Définir, mesurer et promouvoir la qualité de vie

Workshop II

MESURER la qualité de vie

12 September 2016, Genève

Détection et compréhension du comportement physique dans la vie quotidienne

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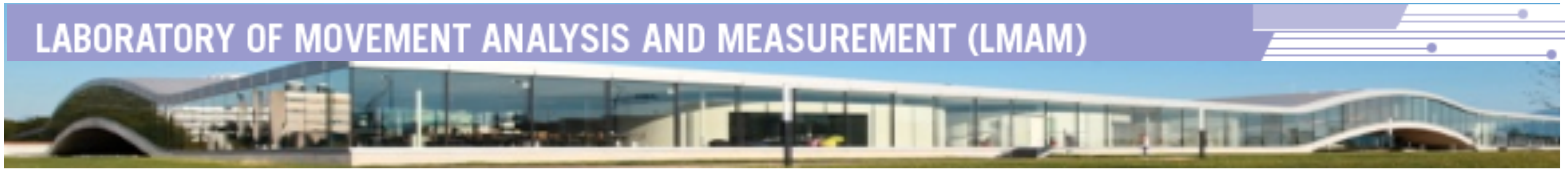


Why measuring physical activity?

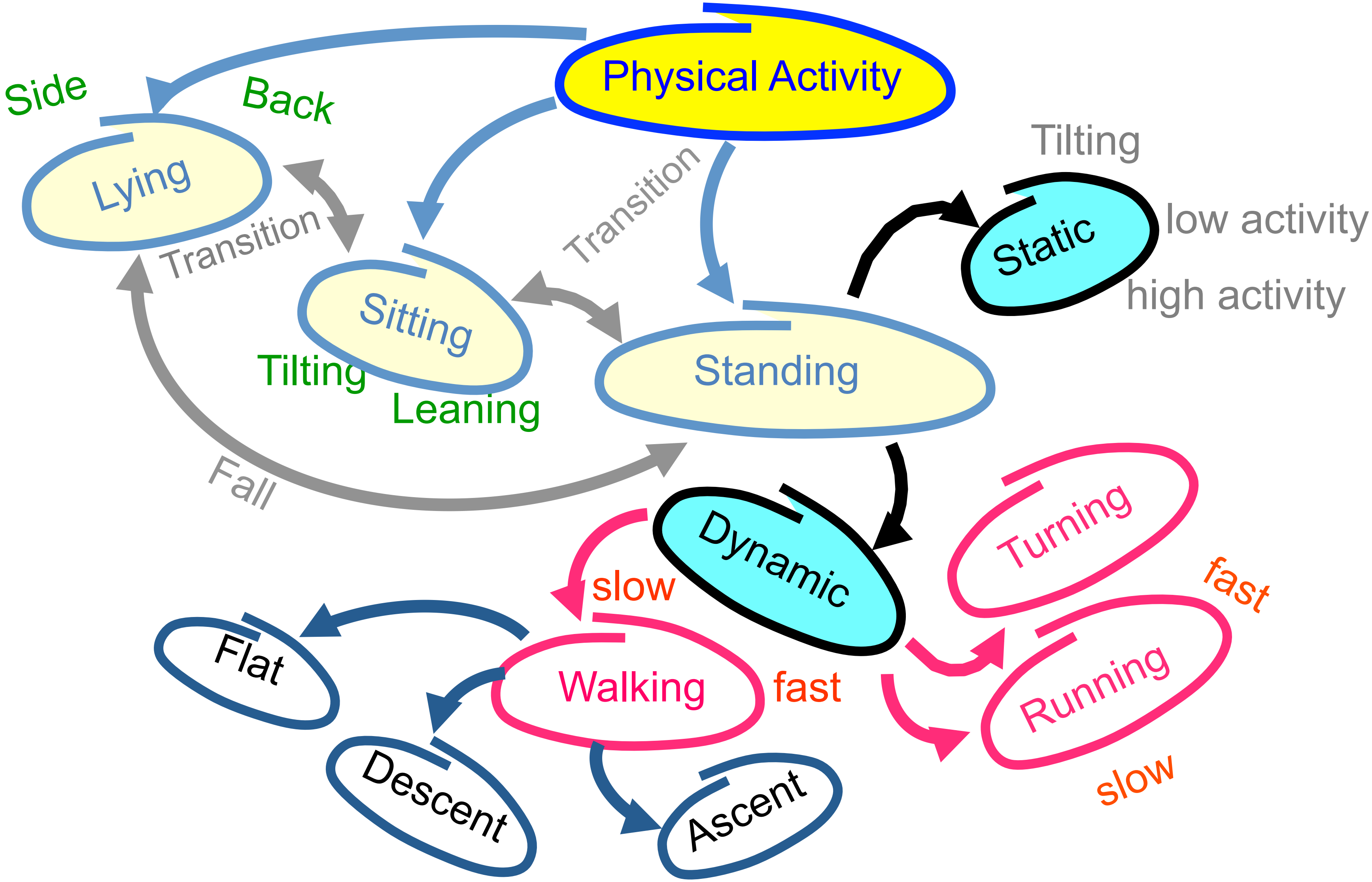
- Fundamental determinant health and wellbeing
- Outcomes for functional independence
- Association with energy expenditure
- Association with risk in many disease:

Fall, CVD, Stroke, Obesity, Parkinson disease, Pain

- Shorter walking periods
- Less frequent walking periods
- Lower gait speed
- Longer rest periods
- Slower transfer between posture
- Avoidance and fear of physical activity
- Less variability in activity

