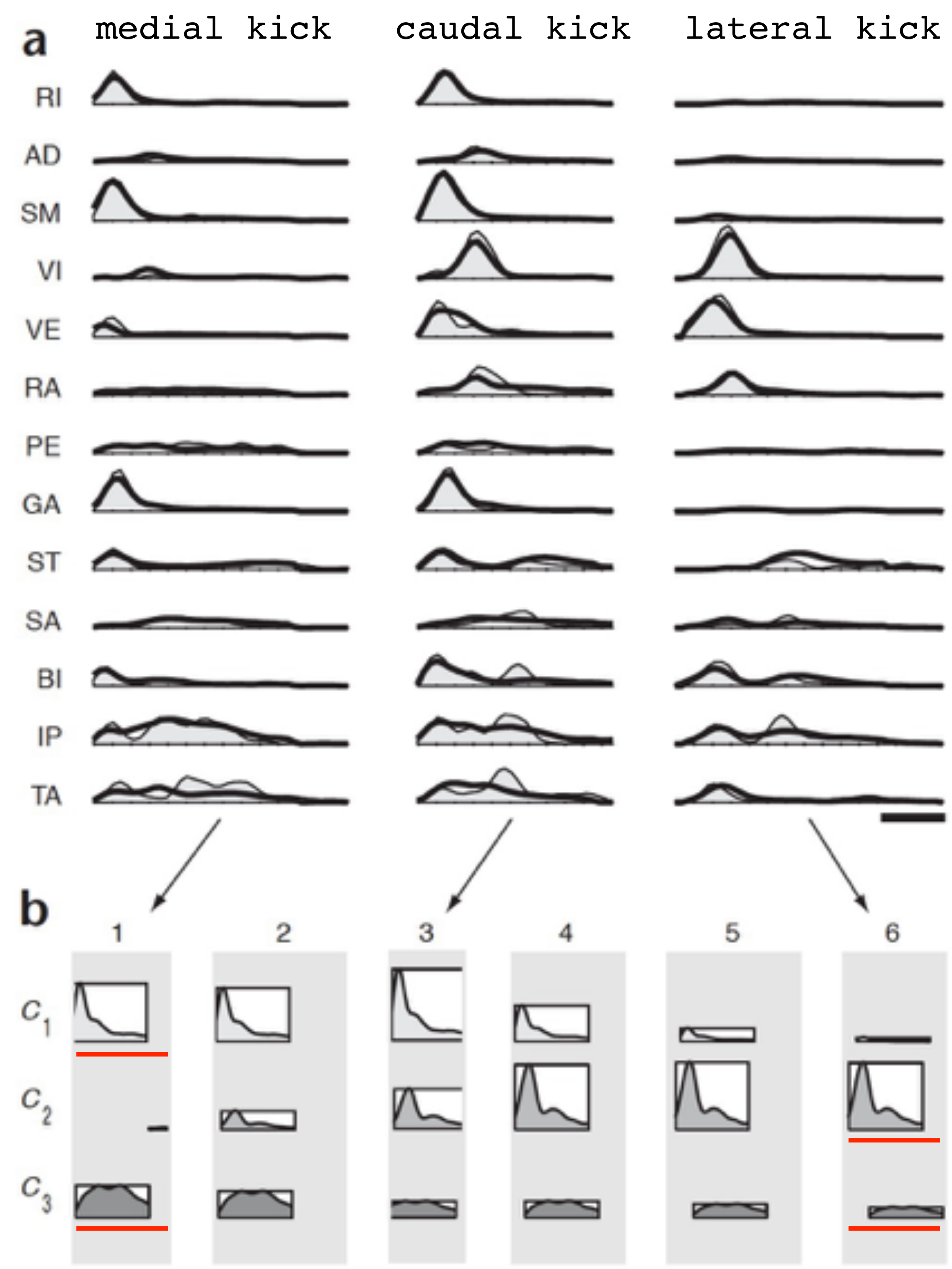


— d'Avella et al., 2003, *Nat Neurosci* 6:300

TIME-VARYING SYNERGIES



13 hindlimb muscles during kicking
300 ms duration

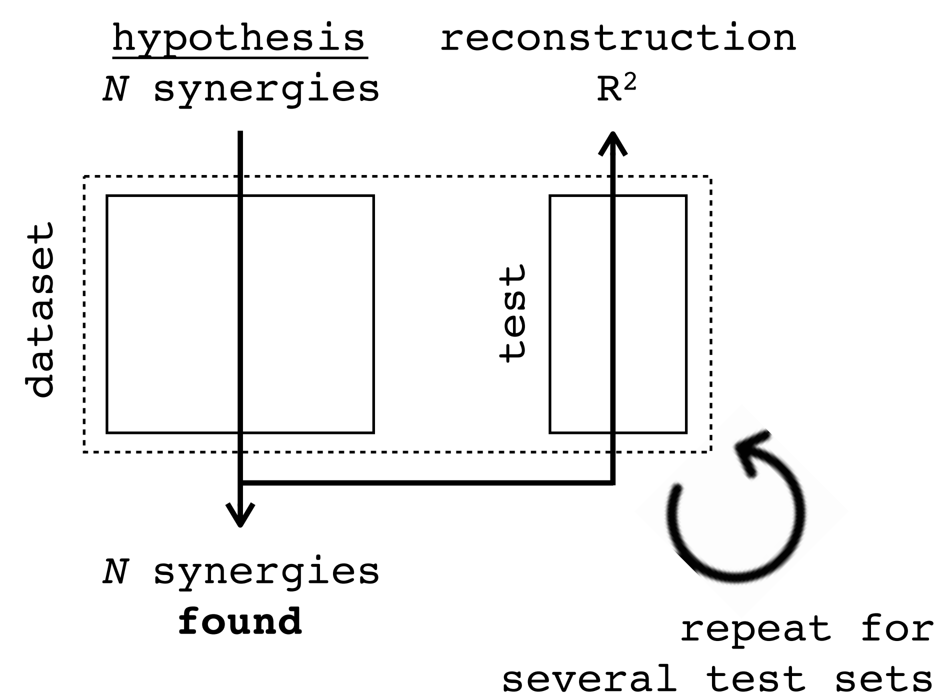


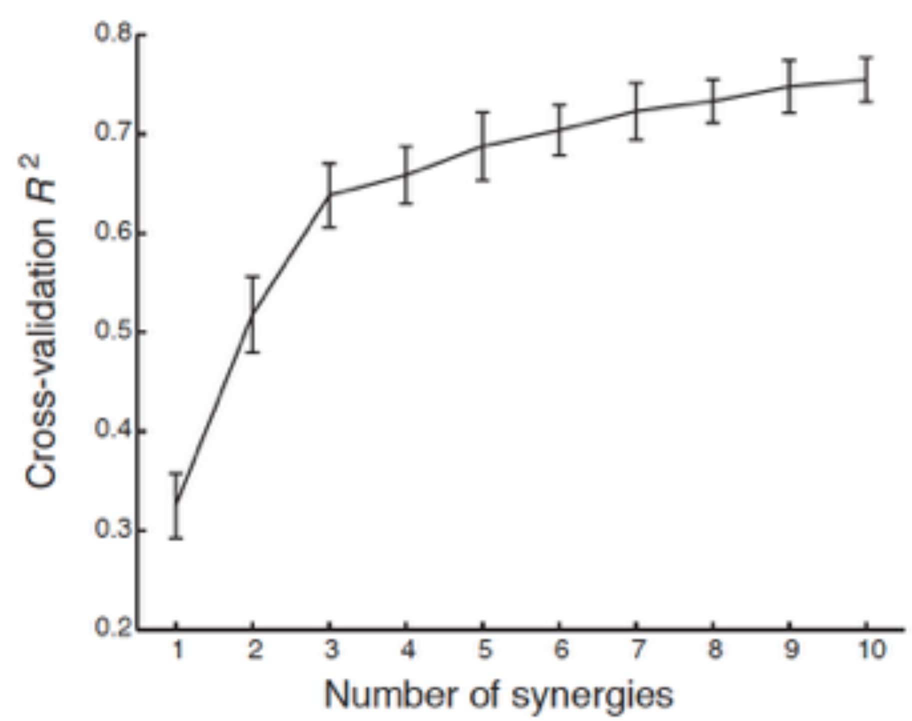
reconstruction of kick muscle patterns as combinations of time-varying synergies

HOW MANY SYNERGIES?

Cross-validation

— too many synergies = over-fitting
— determine the model order (number of synergies) with the best generalization performance = *the best reconstruction of the data not used to fit the model*
— partition of the dataset





LIMITATIONS OF MUSCLE SYNERGIES

- **Criterions**

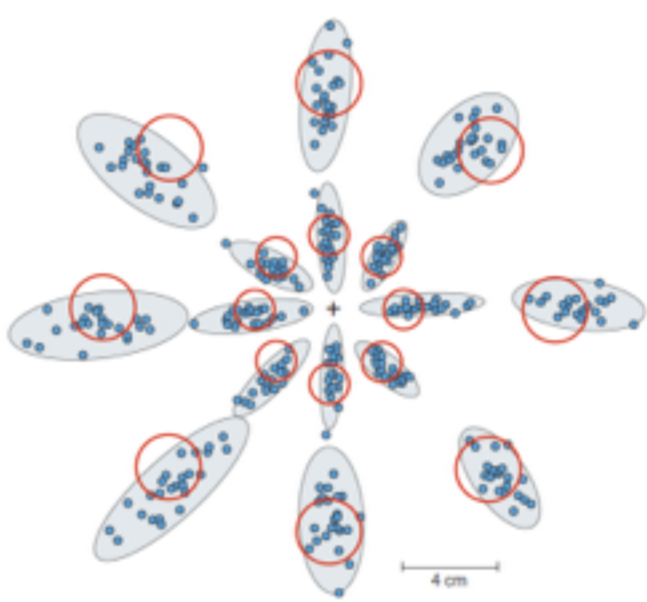
— accuracy in accounting for muscle activity (reconstruction)
— explaining as much variance of muscle activity as possible
— how many synergies

- **Can muscle synergies extracted during an action be used to produce this action?**

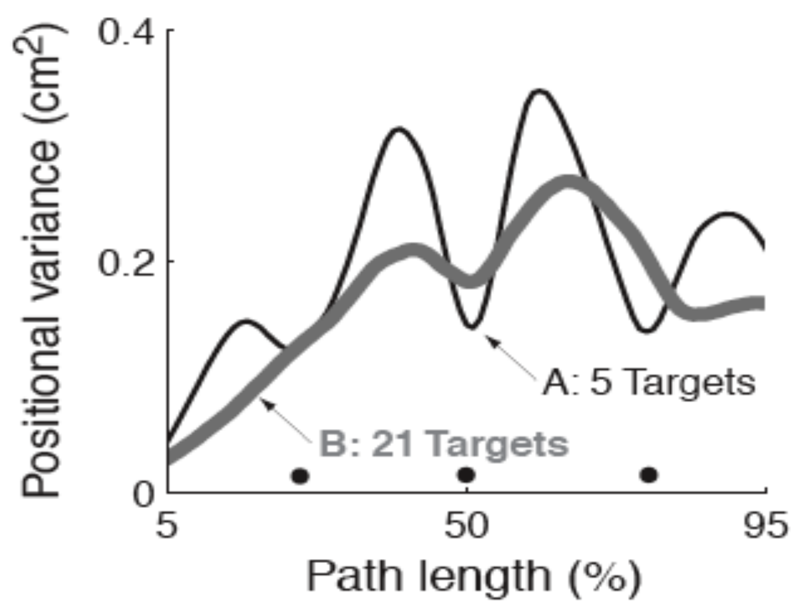
— no consideration for task achievement (e.g. trajectories)
— proper EMG reconstruction, but erroneous kinematics
— requires fine-tuning to achieve satisfactory motor behavior

MOTOR VARIABILITY

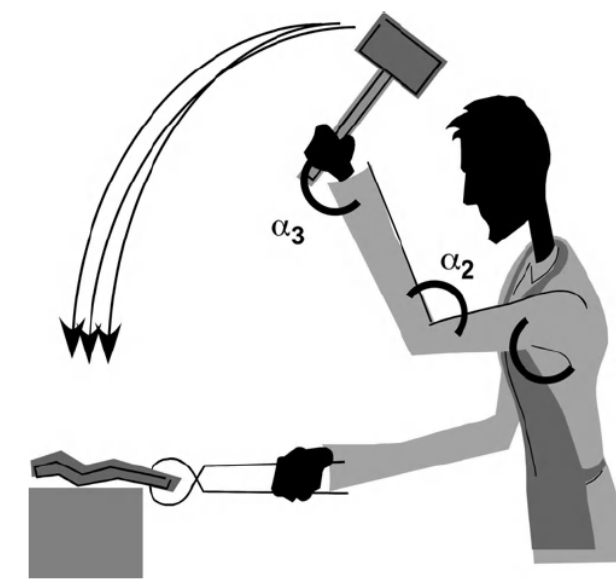
Noise or flexibility?
— variability as noise *vs* structured variability
— how to compare the variability of different motor variables?
— notion of task-relevant and task-irrelevant dimensions
— *uncontrolled manifold* (UCM): **variables that are stabilized by neural control mechanisms are assumed to be less variable than variables not relevant to the motor task**



