Nintendo Wii Fit -based balance testing to detect sleep deprivation: Approximate Bayesian computation -approach

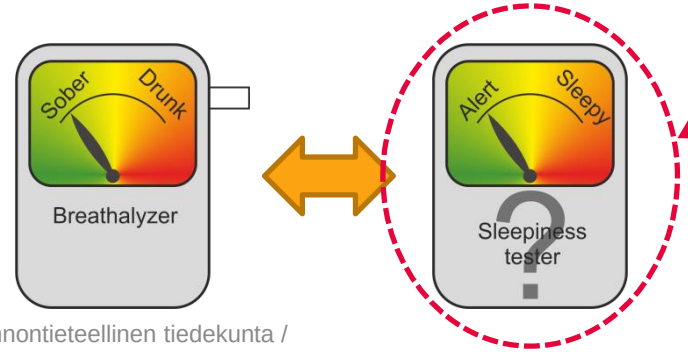
Aino Tietäväinen, Lic. Phil.,
Prof. Edward Hæggström,
Prof. Jukka Corander
Dr. Michael Gutmann
Dr. Esko Keski-Vakkuri

Motivation

[1]Dawson and Reid, *Nature*, 388(6639), p. 235, 1997.

- Sleepiness causes accidents & deteriorates health.
  - 10-30% traffic accidents (yet, 60% drive while sleepy!)
  - Increases the risk for e.g. diabetes, depression, cardiovascular disease, cancer
- Compares to alcohol:

  Performance(**17 h** awake) = Performance(**0.5‰** *BAC*)[1]
- "Breathalyzer" for sleepiness?



Ultimate goal

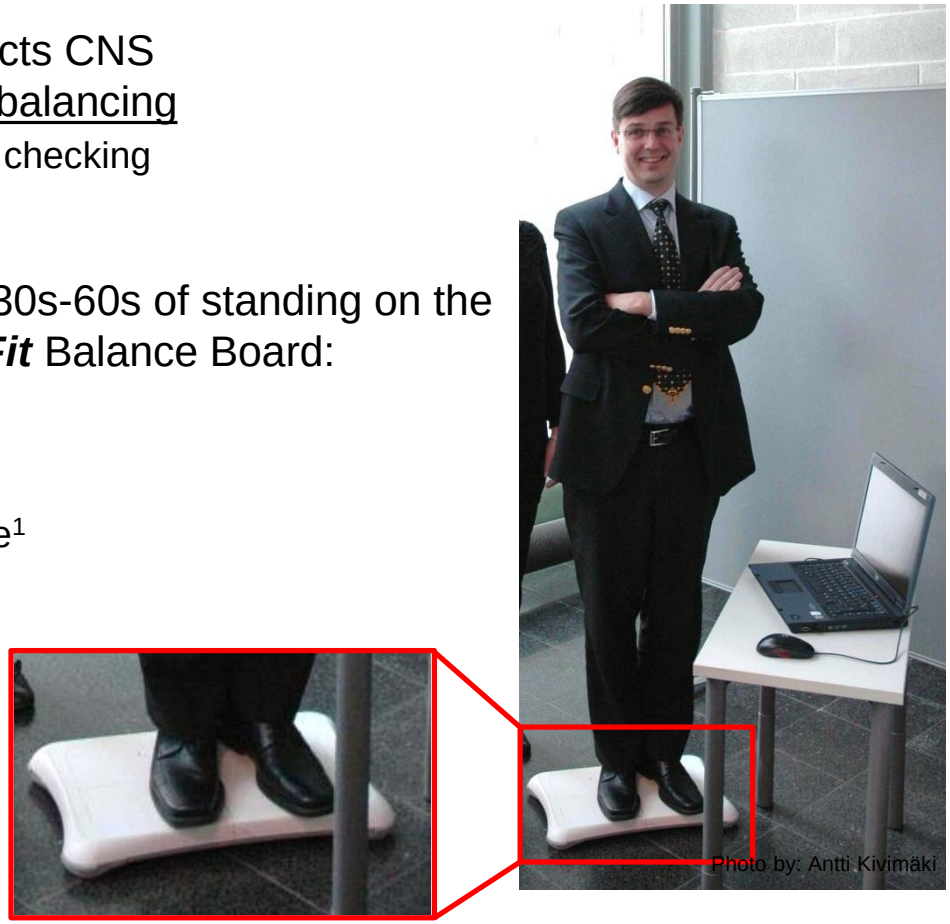
-for the police
-for self-testing

Measuring balance

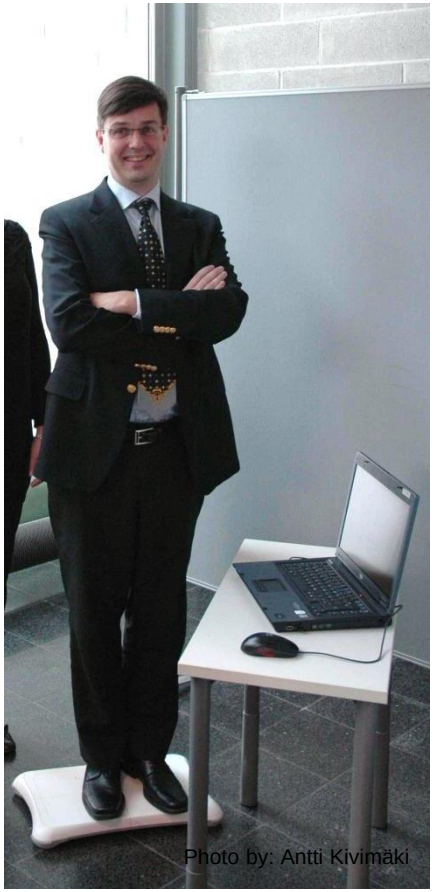
[1]Clark *et al.*, Gait & Posture, 31(3), pp. 307-310, 2010.