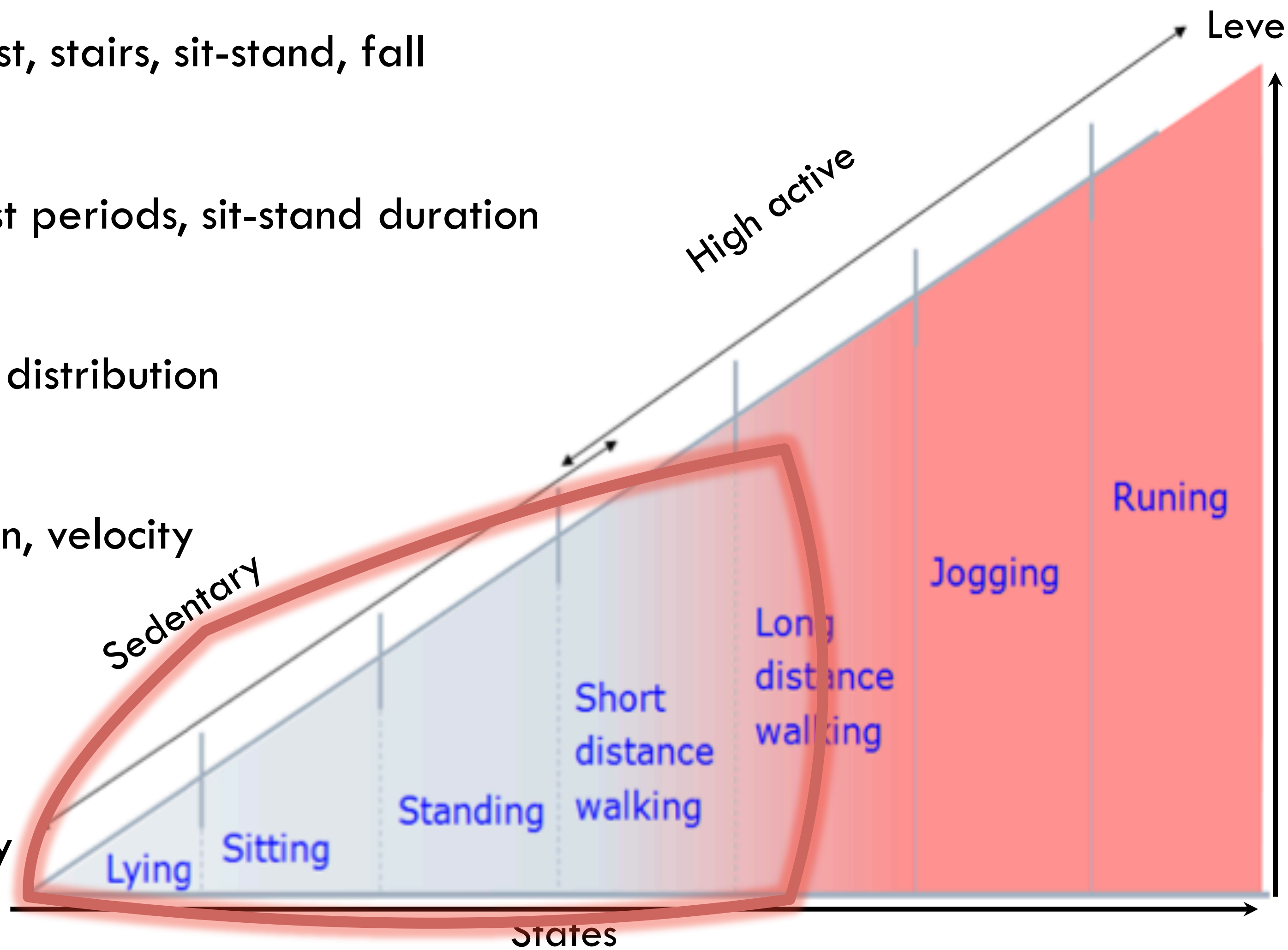
WHO Library Cataloguing in Publication Data, Physical activity and health in Europe: evidence for action / edited by Nick Cavill et al. 2006