— Gordon et al., 1994, *Exp Brain Res* 99:97



— Todorov & Jordan, 2002, *Nat Neurosci* 5:1226



UNCONTROLLED MANIFOLD

Configuration space, CVs and subspaces

— controlled variables (CVs)

— *uncontrolled manifold* (UCM)

set of all configurations that lead to the same values of CVs

```
task – pressing with
two effectors with
a total force of 10 N
```

configuration space (F_1, F_2)

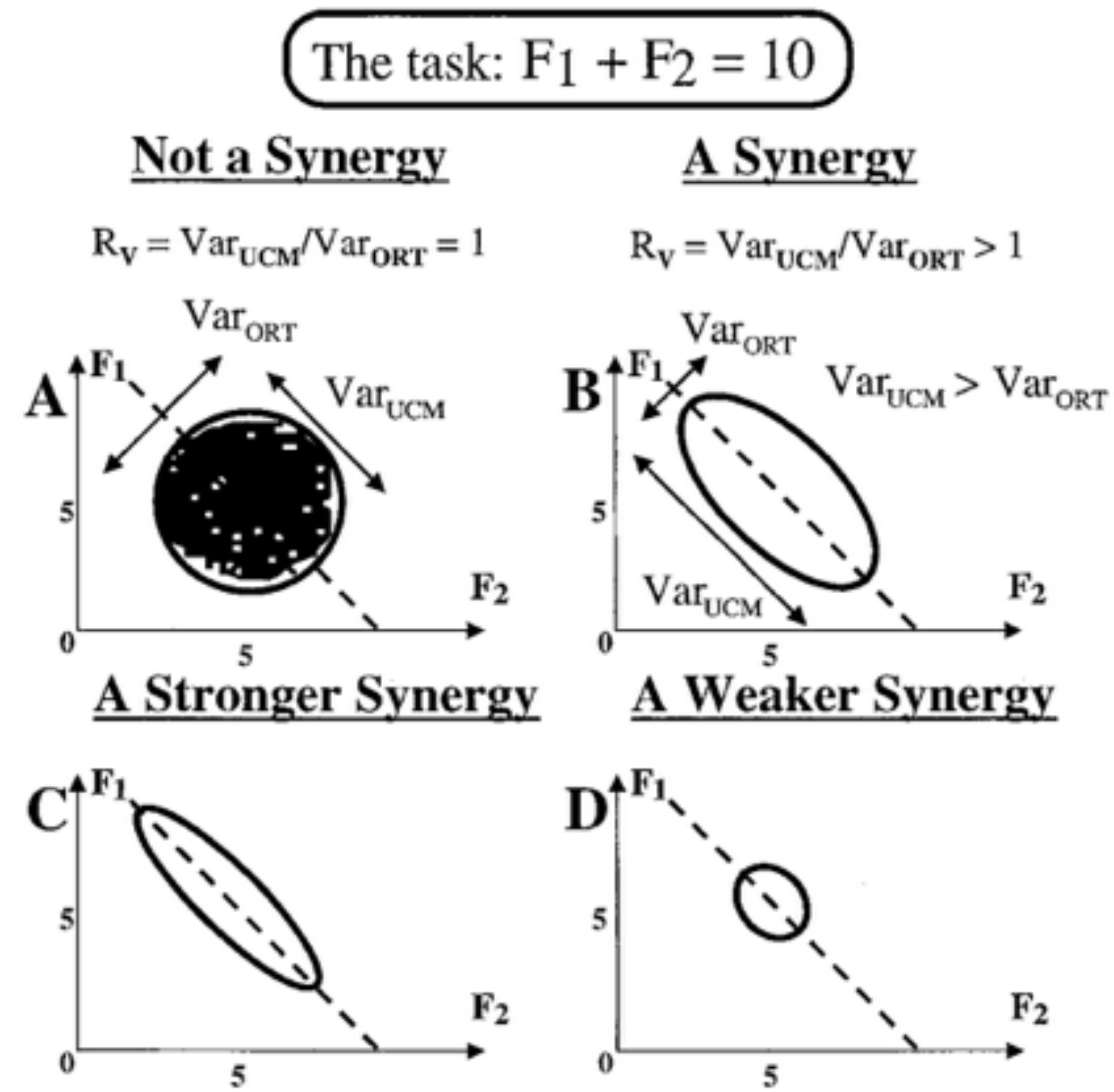
$CV = F_1 + F_2$

UCM – $F_1 + F_2 = 10$

alternative hypothesis

CVs = F_1, F_2

UCM – $F_1 = 5$ and $F_2 = 5$



— Latash et al., 2002, *Exerc Sports Sci Rev* 30:26

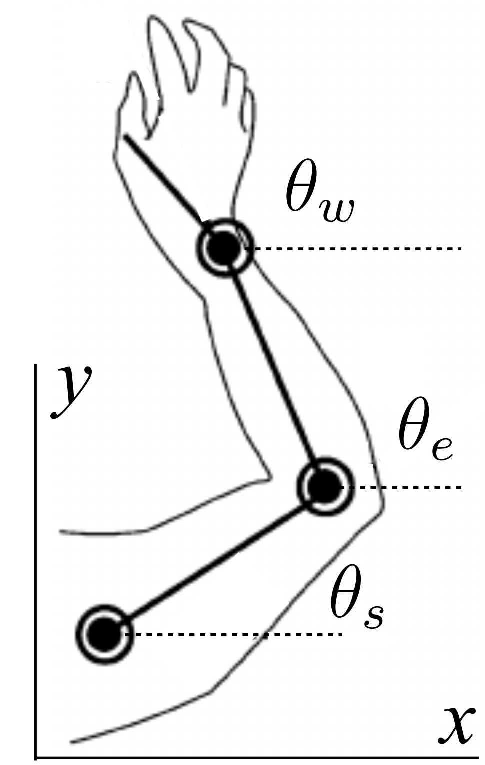
UNCONTROLLED MANIFOLD

Formal example

— final posture of a redundant arm

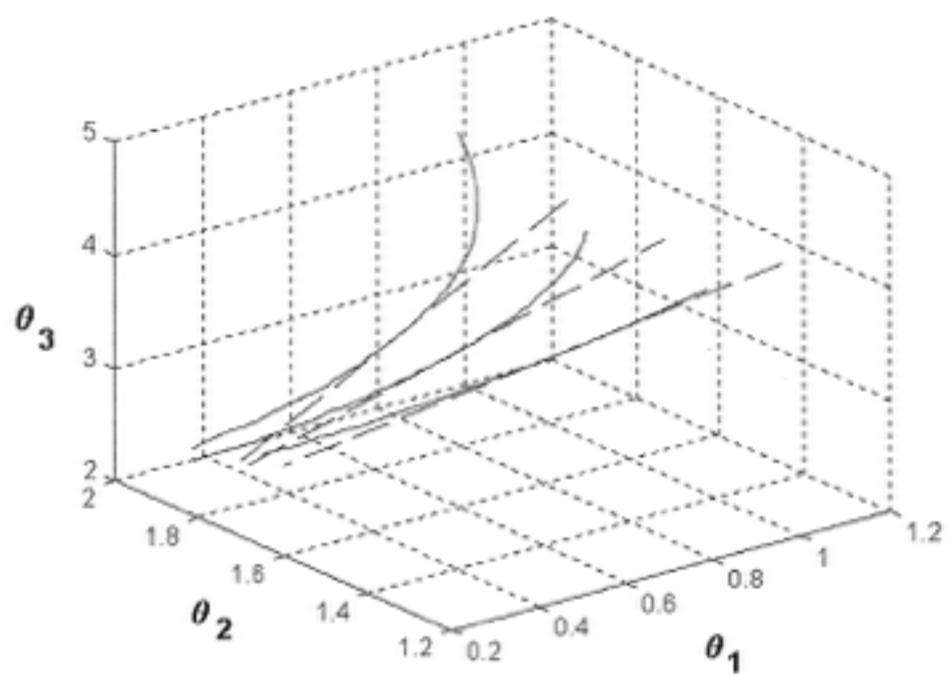
$$\begin{cases} x = L_s \cos\theta_s + L_e \cos\theta_e + L_w \cos\theta_w \\ y = L_s \sin\theta_s + L_e \sin\theta_e + L_w \sin\theta_w \end{cases}$$

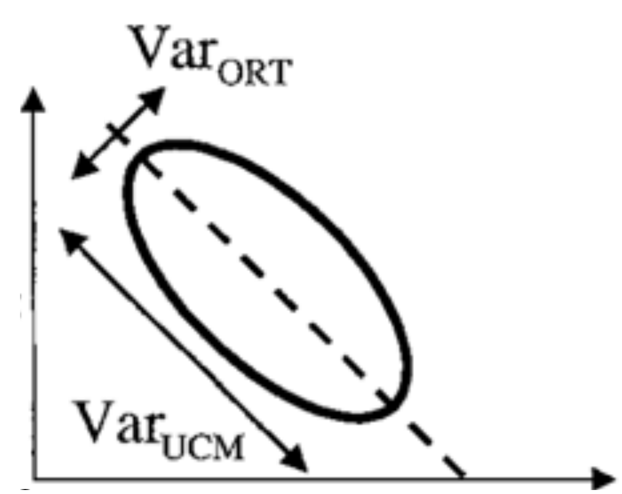
$$\mathbf{J}(\Theta^0) = \begin{pmatrix} -L_s \sin\theta_s^0 & -L_e \sin\theta_e^0 & -L_w \sin\theta_w^0 \\ L_s \cos\theta_s^0 & L_e \cos\theta_e^0 & L_w \cos\theta_w^0 \end{pmatrix}$$



linearized UCM – null space of Jacobian matrix

$$\{\ \varepsilon\ /\ \mathbf{J}(\Theta^0)\varepsilon = 0\ \}$$





analysis – projection of final postures on the linearized UCM and its complement and calculus of variance

— Scholz and Schöner, 1999, *Exp Brain Res* 126:289

UNCONTROLLED MANIFOLD

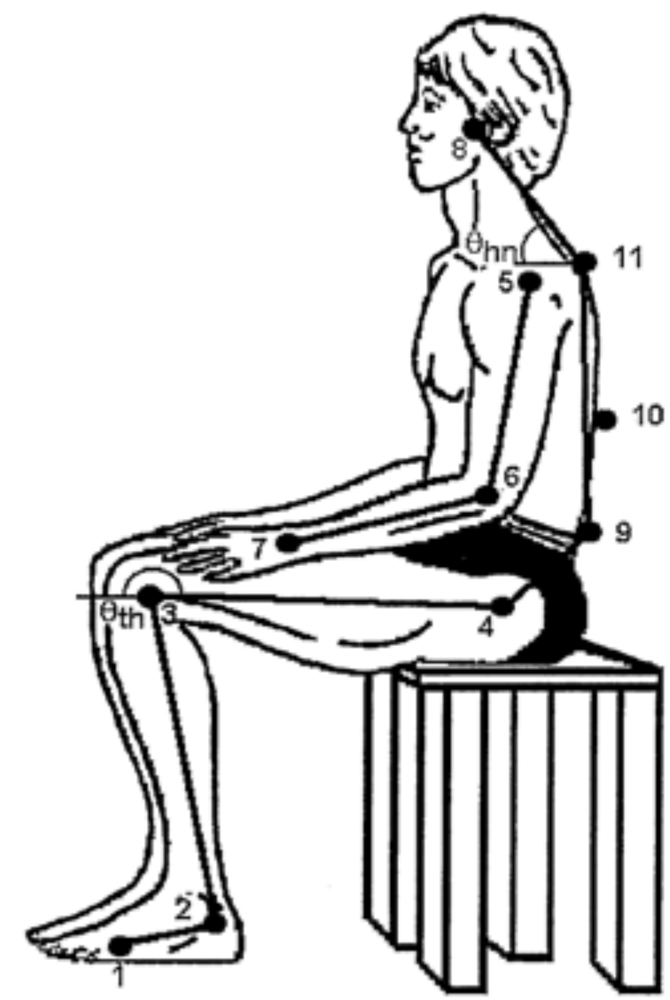
Sit-to-stand task

what are the CVs — center of mass (CM), head or hand position?