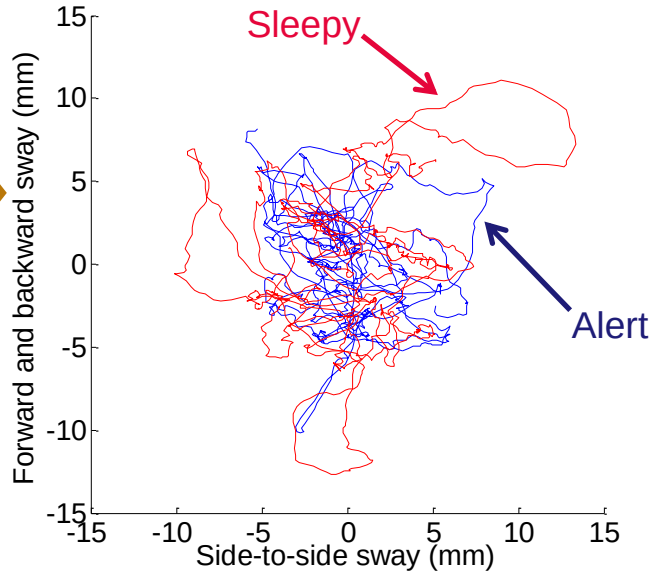
- Sleepiness affects CNS
  + CNS used in balancing
  = balance test for checking sleepiness?

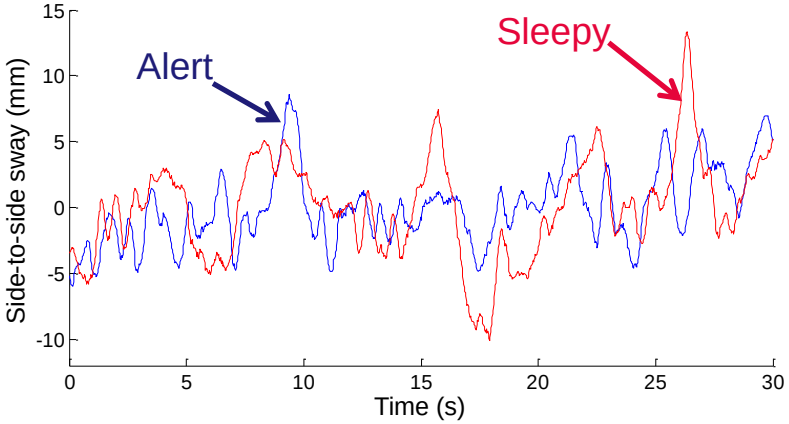
- Easy and fast: 30s-60s of standing on the ***Nintendo Wii Fit*** Balance Board:
  - Portable
  - Wireless
  - Inexpensive
  - Valid & reliable[1]



Measuring balance

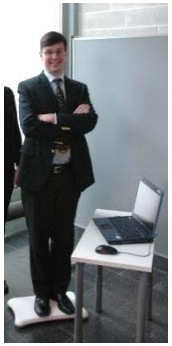


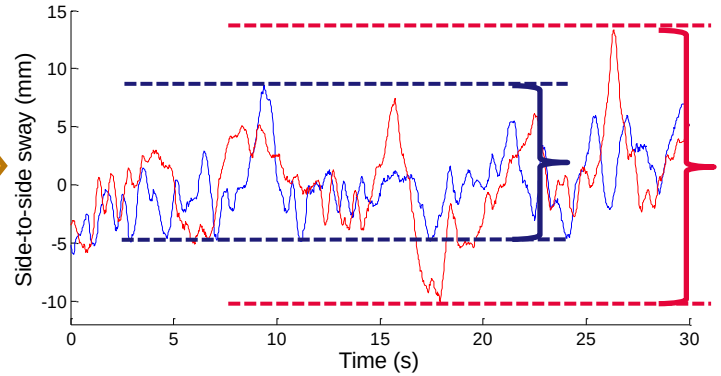




Quantifying balance

-How to extract information?





<u>Sway measures</u>

Alert: 14 mm

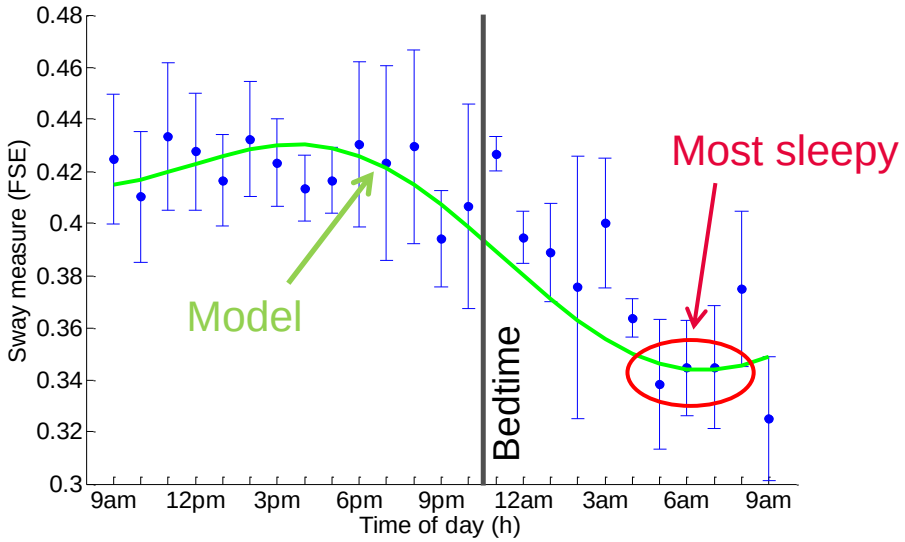
Sleepy: 24 mm

1. Conventional
   - Related to sway amplitude, velocity and frequency
2. Nonlinear
   - "Algorithms", quantify the structure of the sway signal
     - Fuzzy Sample Entropy (FSE, regularity of the signal)
3. Parameter inference from sway model
   - May be interpreted physiologically