Activities of daily living

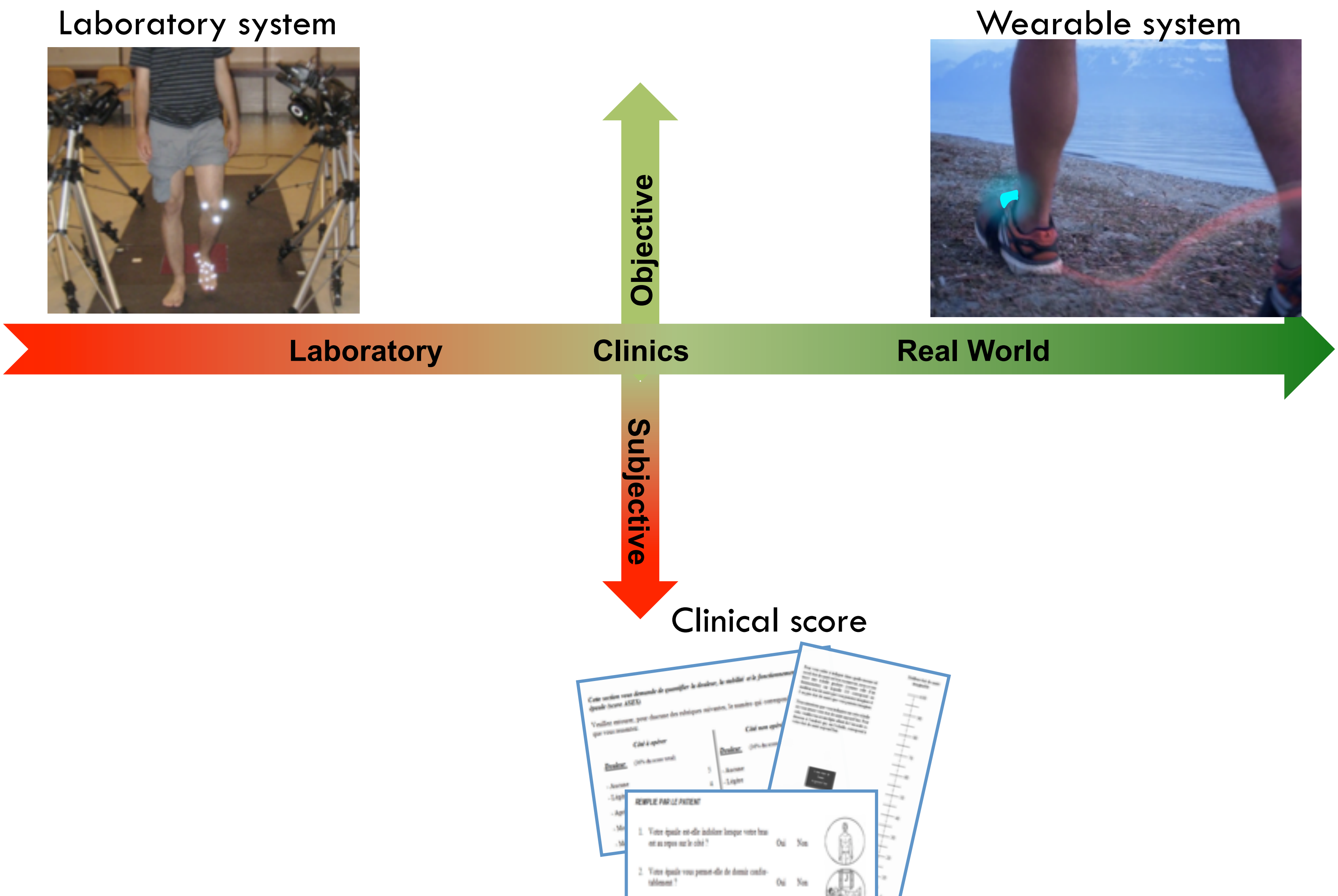


ADL characteristics in disease

- Type and event
  - walking, rest, stairs, sit-stand, fall
- Duration
  - activity/rest periods, sit-stand duration
- Frequency
  - How often, distribution
- Intensity
  - Acceleration, velocity
  - cadence
- Pattern
  - Variability
  - Complexity

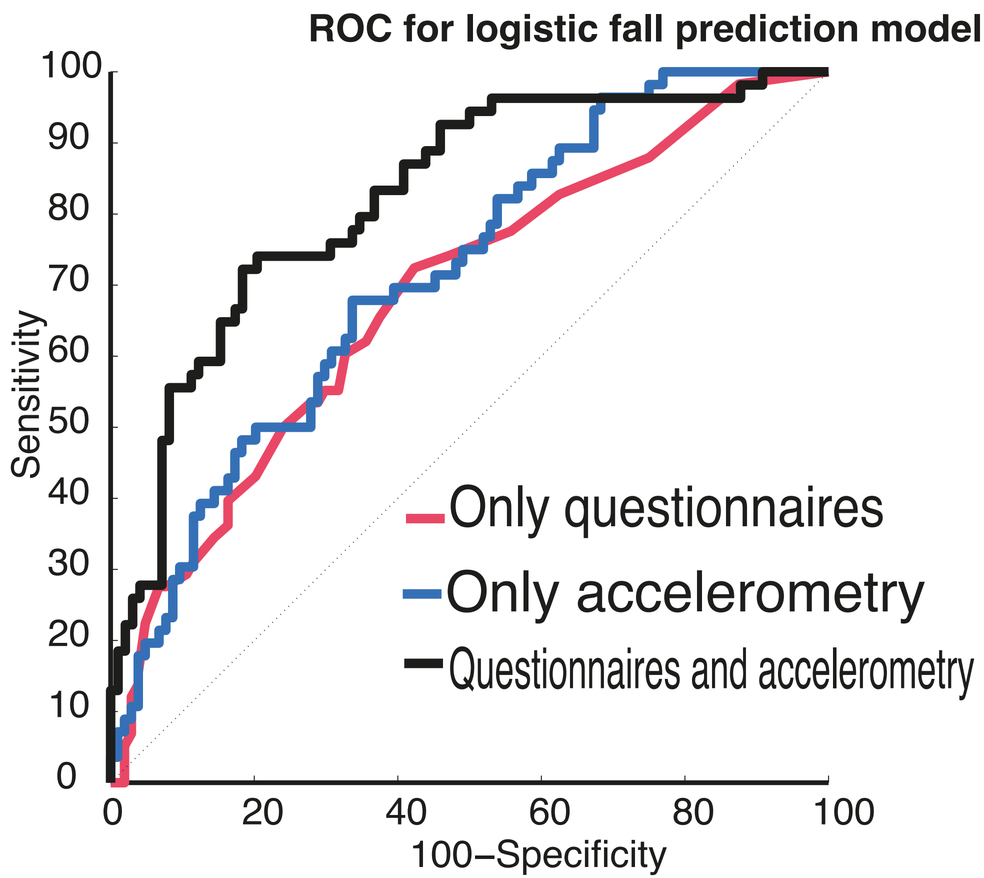


Mobility evaluation in health and disease



Contribution of wearable sensors:
Risk of fall using daily life monitoring

- Trunk accelerometer
- 8 days
- Walking quantity and gait characteristics was associated with fall
- Highest fall prediction when accelerometer is used



Van Schooten, et.al, Journals of Gerontology: MEDICAL SCIENCES, 2015,

Wearable technology today

- Consumer devices
  - Pedometer, Smartphone, Fitness tracker
    - High rate of decline after one year*
      - Functionality?
      - Validity?
      - Usability?
- Research oriented devices
  - Inertial sensors(accelerometer, gyroscope)
  - GPS, Barometer
  - Gait, activity(sit/stand lie, walk)
  - Walking intensity
  - Energy expenditure
  - Validation?

*Rock Health, Biosensing Wearable report, 2014

Motion sensors: body worn

- Subject specific
- Discrete
- Ubiquitous
- Electronic protection

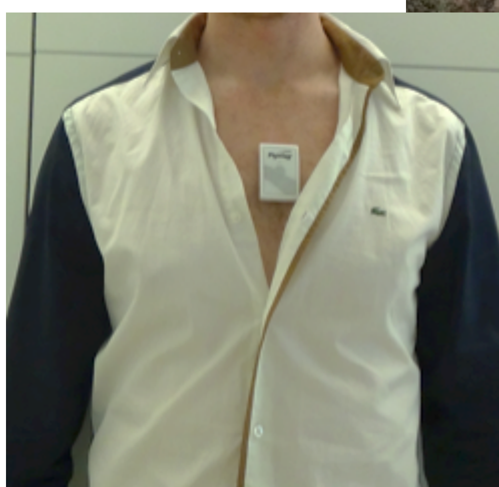
+Fixed place
+Present for all activity
+Ideal for feedback
- Hand movement artefact