$\mathbf{r} = f(\boldsymbol{\Theta}) \qquad \mathbf{r} - \mathbf{r}^0 = \mathbf{J}(\boldsymbol{\Theta}^0)(\boldsymbol{\Theta} - \boldsymbol{\Theta}^0)$

d	dimension of task-space	
n	dimension of joint-space	
$\mathbf{r}$	task-space variable	$\dim d$
$\boldsymbol{\Theta}$	joint-space variable	$\dim n$
$\boldsymbol{\Theta}^0$	reference joint-space value	
f	forward kinematics	
$\mathbf{J}$	Jacobian matrix	$\dim d \times n$
$\{\, \varepsilon \,/\, \mathbf{J}(\boldsymbol{\Theta}^0)\varepsilon = 0 \,\}$	null space	$\dim n - d$
$\varepsilon_i \; (i = 1 \ldots n - d)$	basis of the null space	

null space	component	variability per dof
$\parallel$	$\boldsymbol{\Theta}_\parallel = \sum_i^{n-d} \varepsilon_i . (\boldsymbol{\Theta} - \boldsymbol{\Theta}^0)$	$\sigma_\parallel^2 = \frac{\sum \boldsymbol{\Theta}_\parallel^2}{(n-d) N_{\text{trials}}}$
$\perp$	$\boldsymbol{\Theta}_\perp = (\boldsymbol{\Theta} - \boldsymbol{\Theta}^0) - \boldsymbol{\Theta}_\parallel$	$\sigma_\perp^2 = \frac{\sum \boldsymbol{\Theta}_\perp^2}{d N_{\text{trials}}}$

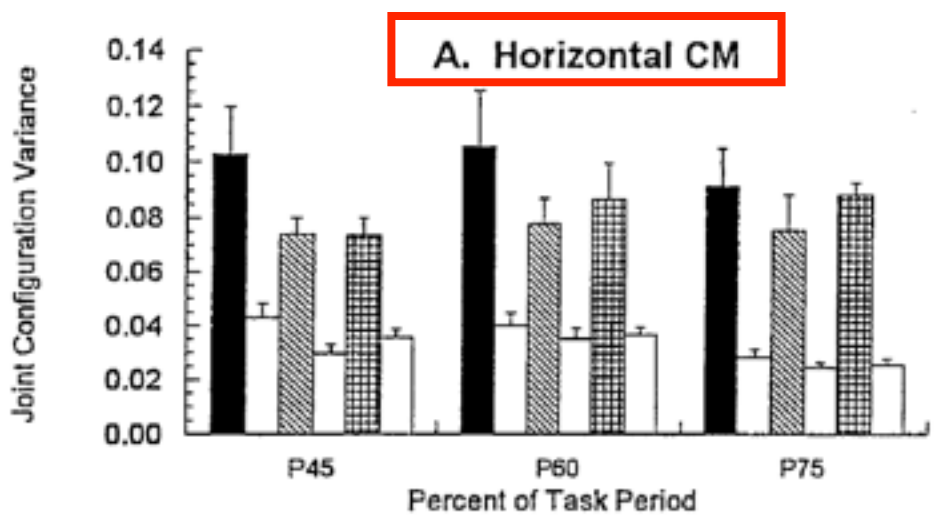


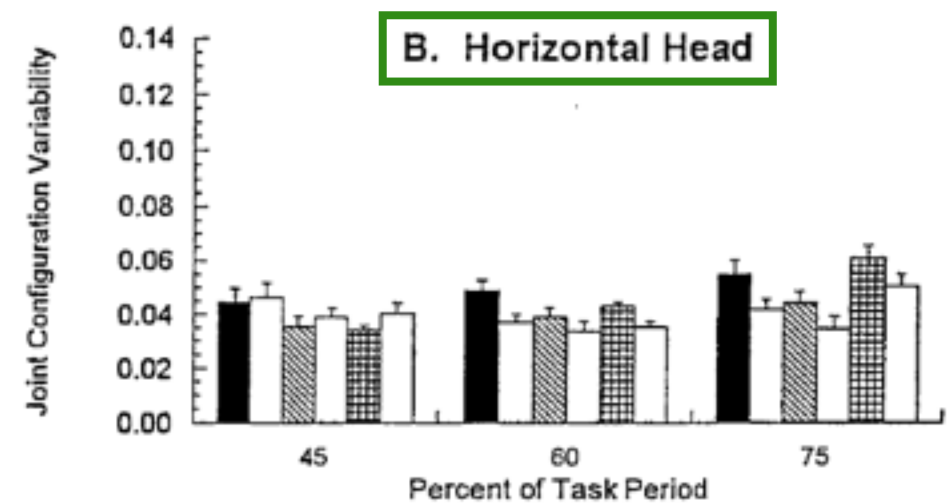
— Scholz and Schöner, 1999, *Exp Brain Res* 126:289

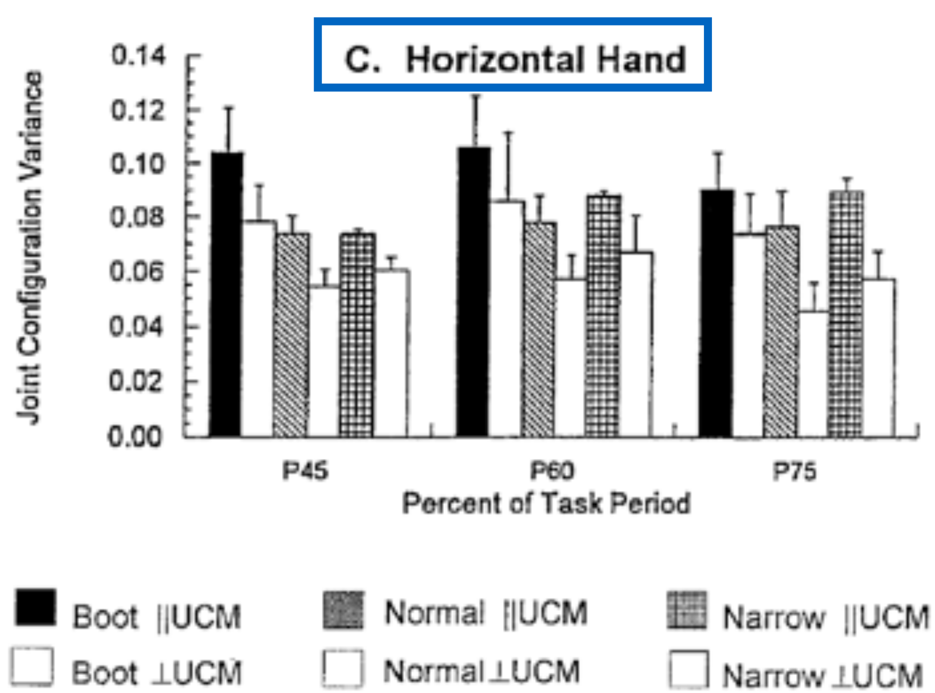
UNCONTROLLED MANIFOLD

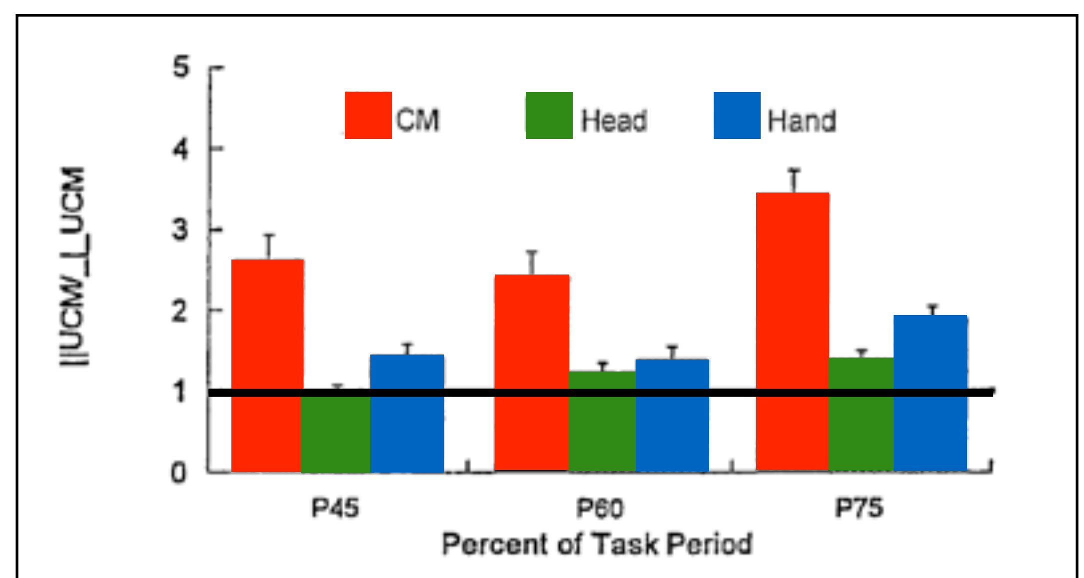
Sit-to-stand task

Boot (*restricted ankle motion*), Normal, Narrow (*base of support*)







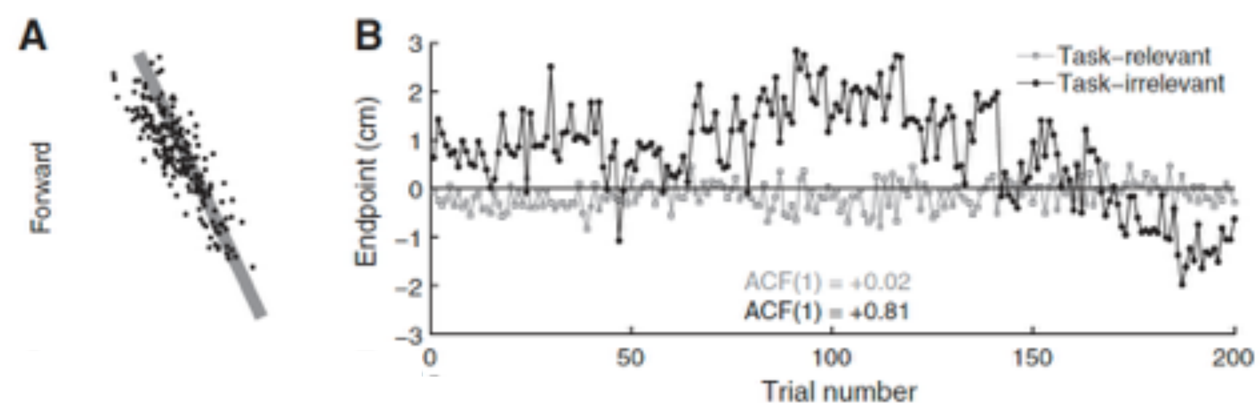


— Scholz and Schöner, 1999, *Exp Brain Res* 126:289

TIME SERIES ANALYSIS

Variability across time/trials

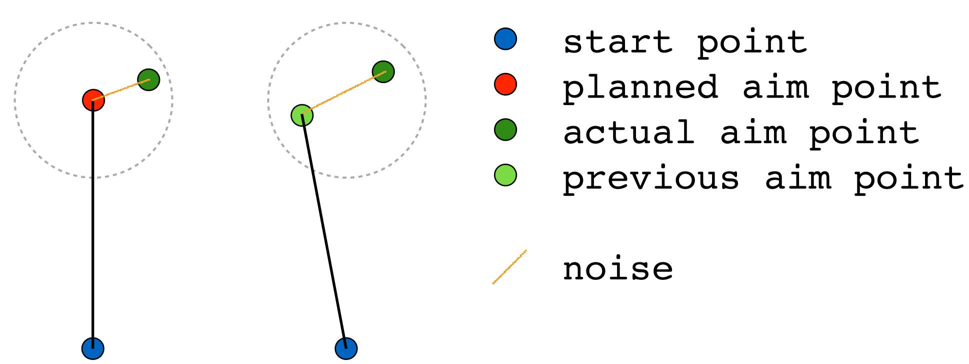
e.g. spatial errors in a pointing task — random effects independently added to a constant mean?



lag 1 autocorrelation

$$\mathrm{ACF}(1) = \frac{\sum_{t=6}^{n-1} x^{(t)}x^{(t+1)} - \frac{1}{n-6}\left(\sum_{t=6}^{n-1} x^{(t)}\right)\left(\sum_{t=6}^{n-1} x^{(t+1)}\right)}{\sum_{t=6}^{n-1} \left(x^{(t+1)}\right)^2 - \frac{1}{n-6}\left(\sum_{t=6}^{n-1} x^{(t+1)}\right)^2}$$

Two strategies



variations in successive movements are not independent

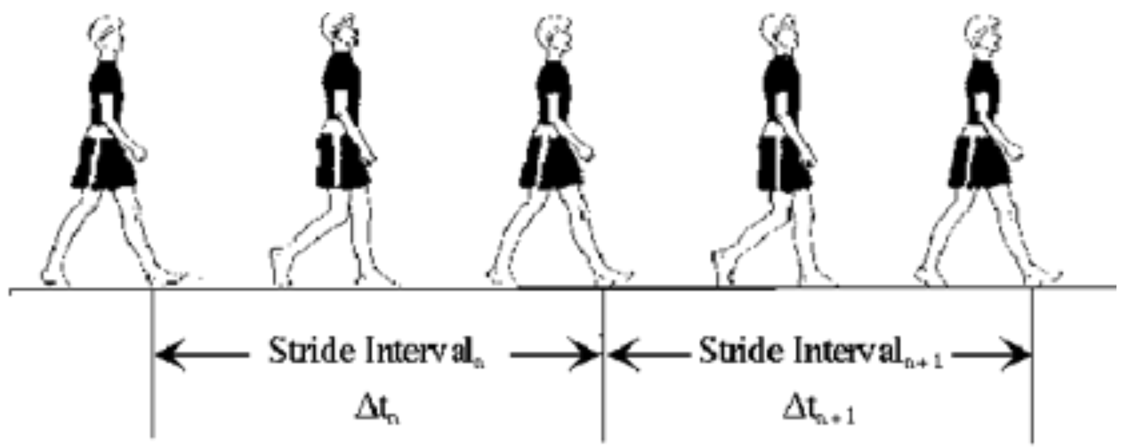
— van Beers et al., 2013, *J Neurophysiol* 109:969