Results

-Laboratory setting

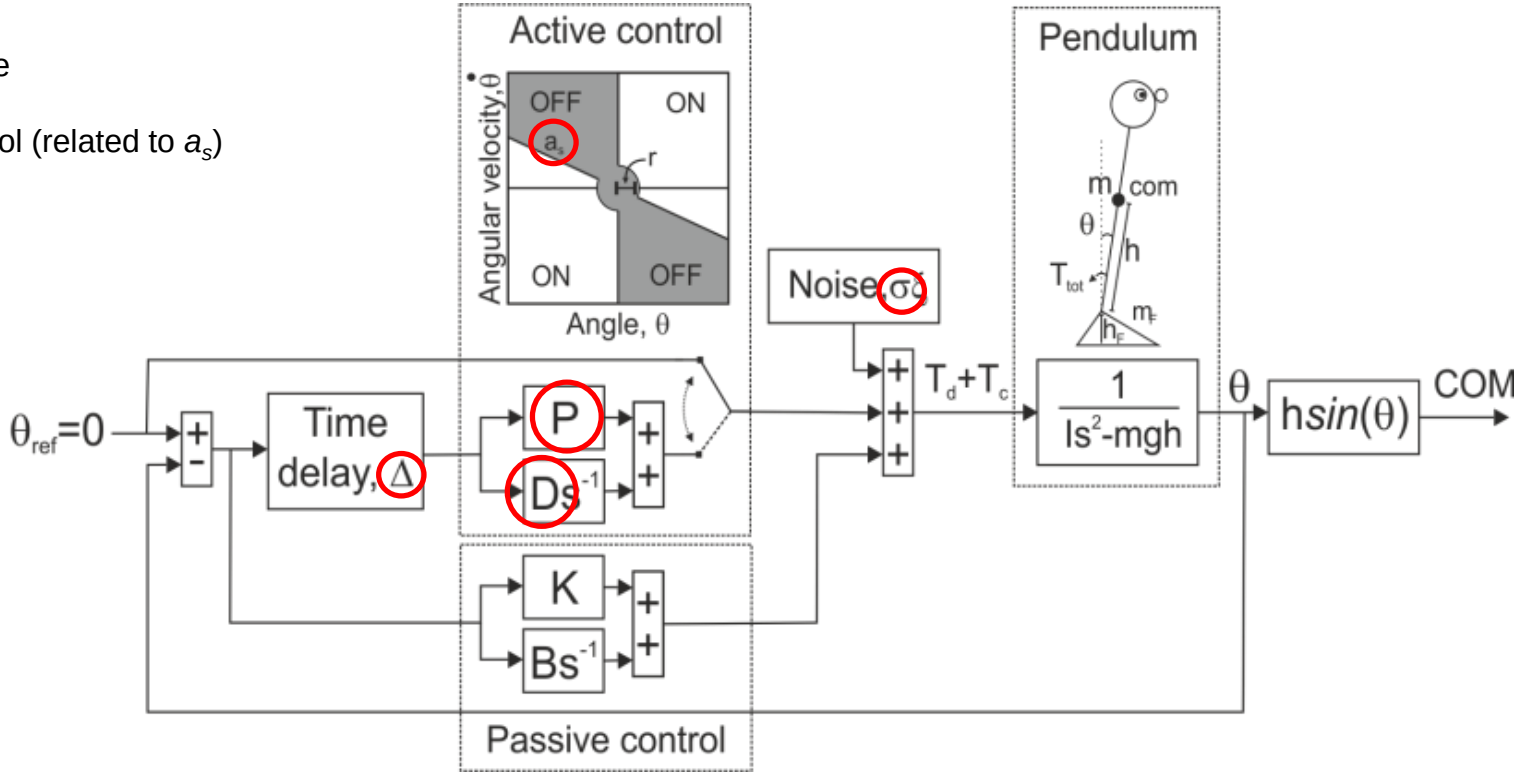
- 15 subjects measured every hour for 24 hours
  → A *reference curve*
  - Challenge: circadian rhythm
- Good correlation (ρ=0.94) between sleepiness model and FSE
- "Most sleepy" detected with 75% accuracy



Single-link inverted pendulum model

Asai *et al., PLoS ONE,* 4(7), p. e6169, 2009

Parameters of interest:
P, Active stiffness
D, Active damping
σ, Intensity of noise
Δ, Time delay
C_{ON}, Level of control (related to a_s)

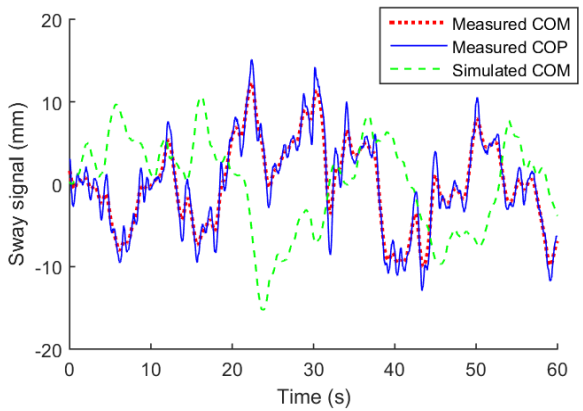


Parameter inference

-Approximate Bayesian Computation (ABC)

[1]Sisson *et al.*, *PNAS,* 104(6), pp. 1760-1765, 2007

What we have:



ABC

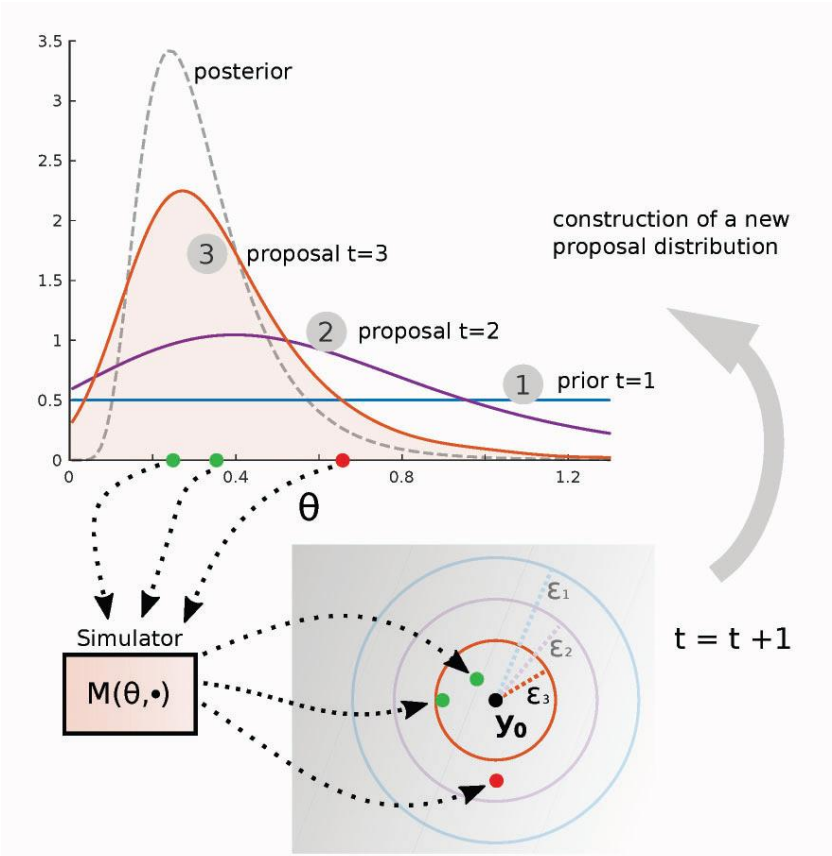
What we want:

P, Active stiffness
D, Active damping
σ, Intensity of noise
Δ, Time delay
C_{ON}, Level of control

- Likelihood function unavailable analytically in closed form
- ABC relies on calculating *summary statistics* Φ_{obs} and Φ_{sim}
  - How to choose?
- Sequential Monte Carlo ABC (SMC-ABC)[1]

Sequential Monte Carlo ABC (SMC-ABC)[1]

[1]Sisson *et al.*, *PNAS,* 104(6), pp. 1760-1765, 2007

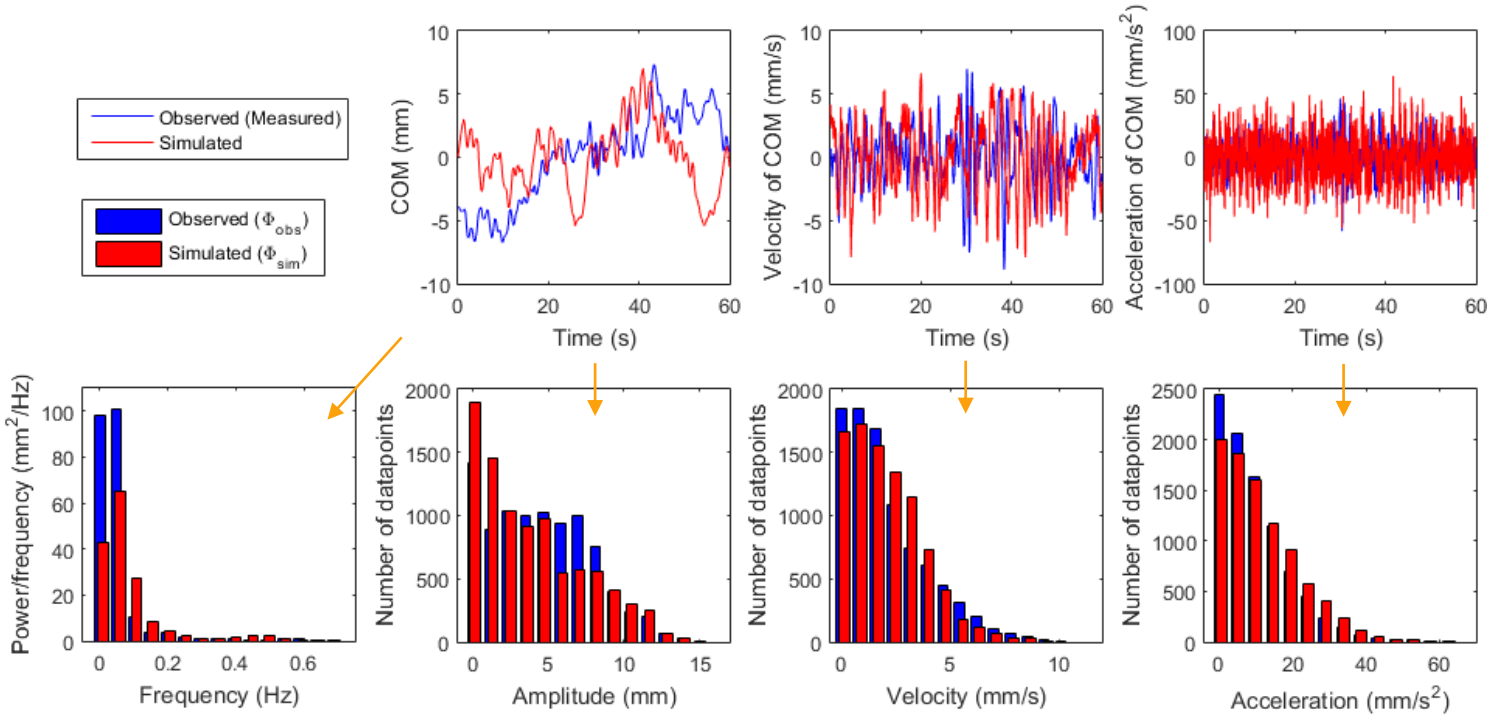


Lintusaari et al., *Syst. Biol.*, (66)1, pp. e66-e82, 2017

- In each iteration:
  - Simulate with different candidate parameter values,
  - Calculate Φ_{obs} and Φ_{sim}, and the discrepancy ρ
  - Continue until N simulations produces $\rho \leq$ threshold ε.
  - When N reached, lower ε (new iteration). Sampling from the new proposal distribution.
  - If maximum number of iterations done, stop.