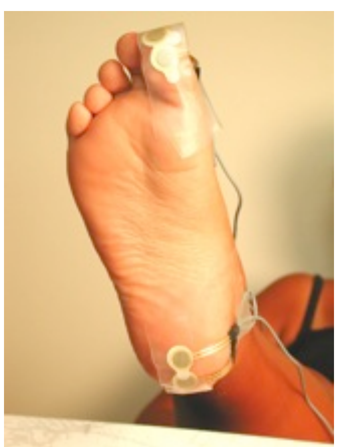
+Large space
+Fixed place
+Most affected by locomotion
+Best placement to measure GRF
- Can be removed indoor

+Integrate many sensors
+Social behavior
+Largely available
+Connected
- not fixed location on body

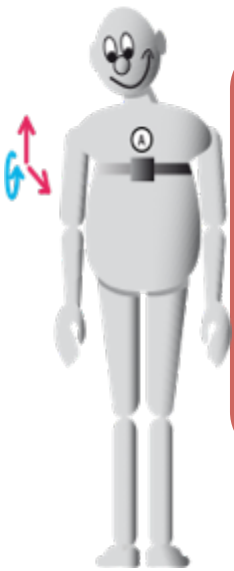
Motion sensors: body fixed

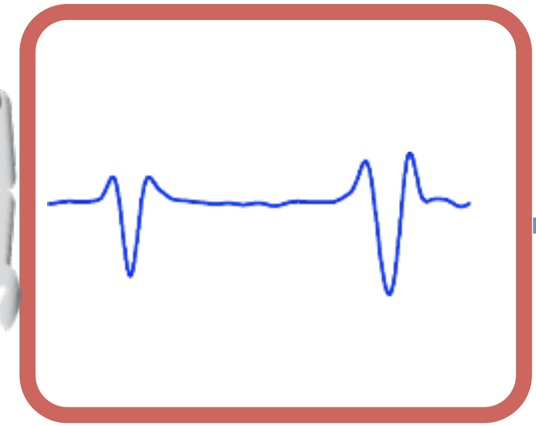
- Optimal location
- Less artifact
- Less comfort
- Less acceptability