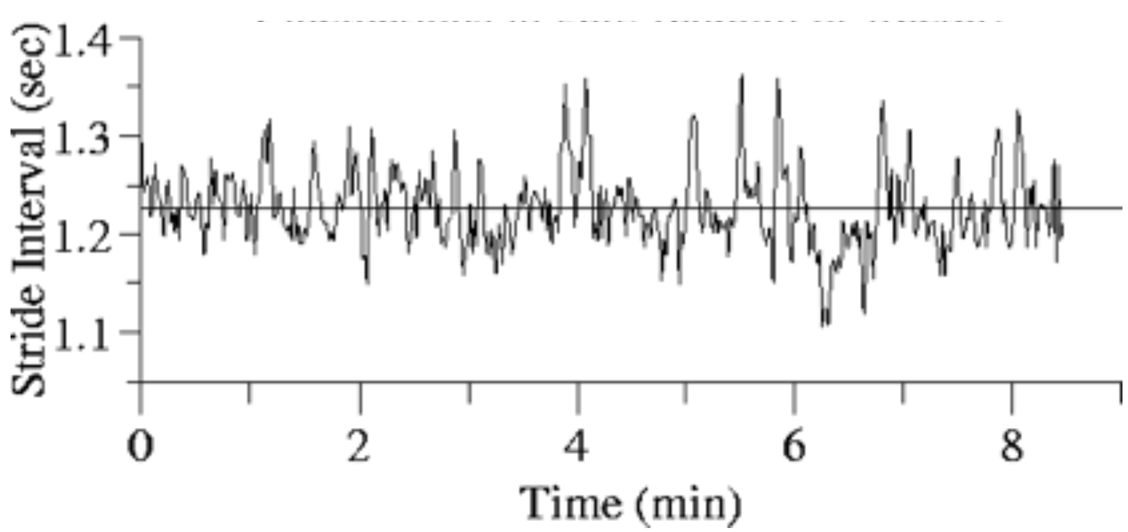
SPECTRUM ANALYSIS

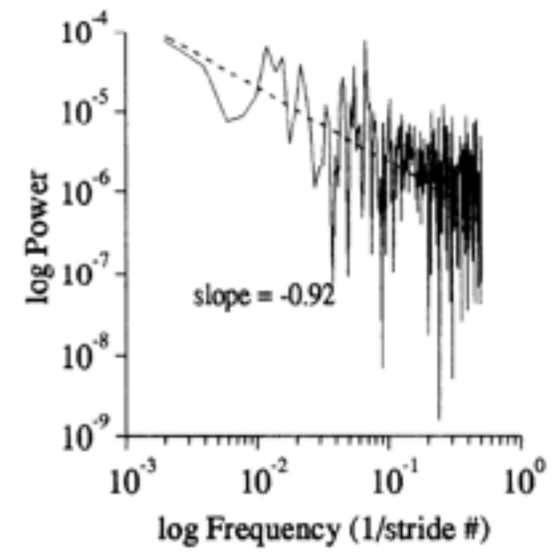
Fourier analysis

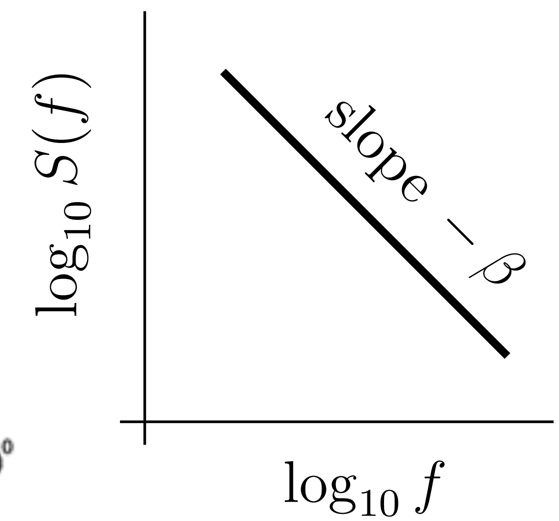
— power spectrum

e.g. *stride interval during locomotion*

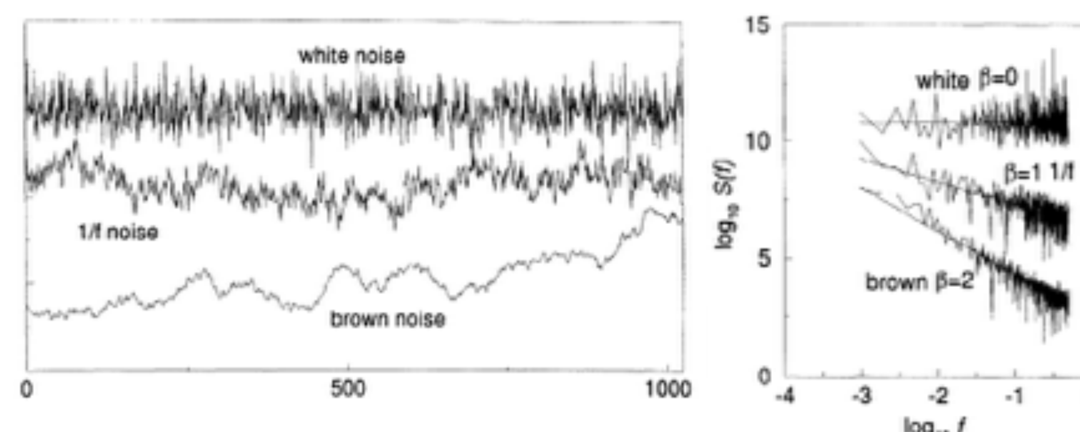








simulations



$\beta = 0$	white noise	$S(f) \approx 1/f^{\beta}$
$\beta = 1$	1/f noise	
$\beta = 2$	Brownian noise	

— Hausdorff et al., 1995, *J Appl Physiol* 78:349

— Hausdorff et al., 1996, *J Appl Physiol* 80:1448

ENTROPY ANALYSIS

Approximate entropy (ApEn)

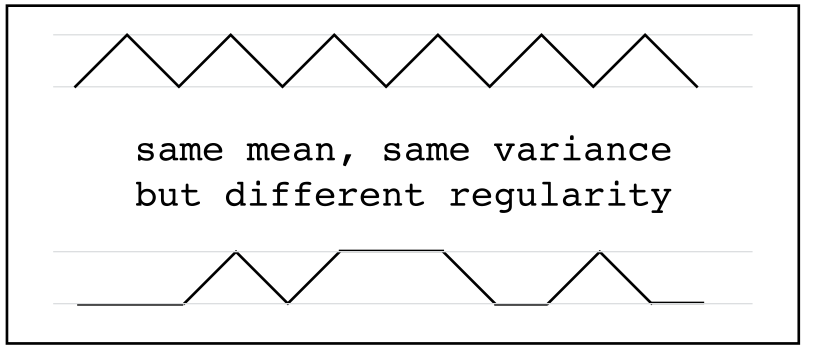
— how to quantify the difference in regularity of physiological signals (e.g. *normal* vs *pathological*)?

m integer, $r > 0$

$u(1), \ldots, u(N)$ time series of raw measurements

$\mathbf{x}(1), \ldots, \mathbf{x}(N-m+1)$ sequence of vectors in $\mathbb{R}^m$

$$\mathbf{x}(i) = [u(i), \ldots, u(i+m-1)]$$



$$C_i^m(r)_{(1 \le i \le N-m+1)} = \frac{\text{number of } \mathbf{x}(j) \;/\; d[\mathbf{x}(i), \mathbf{x}(j)] \le r_{(1 \le j \le N-m+1)}}{N-m+1}$$

$$d[\mathbf{x}(i), \mathbf{x}(j)] = \max_k |\mathbf{x}(i)_k - \mathbf{x}(j)_k|$$

$$\Phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \log(C_i^m(r))$$

$$\text{ApEn} = \Phi^m(r) - \Phi^{m+1}(r)$$

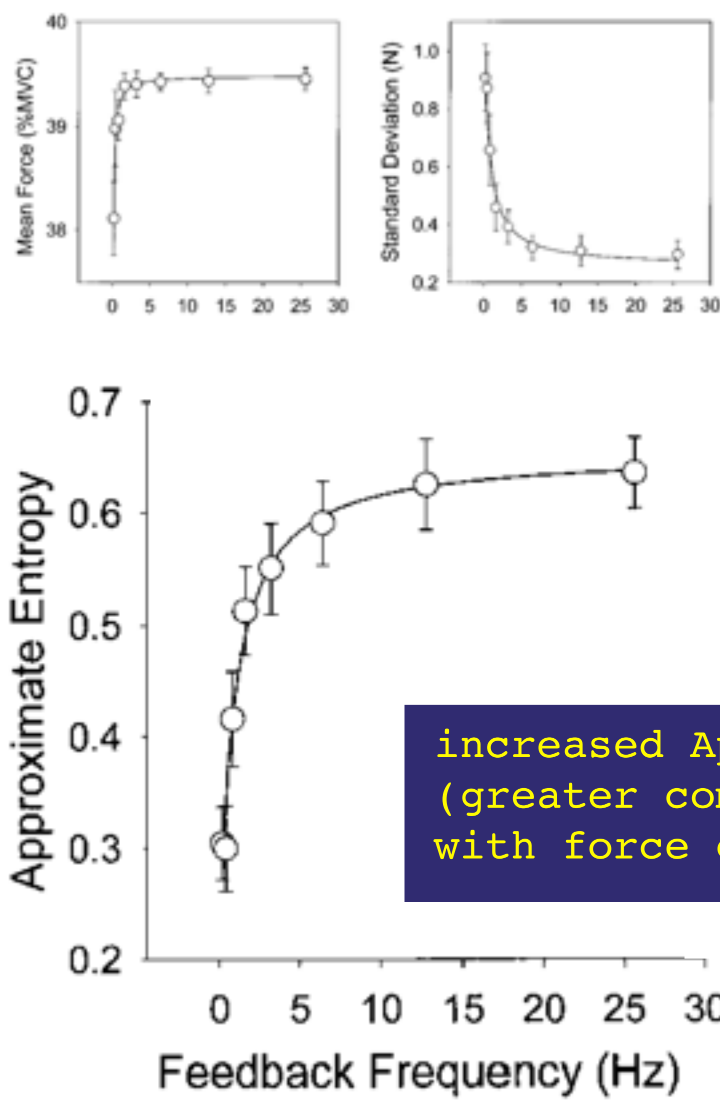
— likelihood that similar patterns of observations will not be followed by additional similar observations
— many repetitive patterns ➔ small ApEn