Summary Statistics

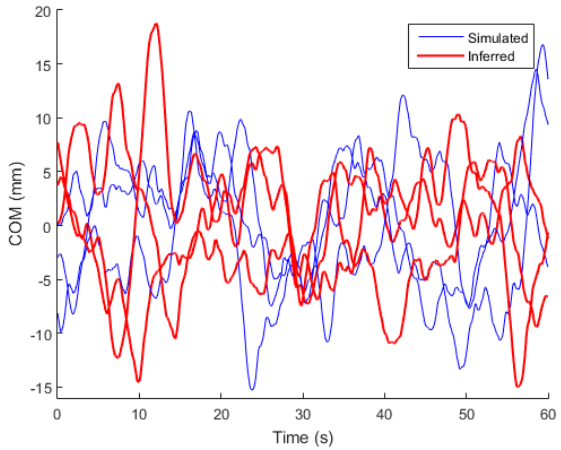
- Amplitude -, velocity -, acceleration histograms & spectrum



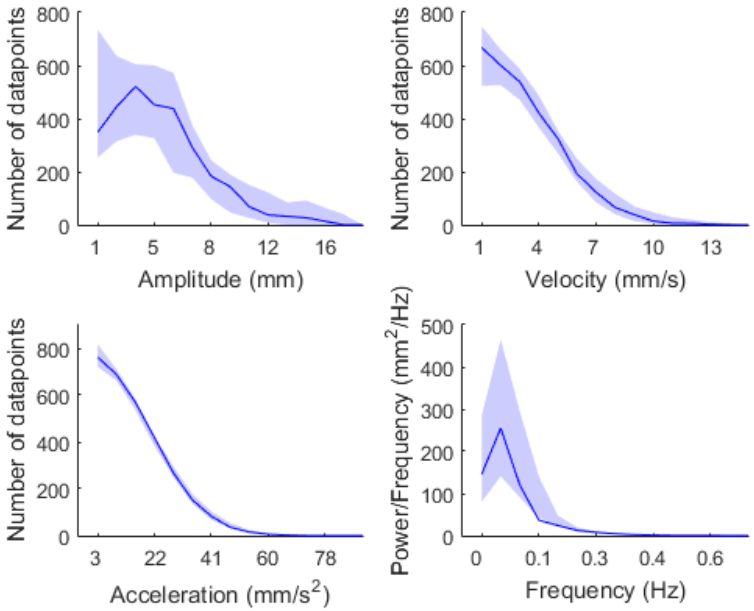
- Discrepancy: $\rho = \frac{1}{l}\sum_{i=1}^{l}\frac{|\Phi_{obs}-\Phi_{sim}|}{|\Phi_{obs}+\Phi_{sim}|}$,

where l=60 is the length of the summary statistics

Results 1/5
-Simulated subjects



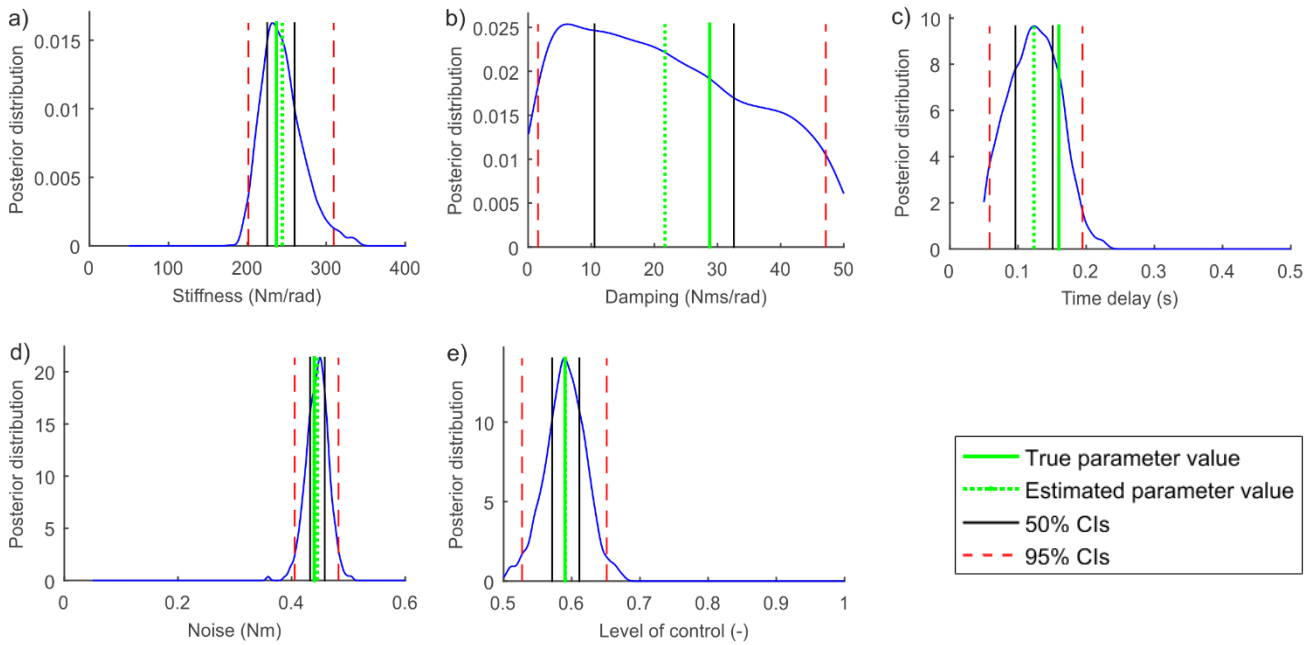
← Inferred sway patterns represent the simulated ones.



- Summary statistics from measured COMs within 95% CIs of inferred summary statistics.