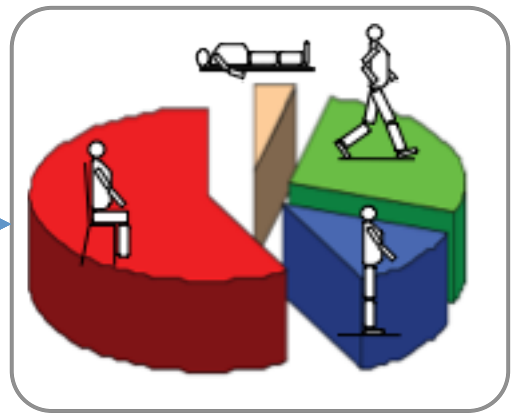


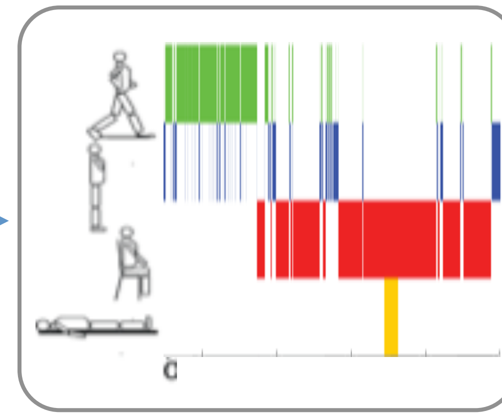


Trunk sensor: activity classification









Transfer

- sit-stand duration ↑
- number of transfer ↓
- trunk tilt ↓

Activity

- duration
- frequency
- gait velocity
- cadence
- Arm usage

↓

Pattern

- smoothness ↓
- gait asymmetry
- gait variability
- body sway

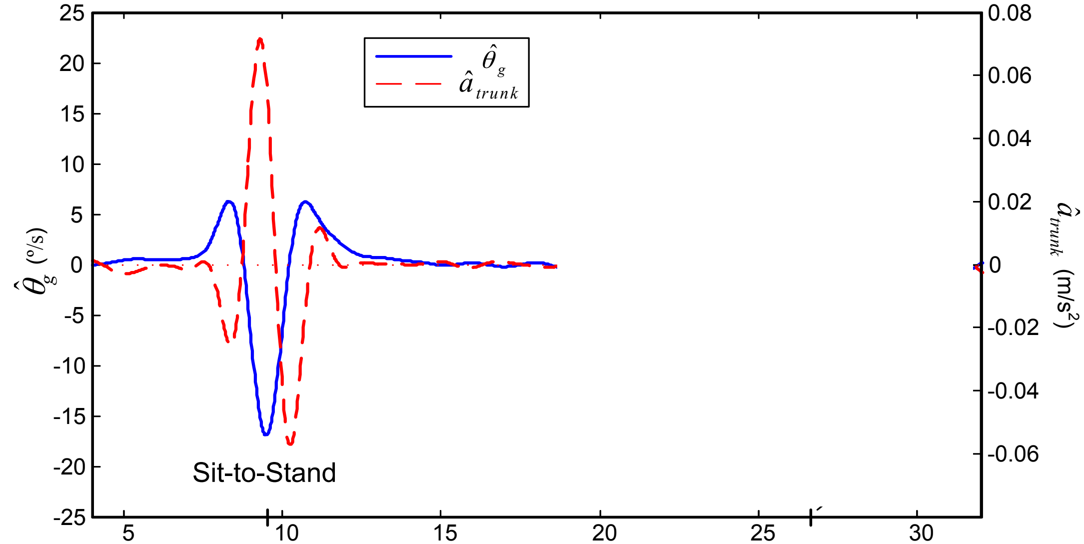
↑

- dynamics ↓

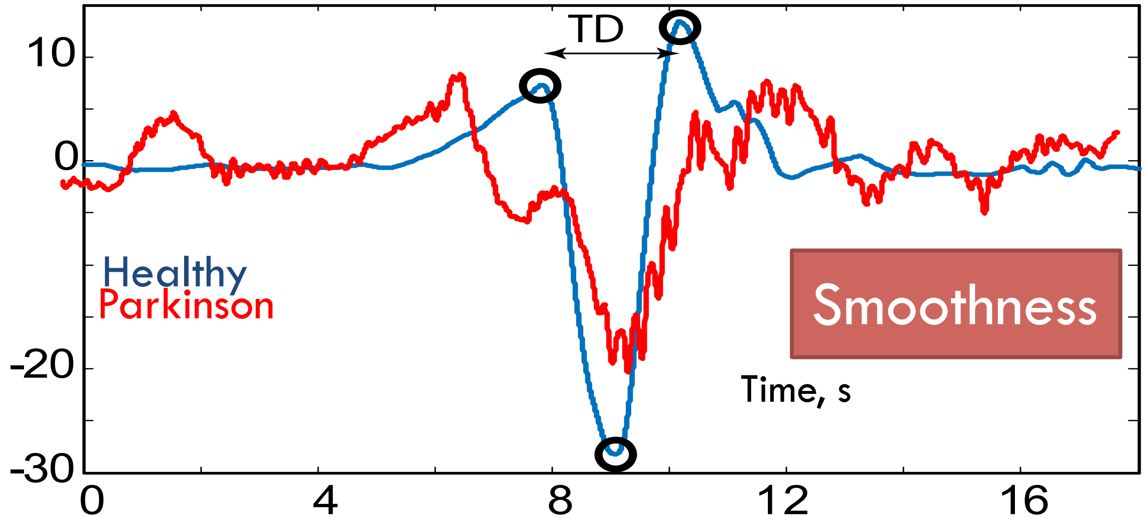
→ **Changes with disease**

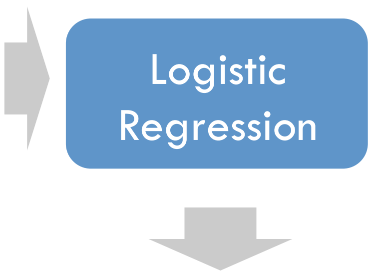
Sit-stand detection

Postural transition



Trunk tilt deg





Si-St/St-Si
Sensitivity of 83%-94%

Salarian et al. (2007), IEEE-TBME