— Pincus et al., 1991, *J Clin Monit* 7:335

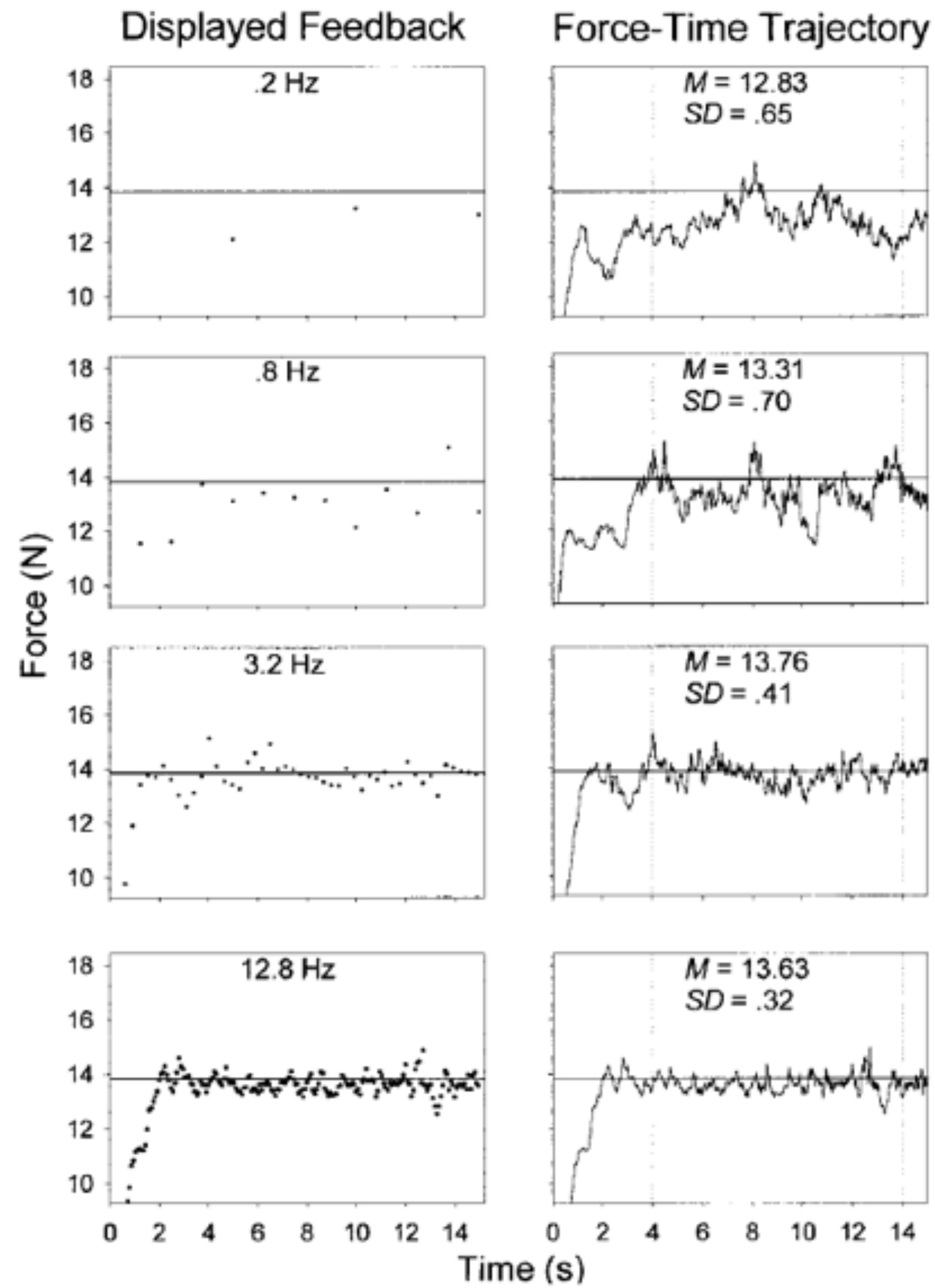
EXAMPLE — ENTROPY ANALYSIS

Isometric force

visual feedback frequency



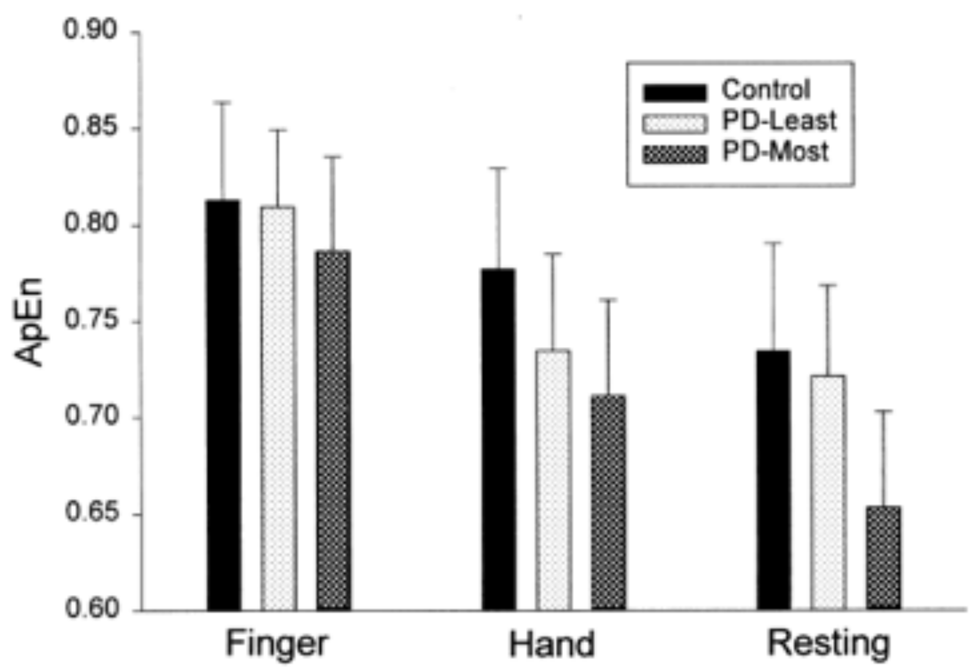
increased ApEn
(greater complexity)
with force output

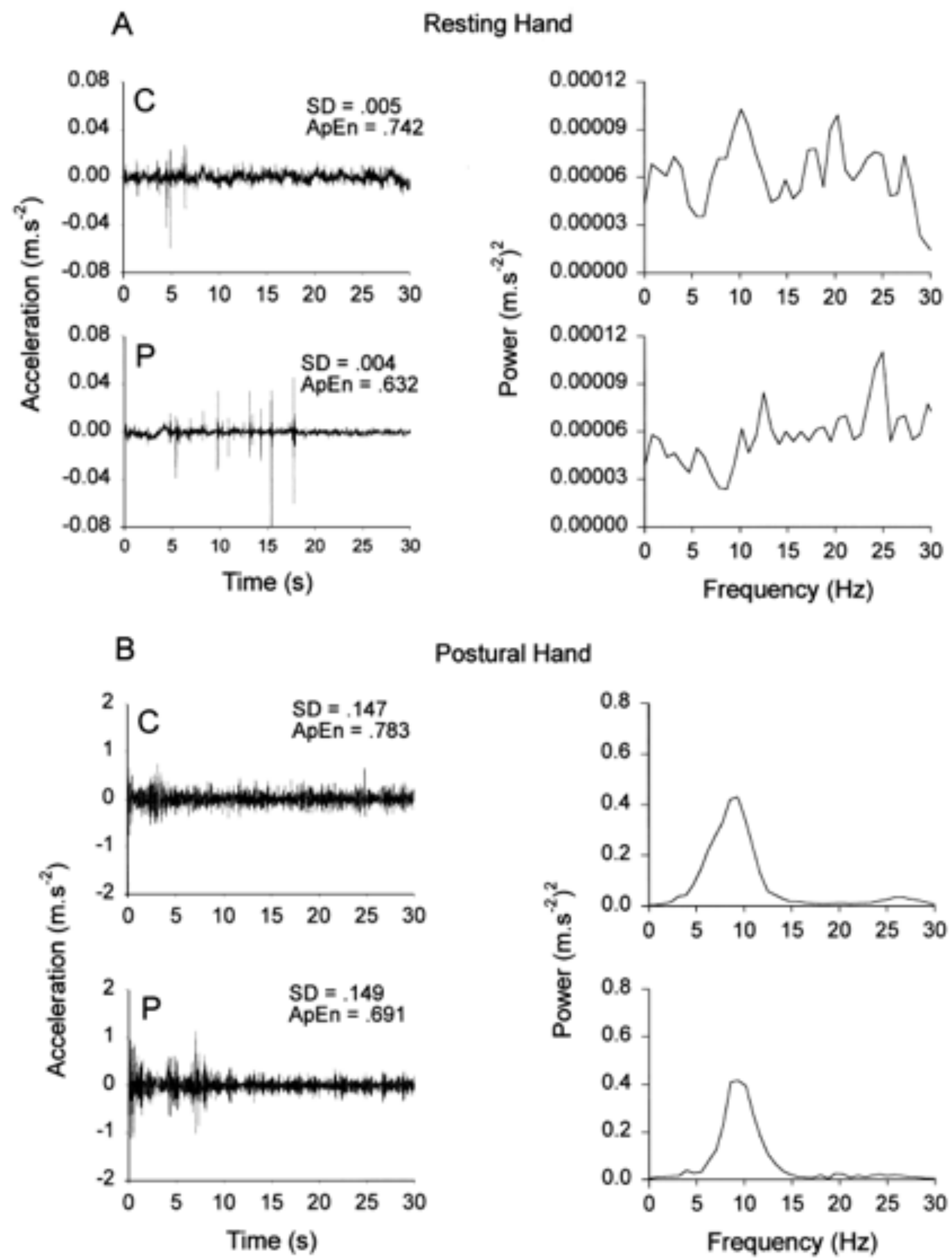


— Slifkin et al., 2000, *J Neurophysiol* 84:1708

EXAMPLE — ENTROPY ANALYSIS

Tremor
in Parkinson's disease






```
reduction of the complexity of
tremor in patient, strong
negative correlation between
UPDRS and ApEn
```

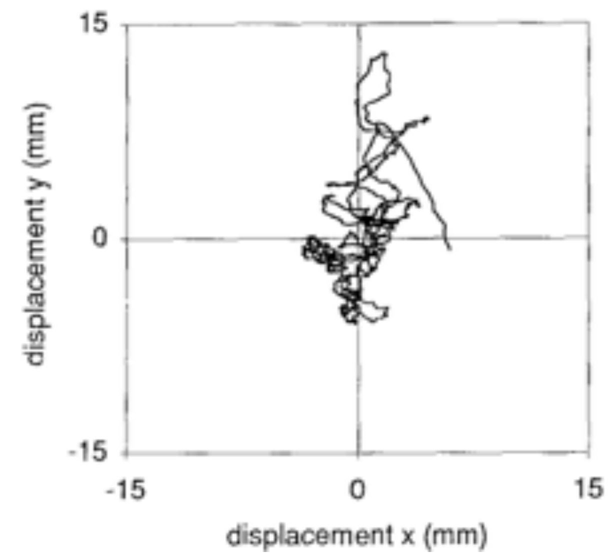
—Vaillancourt and Newell, 2000,
Clin Neurophysiol 111:2046

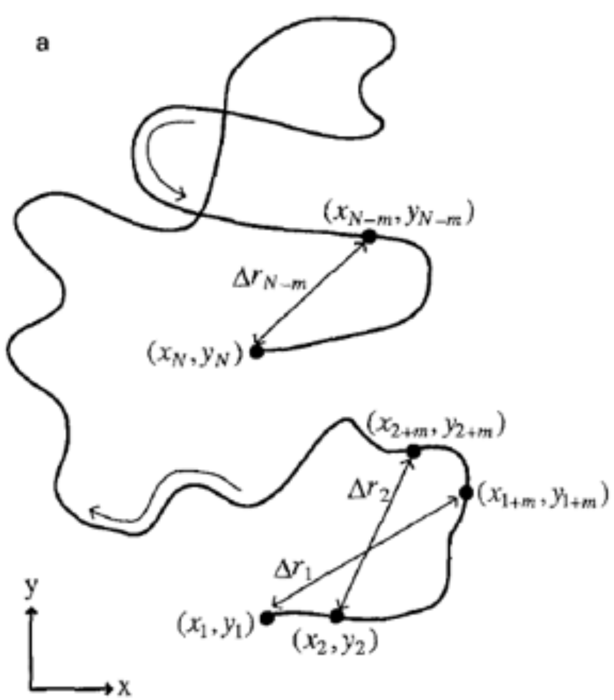
DIFFUSION ANALYSIS

Posture quiet stance

— CoP (center of pressure) trajectory during quiet standing

— summary statistics (length of sway path, average radial area)