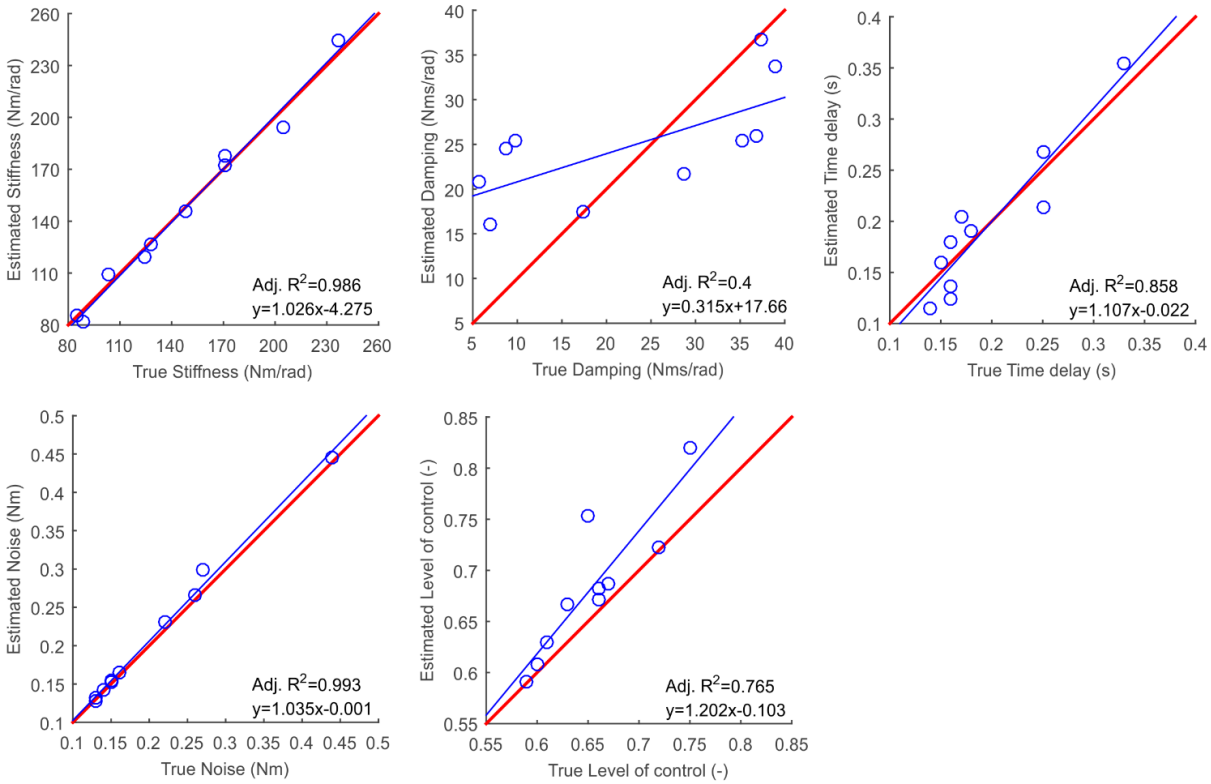
Results 2/5
-Simulated subjects

- Marginal posterior probability density functions for the five parameters of interest



Results 3/5
-Simulated subjects

- Estimated parameter values against true parameter values



Problem with *D*?

Stochastic delay differential equation:

$$T_{tot} = T_g(t) - T_c(t) + T_d(t).$$

f_P 50-times larger than f_D

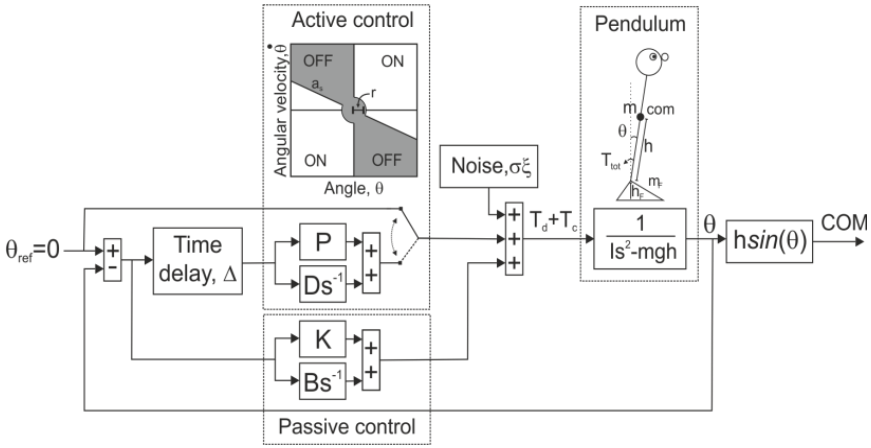
$$I\ddot{\theta}(t) = mgh\theta(t) - \left[K\theta(t) + B\dot{\theta}(t) + f_P\big(\theta(t-\Delta)\big) + f_D\left(\dot{\theta}(t-\Delta)\right)\right] + \sigma\xi(t)$$

$$\begin{cases} f_P\big(\theta(t-\Delta)\big) = P\theta(t-\Delta) \\ f_D\left(\dot{\theta}(t-\Delta)\right) = D\dot{\theta}(t-\Delta) \end{cases}$$

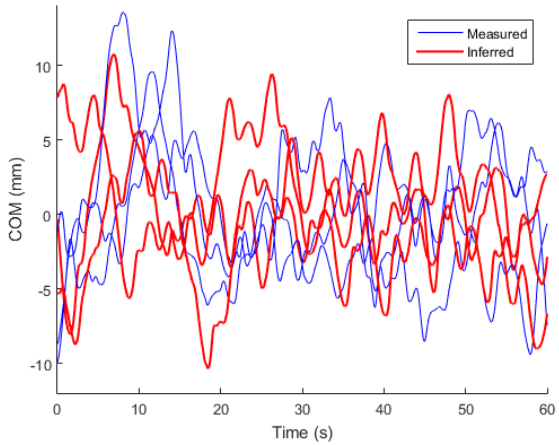
if $\theta(t-\Delta)\left(\dot{\theta}(t-\Delta) - a_s\theta(t-\Delta)\right) > 0$, and $\theta^2(t-\Delta) + \dot{\theta}^2(t-\Delta) > r^2$, and

$$\begin{cases} f_P\big(\theta(t-\Delta)\big) = 0 \\ f_D\left(\dot{\theta}(t-\Delta)\right) = 0 \end{cases}$$