Postural transitions in Elderly during 6h ADL

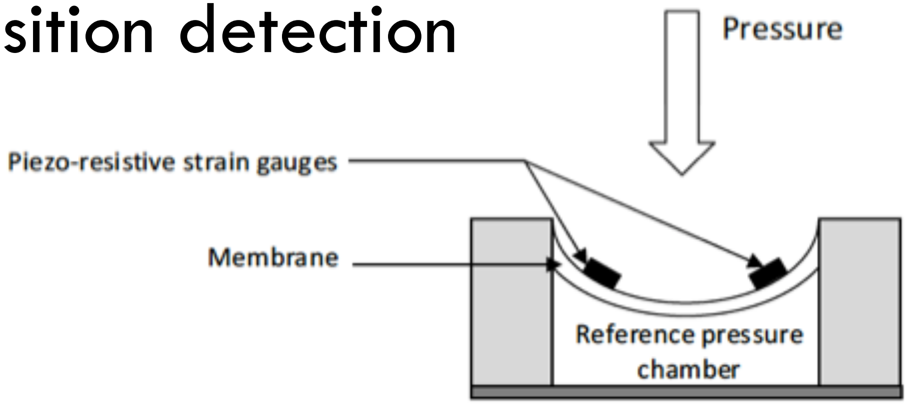
- 10 Health elderly subjects, 6F, 4M
- 10 Frail Elderly subjects, Fried's criteria, 3F, 7M

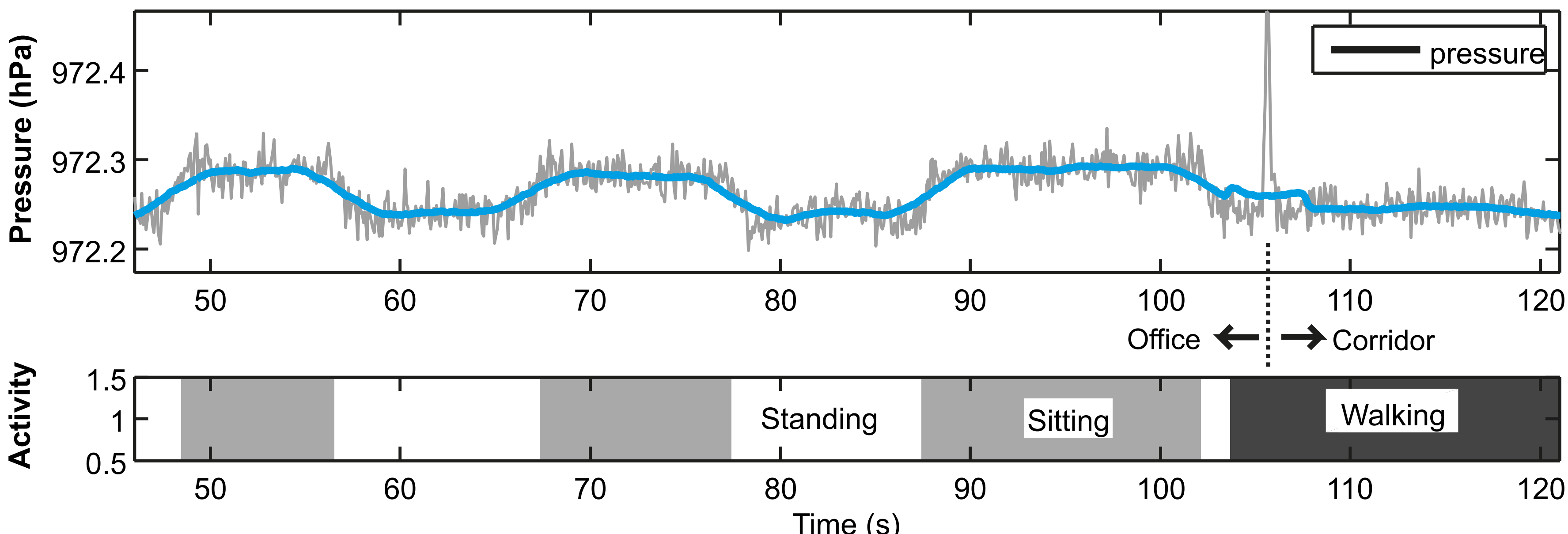
Parameters	Healthy Subjects	Frail Subjects	P-value
SiSt			
Number_{SiSt}	21.4±11.2	10.2±4.15	P<0.05
Rate_{SiSt}	3.6±1.9	1.7±0.69	P<0.05
Duration (s)	2.47±0.22	3.08±0.46	P<0.05
θ (deg)	20.15±1.5	17.9±2.5	P<0.05
a_N, range (mg)	100±20	70±17	P<0.05
StSi			
Number_{StSi}	32.6±14.41	5.20±2.57	P<0.001
Rate_{StSi}	5.43±2.40	0.86±0.42	P<0.001
Duration (s)	2.80±0.40	2.70±0.54	NS
θ (deg)	20.00±2.30	19.00±3.7	NS
a_N, range (mg)	90±10	65±17	P<0.05