For a given Δt (spanning m data intervals):

$$< \Delta r^2 >_{\Delta t} = \frac{\sum_{i=1}^{N-m} (\Delta r_i)^2}{(N-m)}$$

`random walk (Brownian motion)`

$$\langle \Delta r^2 \rangle = 2D\Delta t$$

`fractional Brownian motion`

$$\langle \Delta r^2 \rangle \sim \Delta t^{2H} \quad 0 < H < 1$$

`correlation`

$$C = 2(2^{2H-1} - 1)$$

$H = 1/2 - C = 0 -$ random walk

$H > 1/2 - C > 0 -$ persistence

$H < 1/2 - C < 0 -$ anti-persistence

— Collins and De Luca, 1993, *Exp Brain Res* 95:308

DIFFUSION ANALYSIS

Stabilogram diffusion plot

CoP (center of pressure) trajectory during quiet standing

$H_s > 1/2$ persistence

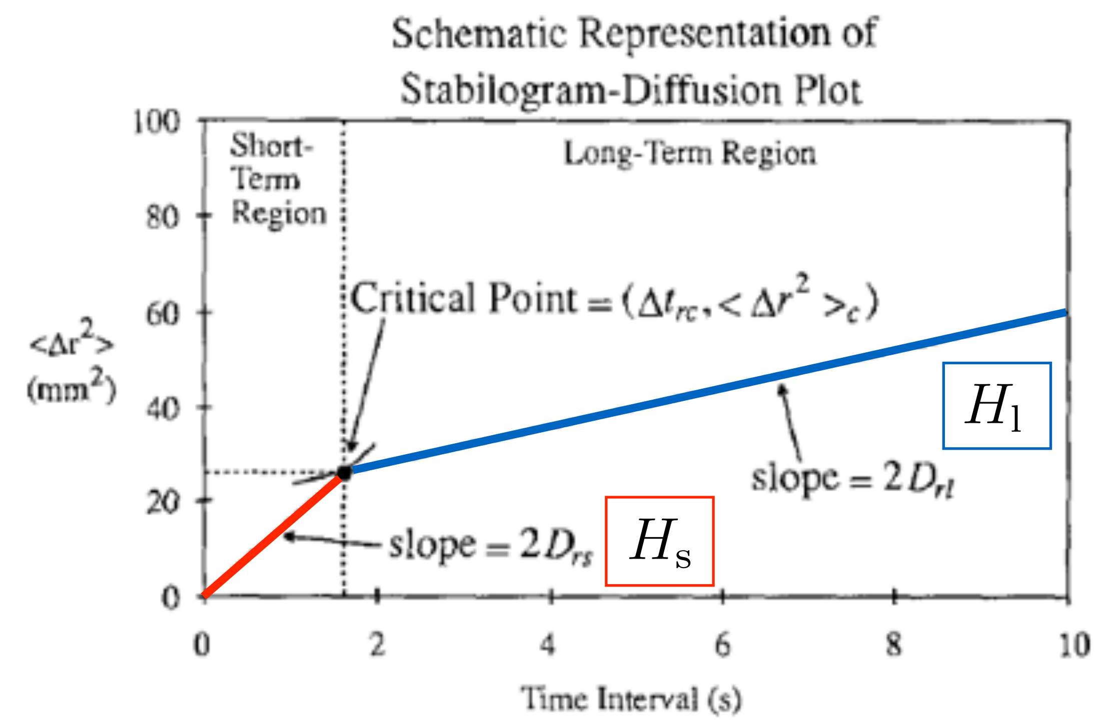
$H_l < 1/2$ anti-persistence

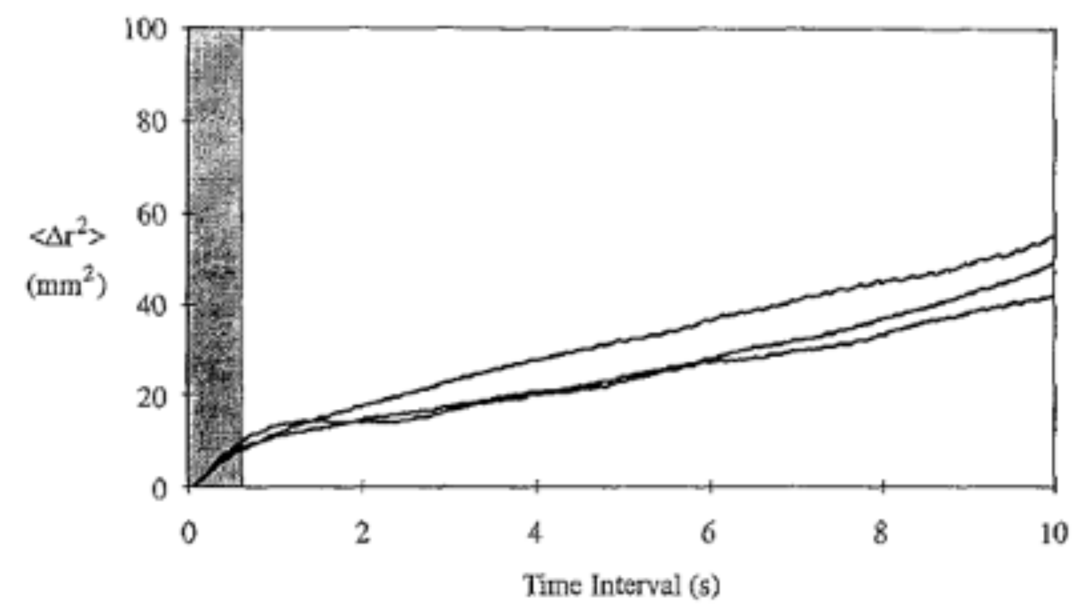
– over short time intervals, the postural system is not controlled (open-loop)

– at long time interval, there is active feedback control (closed-loop)

interpretation?

— Collins and De Luca, 1993, *Exp Brain Res* 95:308





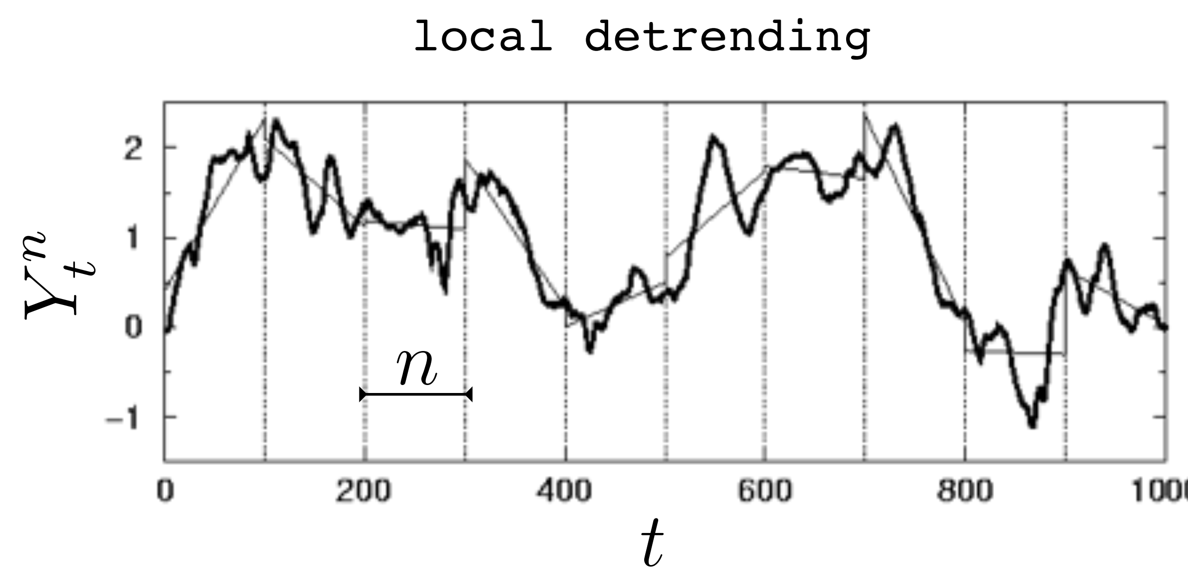
FRACTAL ANALYSIS

Detrended fluctuation analysis

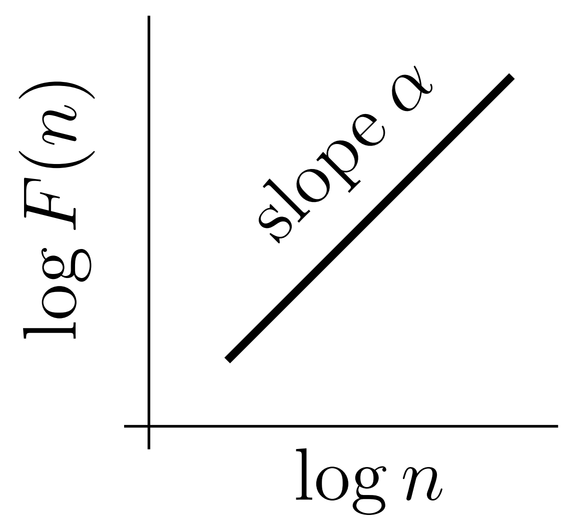
$$x_t \quad (t = 1 \ldots N)$$

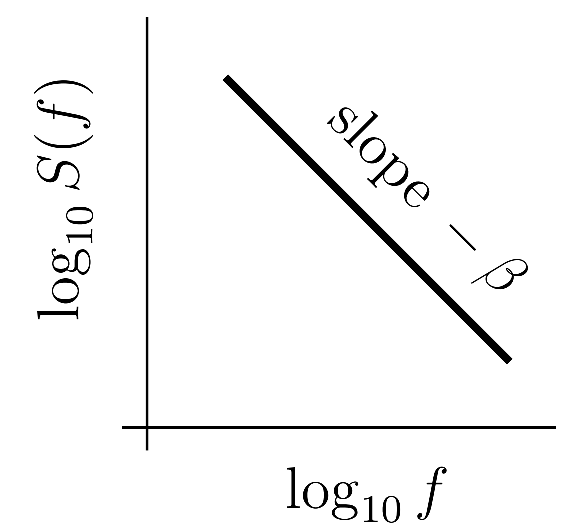
$$X_t = \sum_{i=1}^{t} (x_i - \langle x \rangle)$$

$$F(n) = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (X_t - Y_t^n)^2}$$



- $\alpha < 1/2$: anti-correlated
- $\alpha \simeq 1/2$: uncorrelated, white noise
- $\alpha > 1/2$: correlated
- $\alpha \simeq 1$: 1/f-noise, pink noise
- $\alpha > 1$: non-stationary, unbounded
- $\alpha \simeq 3/2$: Brownian noise





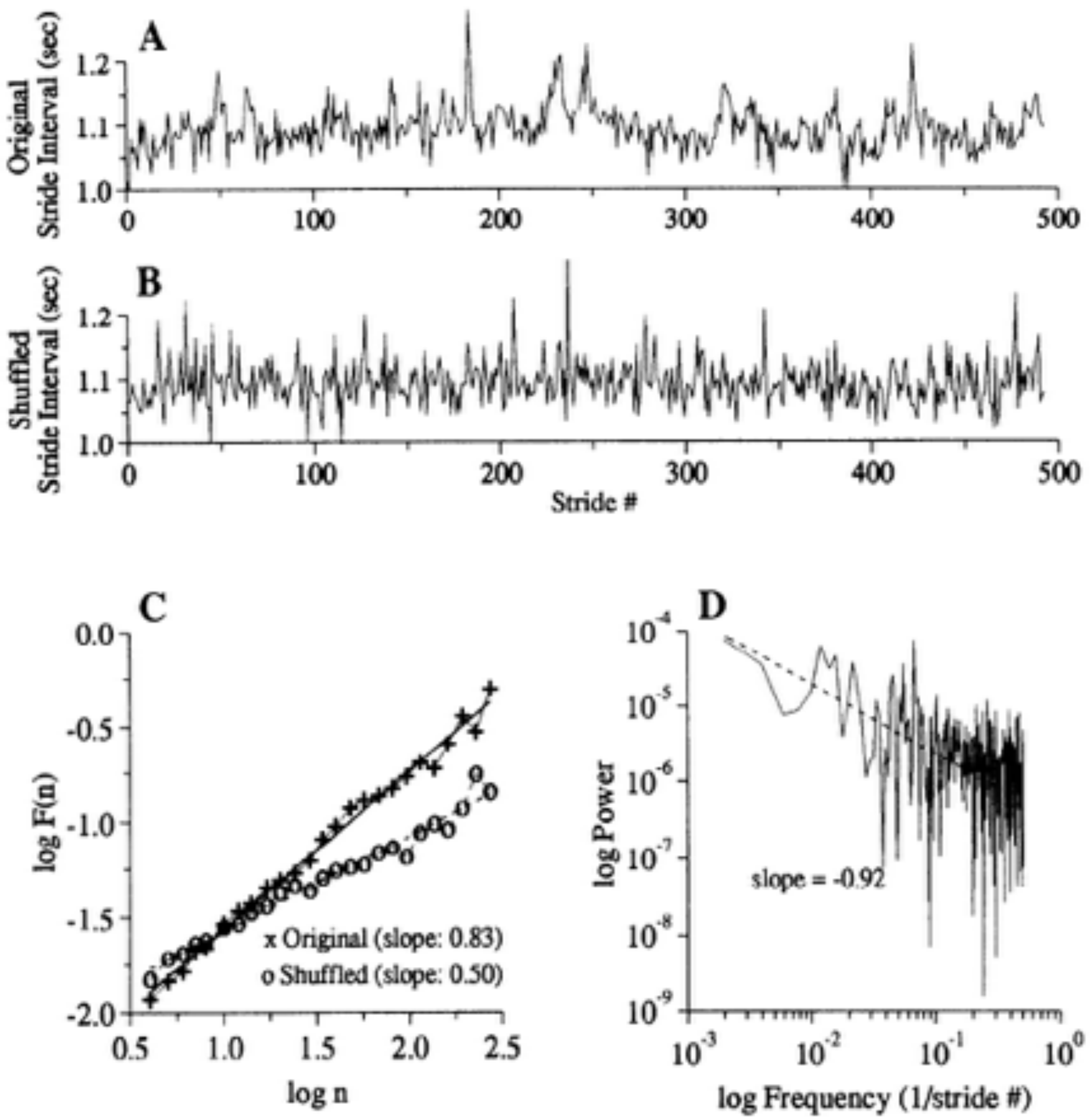
lower α – less correlated structure, less predictability

$\alpha = (\beta + 1)/2$ (data of infinite length)

EXAMPLE — FRACTAL ANALYSIS

Stride interval during locomotion

9-min walking at self-determined speed



— noisy fluctuations in stride duration during walking display complex fractal properties