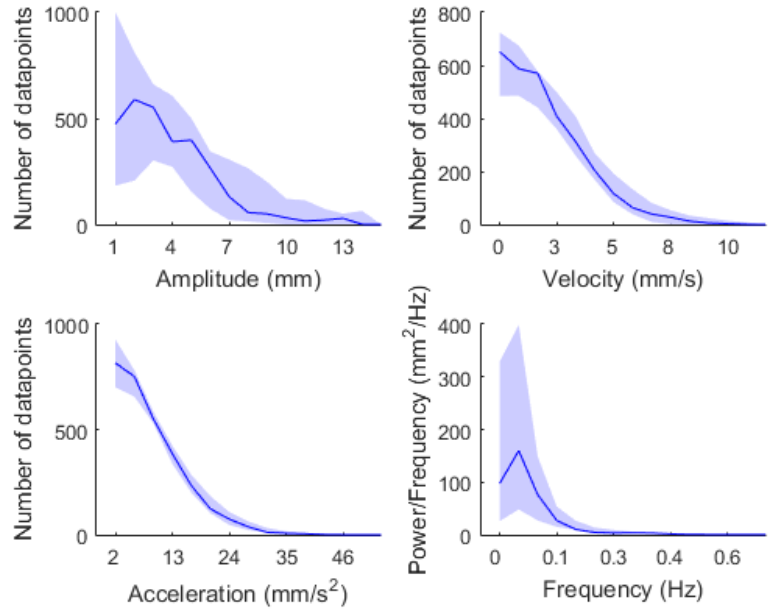
otherwise.



Results 4/5
-Real subjects



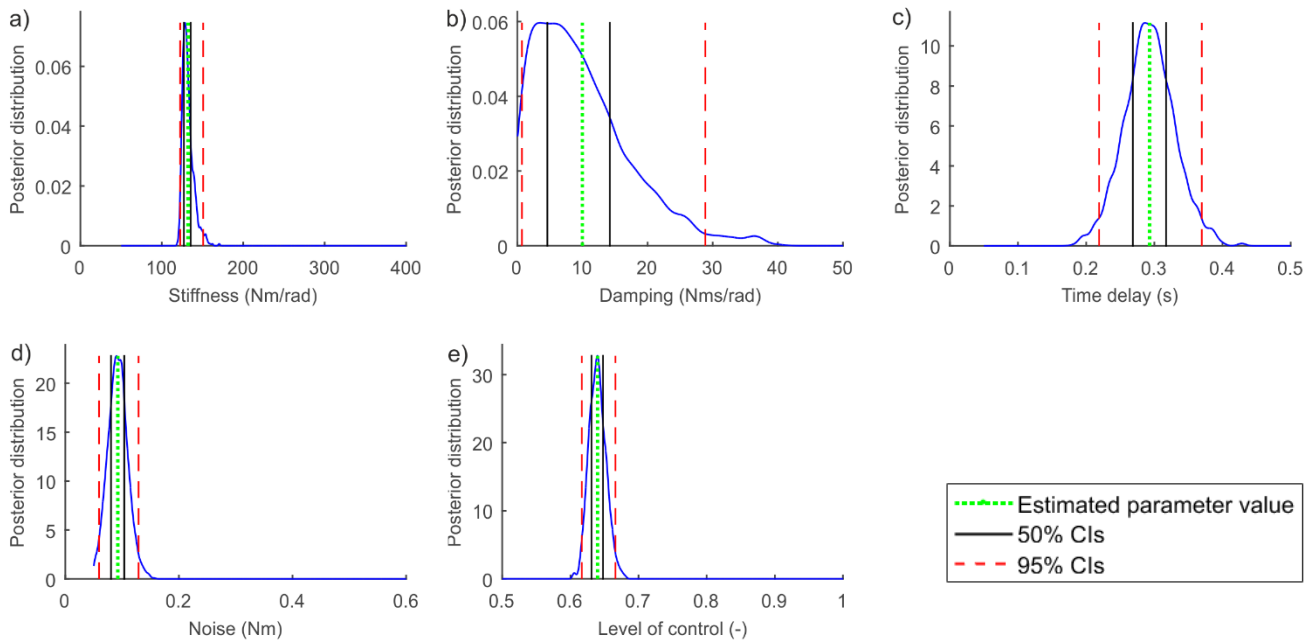
← Inferred sway patterns represent the measured ones.