Ganea et al. (2012) IEEE TMBE

Barometric pressure

- Improving Sit-Stand Transition detection
  - Sensitivity: 92%
  - Specificity: 98%



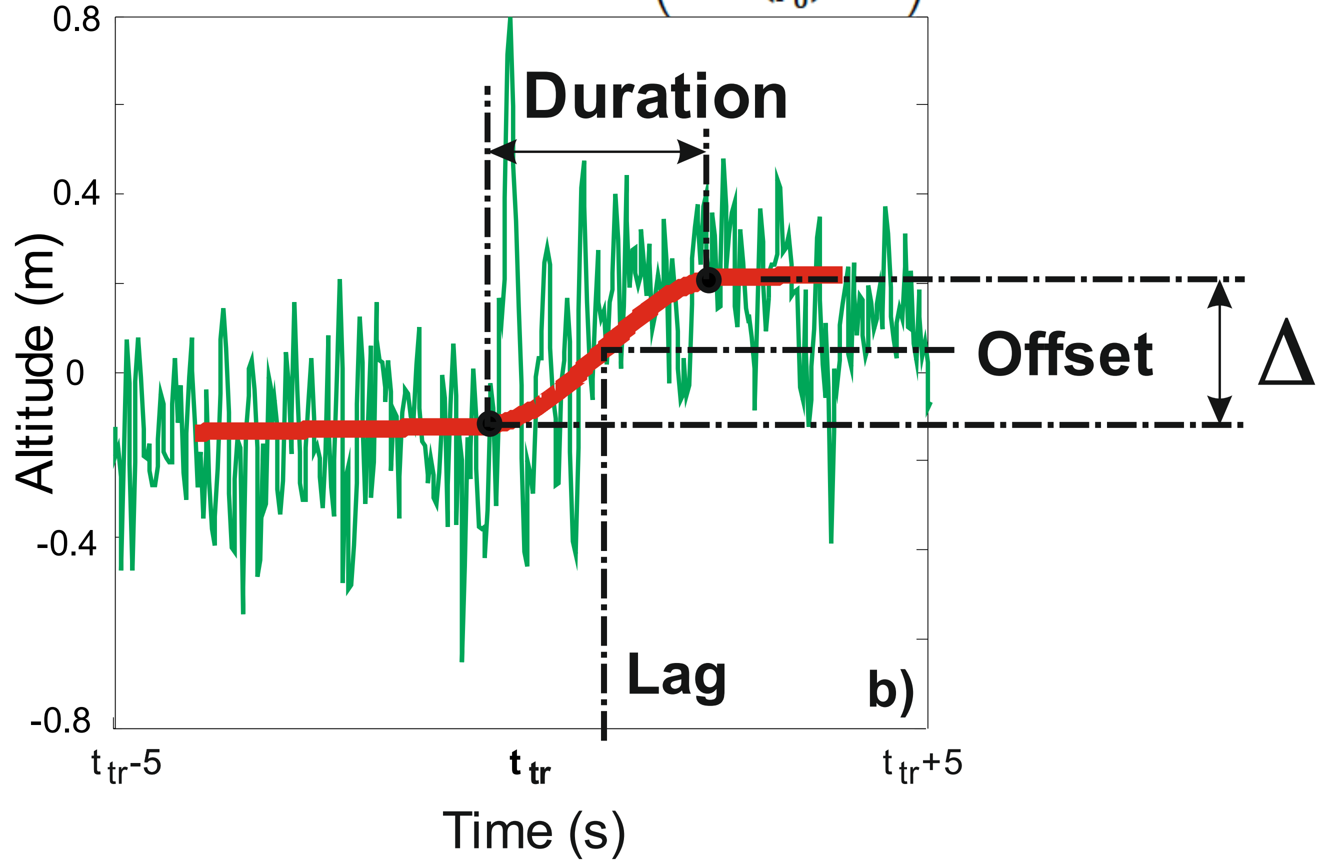


Massé et al. Medical Engineering Physics, 2014

Stand-sit: pressure features

- Sinusoidal fitting of altitude signal

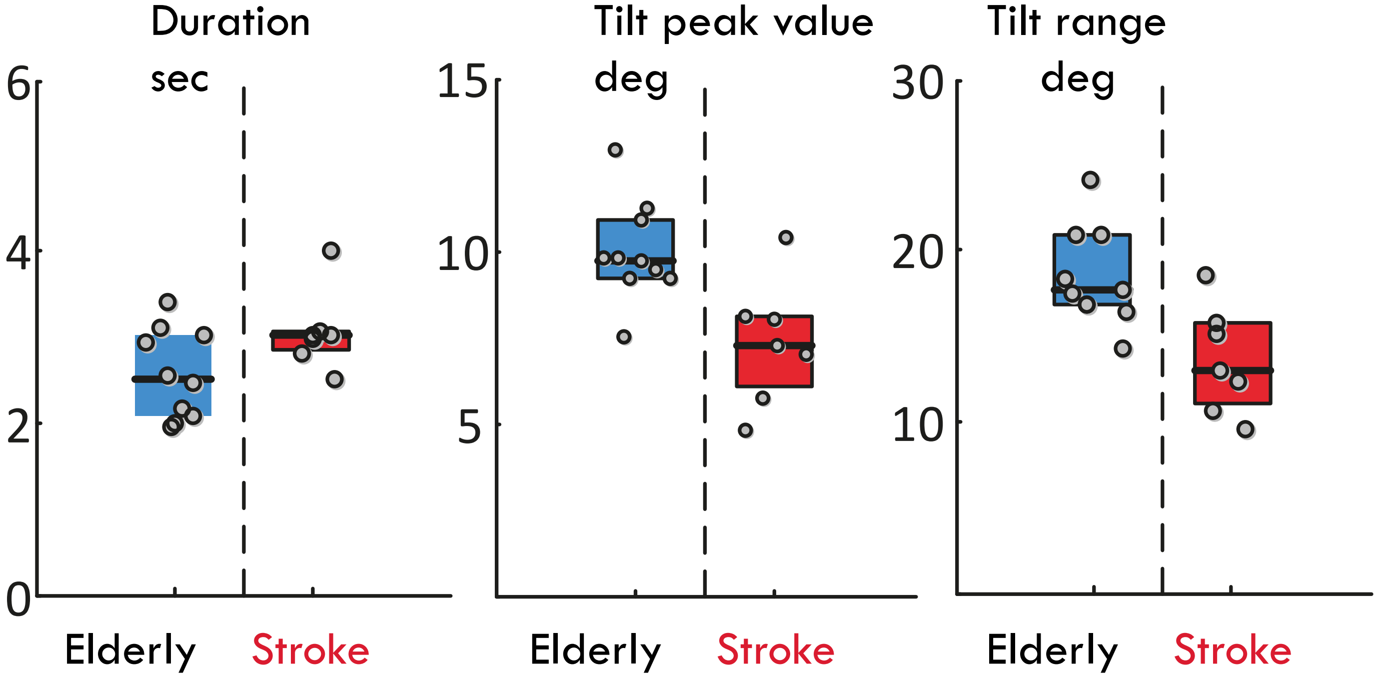
$$Altitude\ (P) = 44.330 \times \left(1 - \left(\frac{P}{P_0}\right)^{\frac{1}{5.255}}\right)$$

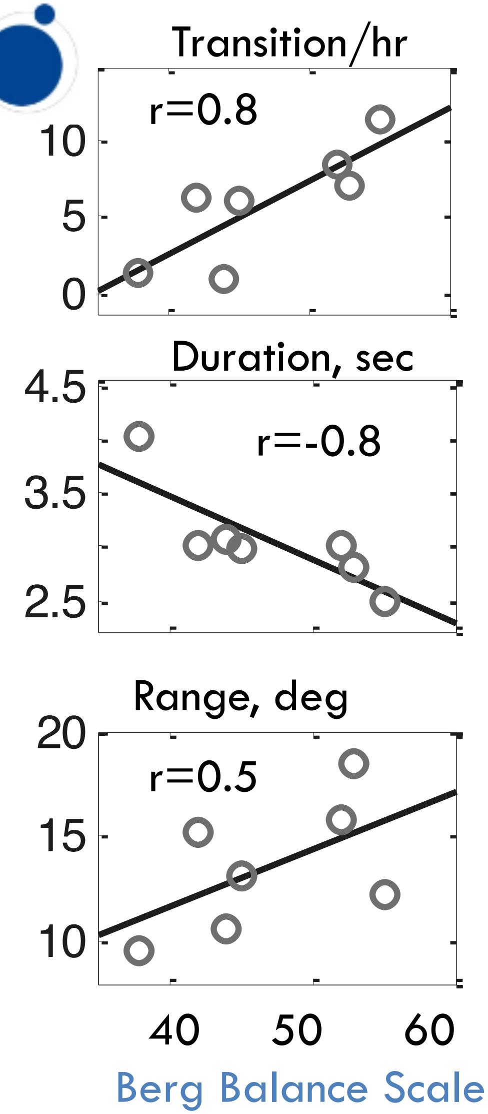


Massé, F., Aminian, K., et al., IEEE TNSRE, in Press

Elderly vs. stroke patients

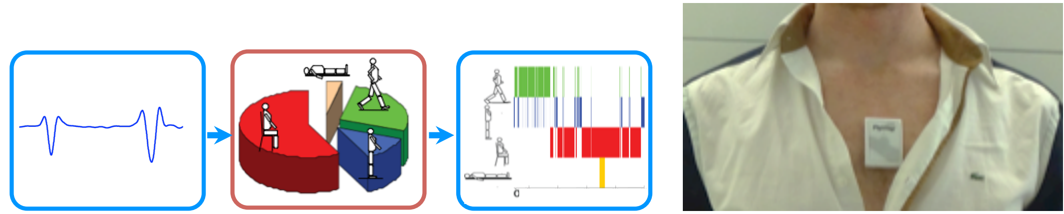
- Preliminary data
  - 10 Elderly (4.6h), 7 stroke(42h)
  - Outdoor, daily conditions
  - Using Inertial +Barometric sensor