— variability not simply attributable to uncorrelated random fluctuations, but exhibited long-range power-law correlations and self-similarity, indicative of a fractal process

— long-memory processes

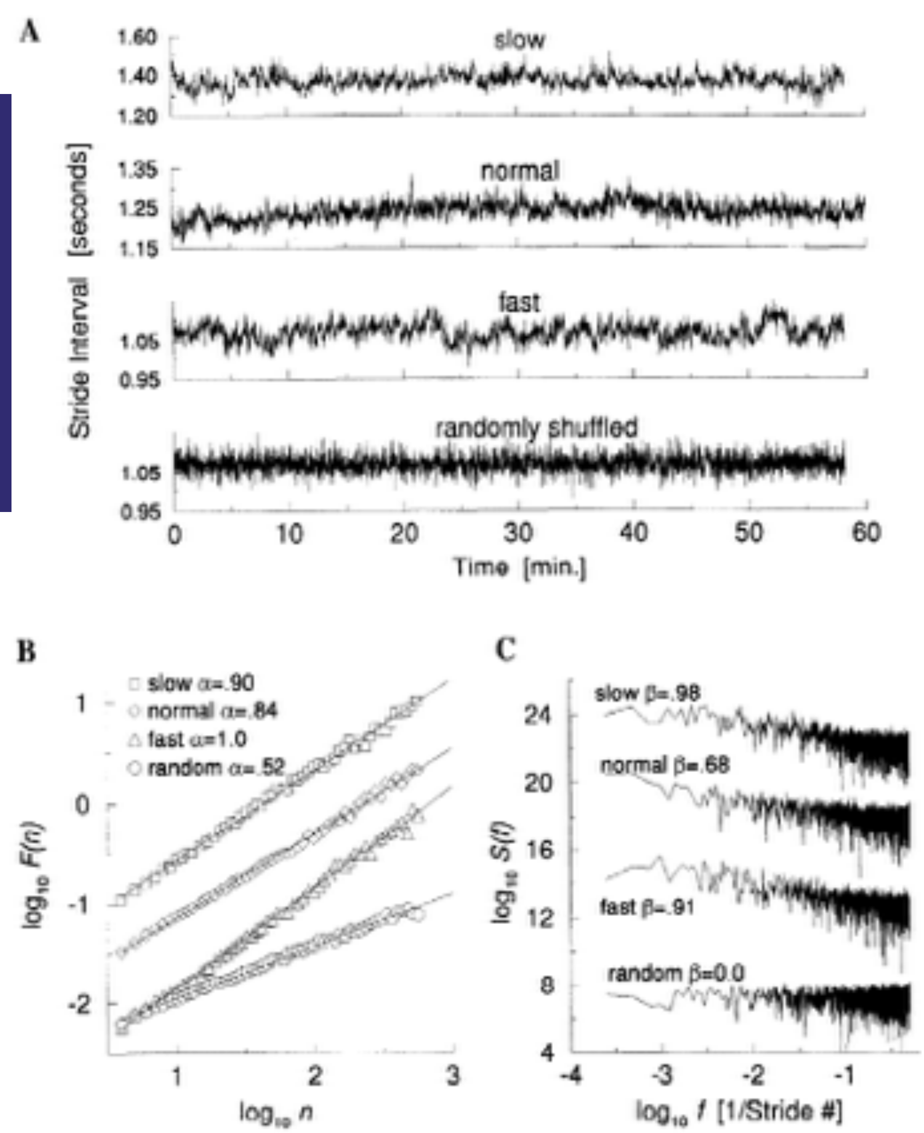
— Hausdorff et al., 1995, *J Appl Physiol* 78:349