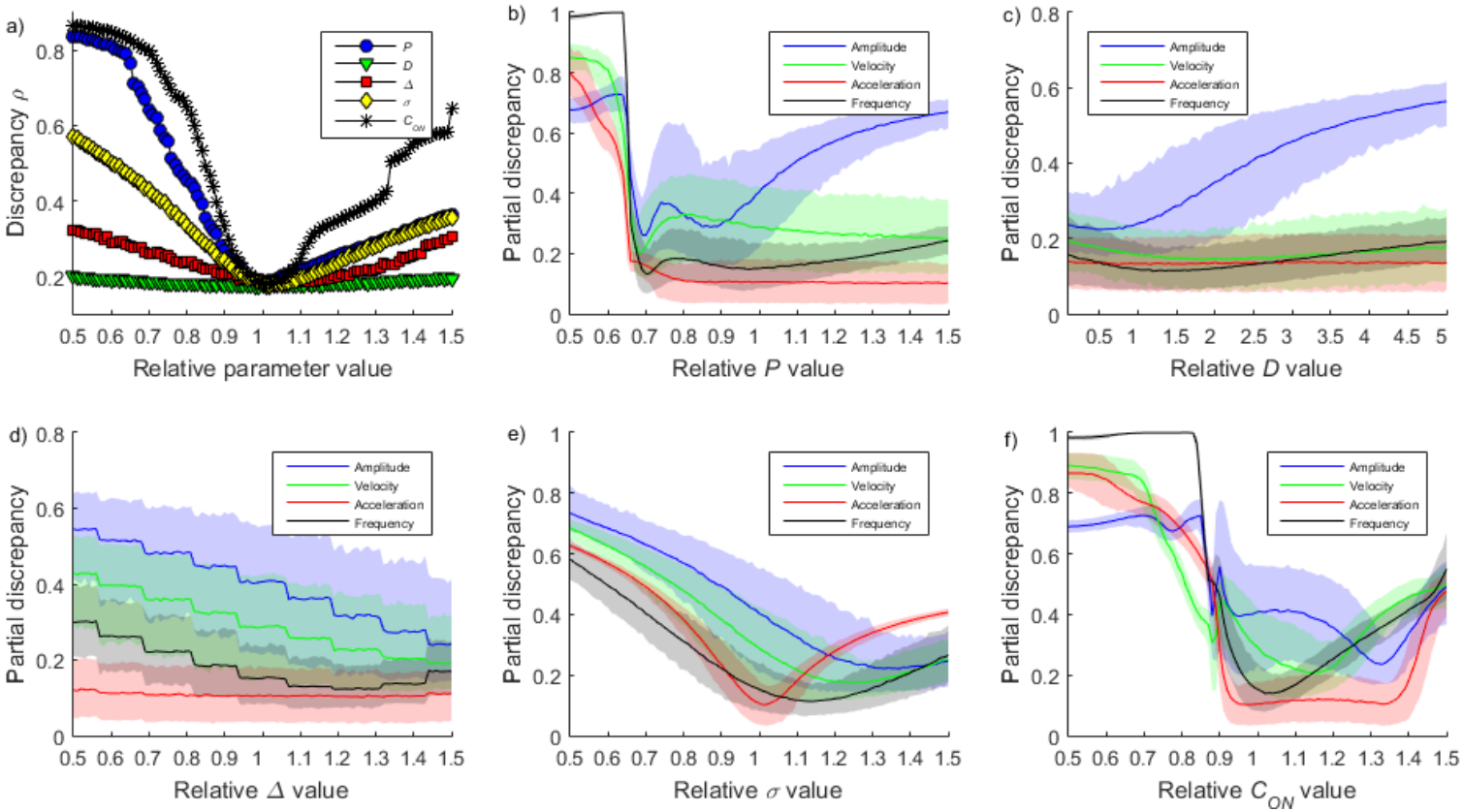
- Summary statistics from measured COMs mostly within the 95% CIs of inferred summary statistics.

Results 5/5
-Real subjects

- Marginal posterior probability density functions for the five parameters of interest



Sensitivity Analysis
-Simulated subjects



What next?

[1]Gutmann & Corander, *JMLR,* 17(125), pp. 1-47, 2016.

- SMC-ABC still slow (requires clusters)
  - → Another ABC code: BOLFI[1] (Bayesian optimization in Likelihood-Free Inference)
- Some work with the summary statistics needed
- Sleepiness data (N=21, TA=24 h) needs to be implemented

Thank you!

A. Tietäväinen, M.U. Gutmann, E. Keski-Vakkuri, J. Corander, and E. Hæggström, ”Bayesian inference of physiologically meaningful parameters from body sway measurements”, *Sci. Rep.* (accepted)

Additional material: SMC-ABC

Sisson *et al.*, *PNAS,* 104(6), pp. 1760-1765, 2007

ABC-PRC Algorithm (corrected):

PRC1 Initialize $\epsilon_1, \ldots, \epsilon_T$, and specify initial sampling distribution μ_1.
Set population indicator $t = 1$.

PRC2 Set particle indicator $i = 1$.

PRC2.1 If $t = 1$ sample $\theta^{**} \sim \mu_1(\theta)$ independently from μ_1.
If $t > 1$ sample θ^* from the previous population $\{\theta_{t-1}^{(i)}\}$ with weights $\{W_{t-1}^{(i)}\}$, and perturb the particle to $\theta^{**} \sim K_t(\theta \mid \theta^*)$ according to a transition kernel K_t.

Generate a data set $x^{**} \sim f(x \mid \theta^{**})$.
If $\rho(S(x^{**}), S(x_0)) \geq \epsilon_t$ then go to PRC2.1.

PRC2.2 Set

$$\theta_t^{(i)} = \theta^{**} \qquad \text{and} \qquad W_t^{(i)} = \begin{cases} \pi\left(\theta_t^{(i)}\right) / \mu_1\left(\theta_t^{(i)}\right) & \text{if} \quad t = 1 \\ \pi\left(\theta_t^{(i)}\right) / \sum_{j=1}^{N} W_{t-1}\left(\theta_{t-1}^{(j)}\right) K_t\left(\theta_t^{(i)} | \theta_{t-1}^{(j)}\right) & \text{if} \quad t > 1 \end{cases}$$

where $\pi(\theta)$ denotes the prior distribution for θ.
If $i < N$, increment $i = i + 1$ and go to PRC2.1.

PRC3 Normalize the weights so that $\sum_{i=1}^{N} W_t^{(i)} = 1$.
If $ESS = \left[\sum_{i=1}^{N} (W_t^{(i)})^2\right]^{-1} < E$ then resample with replacement, the particles $\{\theta_t^{(i)}\}$ with weights $\{W_t^{(i)}\}$ to obtain a new population $\{\theta_t^{(i)}\}$, and set weights $\{W_t^{(i)} = 1/N\}$.

PRC4 If $t < T$, increment $t = t + 1$ and go to PRC2.