EXAMPLE — FRACTAL ANALYSIS

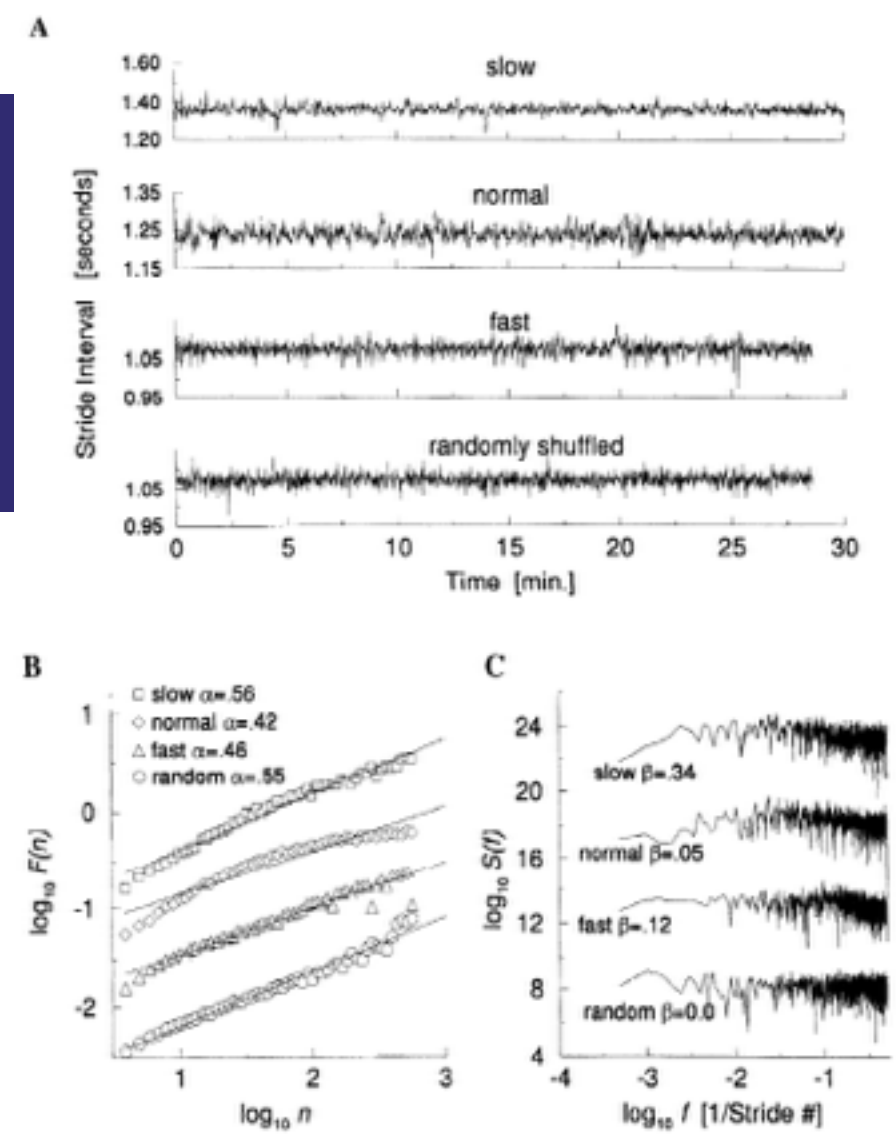
Stride interval during locomotion

1-hour walking at usual, slow and fast paces w/o metronome

spontaneous



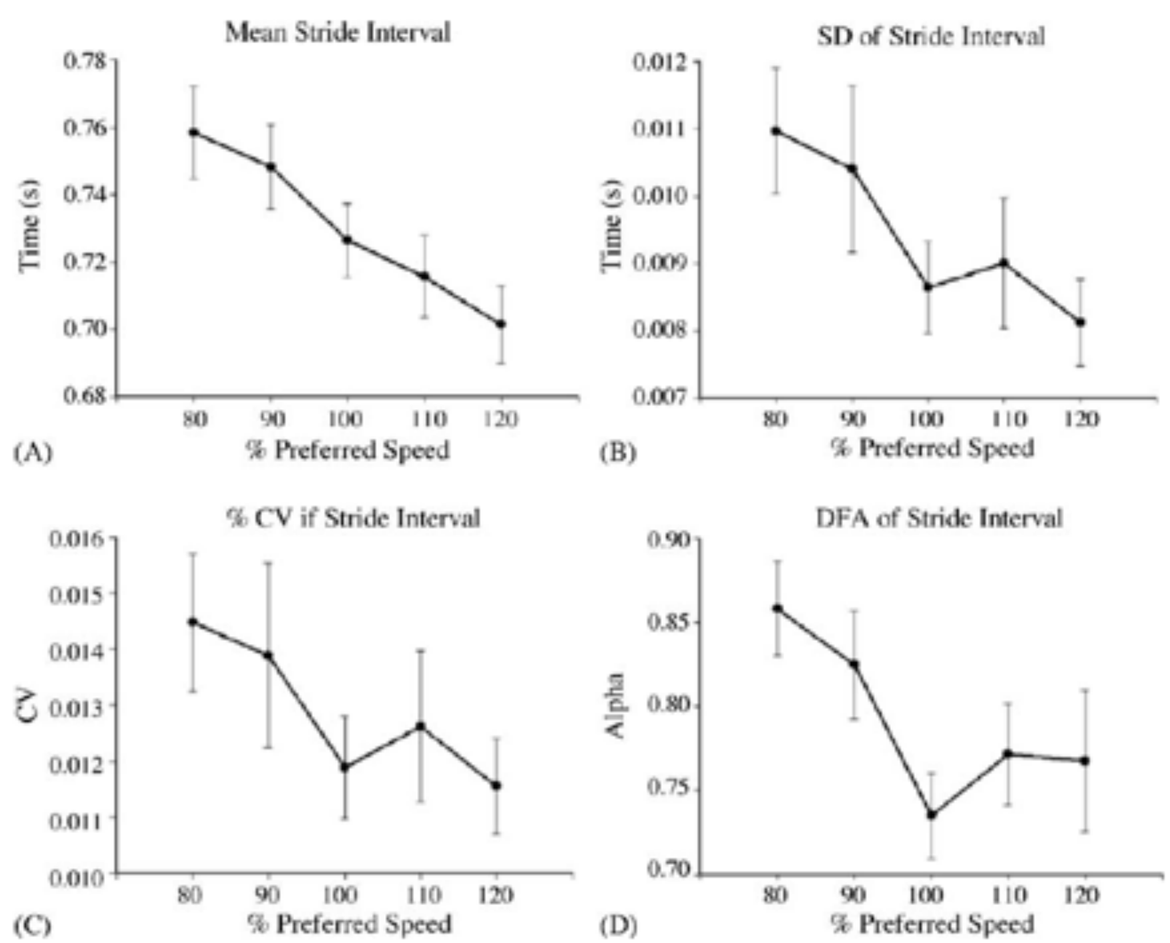
metronome

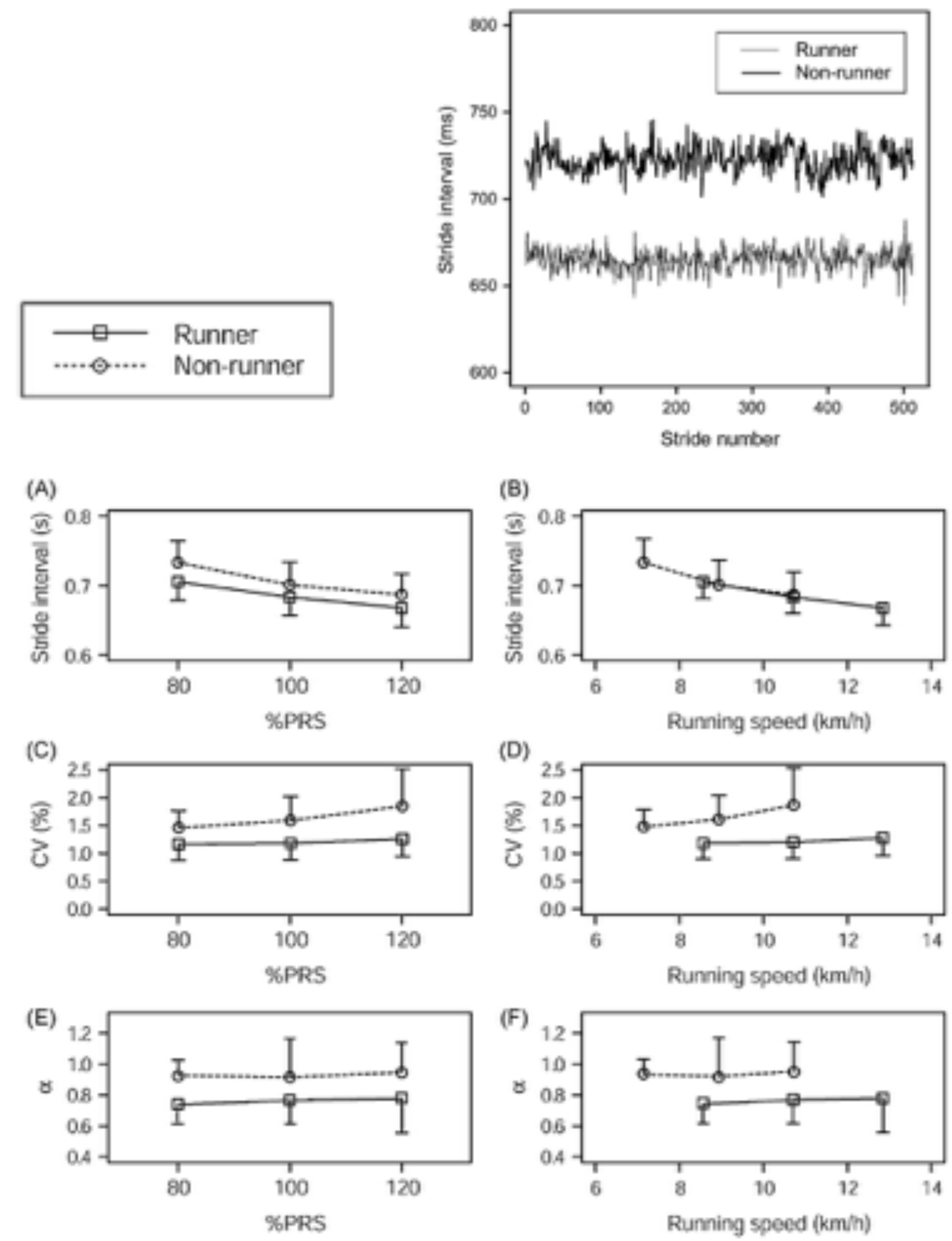


— Hausdorff et al., 1996, *J Appl Physiol* 80:1448

EXAMPLE — FRACTAL ANALYSIS

Running





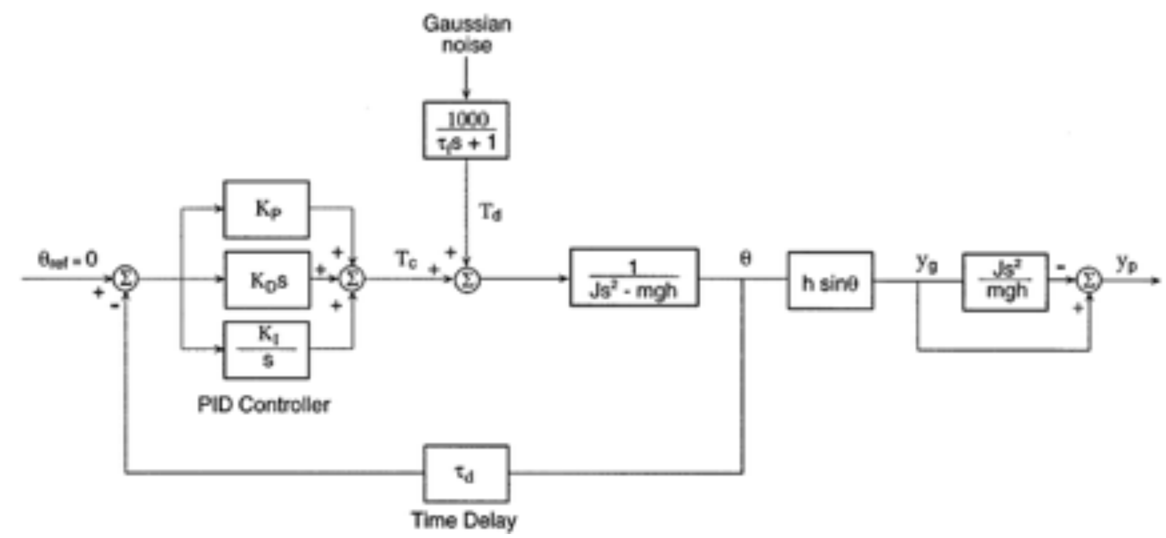
— Jordan et al., 2006, *Gait Posture* 24:120

— Nakayama et al., 2010, *Gait Posture* 31:331

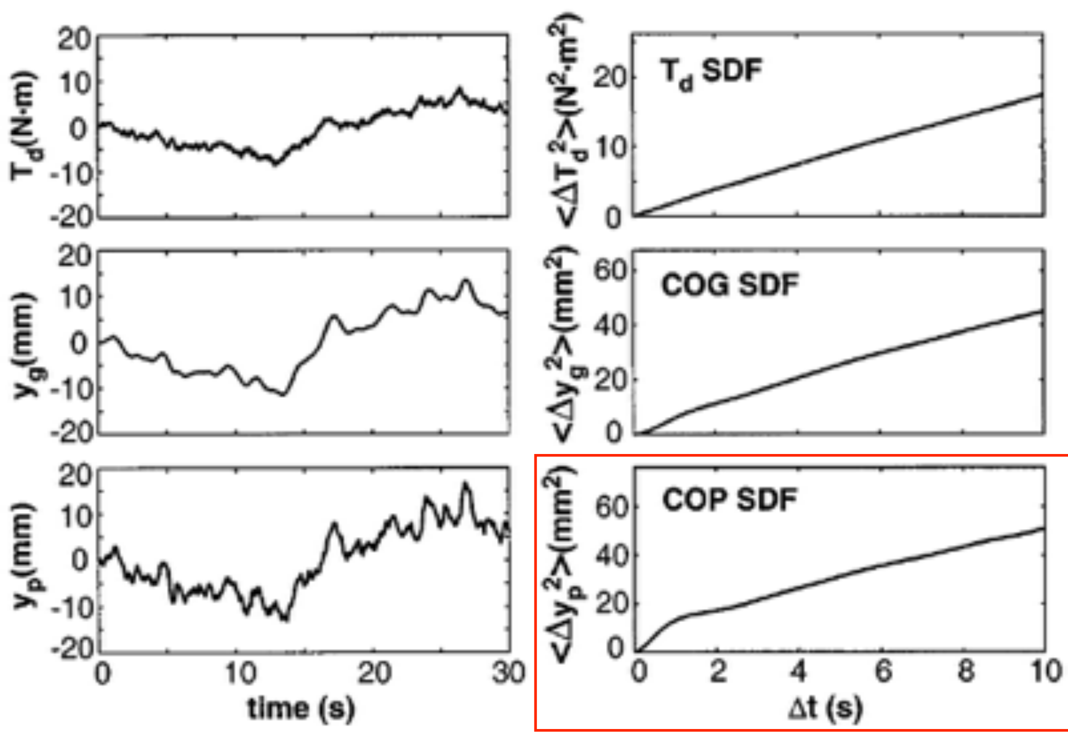
MODELING PROPERTIES OF TIME SERIES

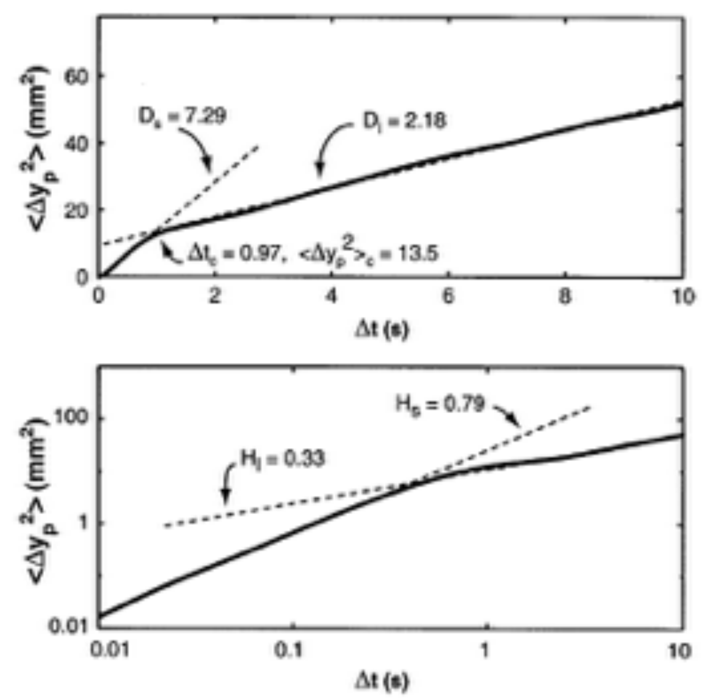
Postural sway

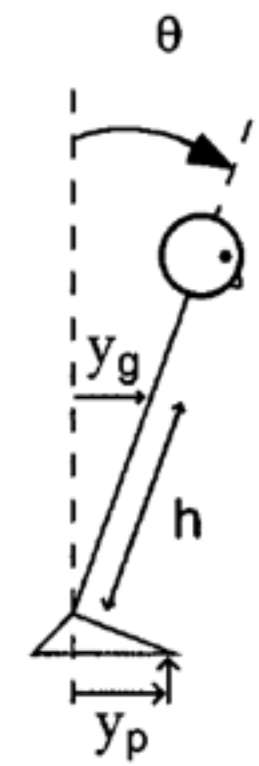
classical feedback control model



stabilogram diffusion plot







D_s	D_l	Δt_c	$<\Delta y_p^2>_c$	H_s	H_l
7.29	2.18	0.97	13.05	0.79	0.33
7.27±4.11	2.51±1.76	0.97±0.46	12.6±10.71	0.77±0.04	0.38±0.1

— Peterka, 2000, *Biol Cybern* 82:335

— Collins and De Luca, 1993, *Exp Brain Res* 95:308

MODELING PROPERTIES OF TIME SERIES

- **Postural sway**

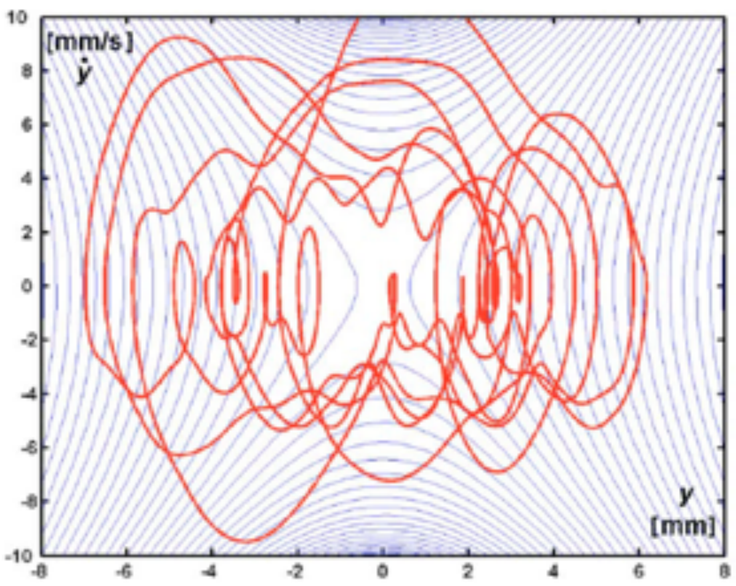
— classical feedback control model
— can reproduce some experimental characteristics
— when driven by suitable noise

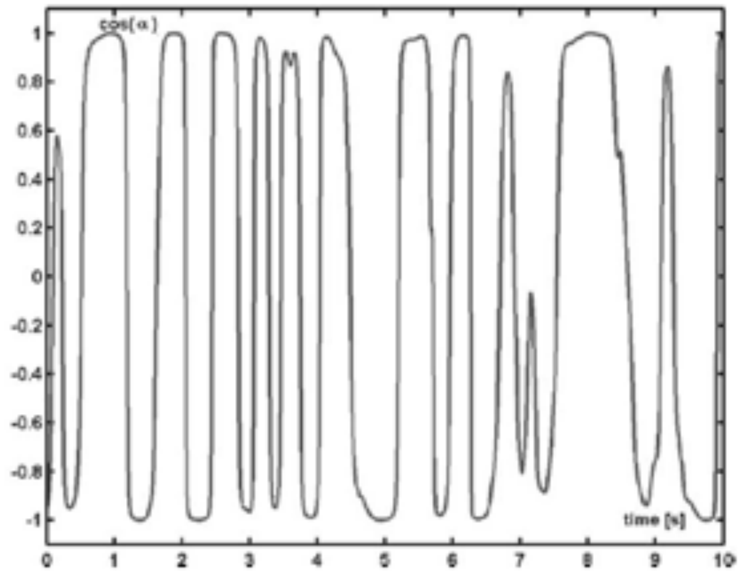
- **But**

— the sway pattern (CoM) is not the result of a specific control action (magnitude of action ≈ size of noise)
— intermittency: stabilization phase

data	0.40±0.29 s
model	0.02±0.03 s

— Bottaro et al., 2005, *Hum Mov Sci* 24:588





DISCLAIMER ON TIME SERIES ANALYSIS

- **Methods sensitive to the nature of the signal**

duration, sampling frequency, nonstationarity
e.g. *an increase in entropy cannot generally be interpreted as a reflection of the same physiological changes across all studies*

- **Unreliable?**

— two-stage model of Collins and De Luca (1993): statistical artifacts? (Delignières et al. 2003)
— disappearance of fractal correlations in stride interval series in metronomic conditions (Hausdorff et al. 1996): not confirmed by an ARMA method (Delignières and Torre 2009)

- **Loss-of-complexity hypothesis**

— Delignières et al., 2003, *J Mot Behav* 35:86
— Delignières and Torre, 2009, *J Appl Physiol* 106:1271