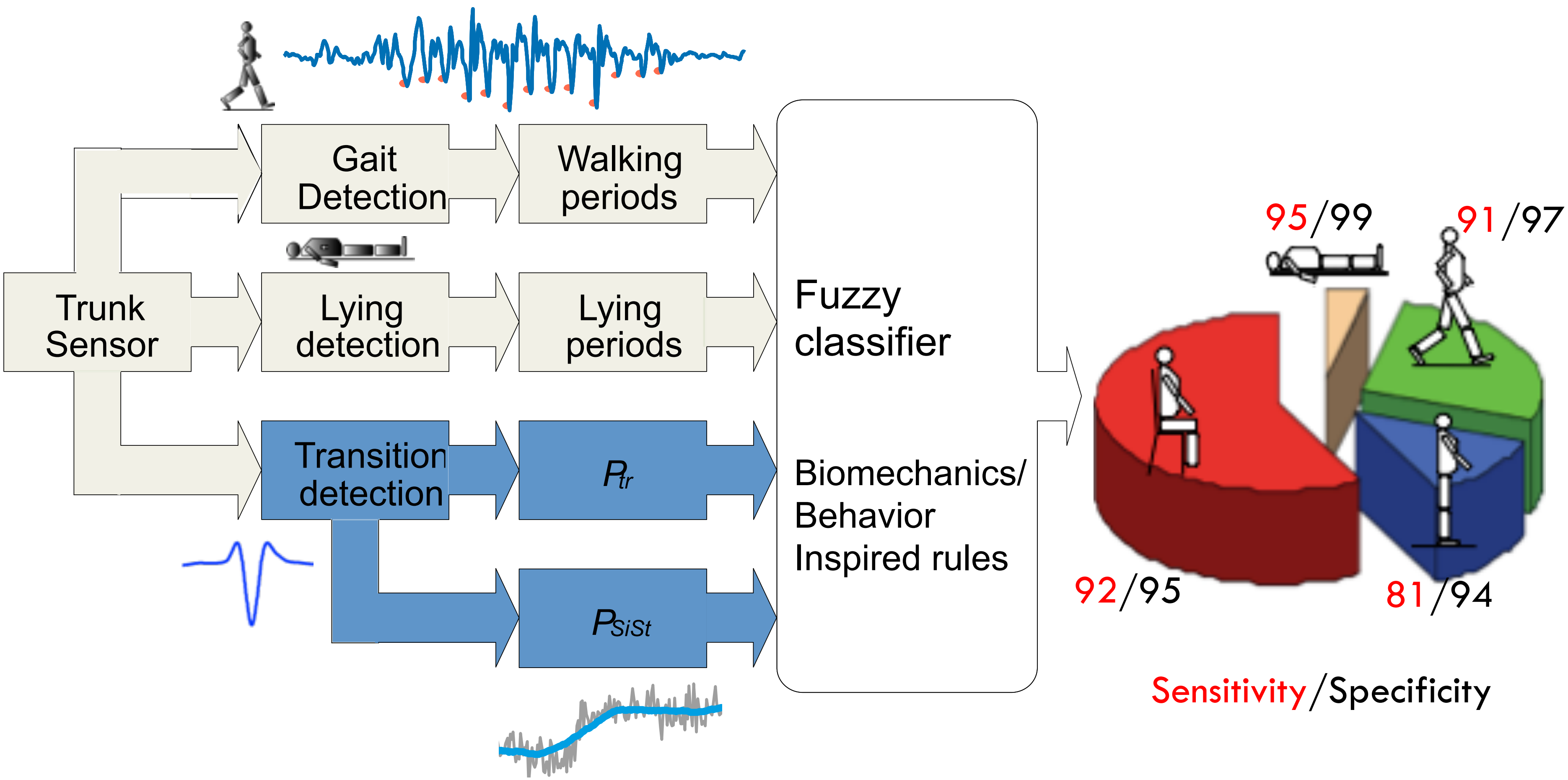




Fabien Massé, PhD thesis 2015

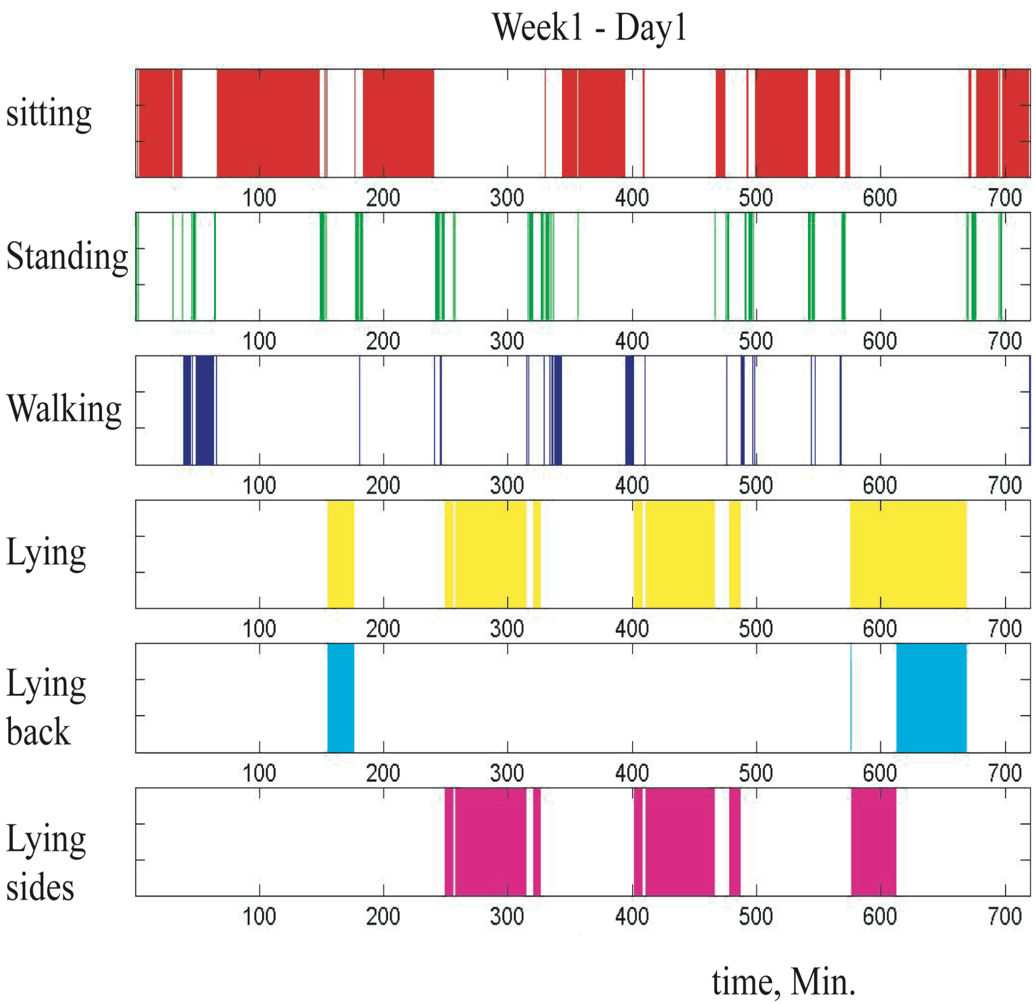
Activity classification

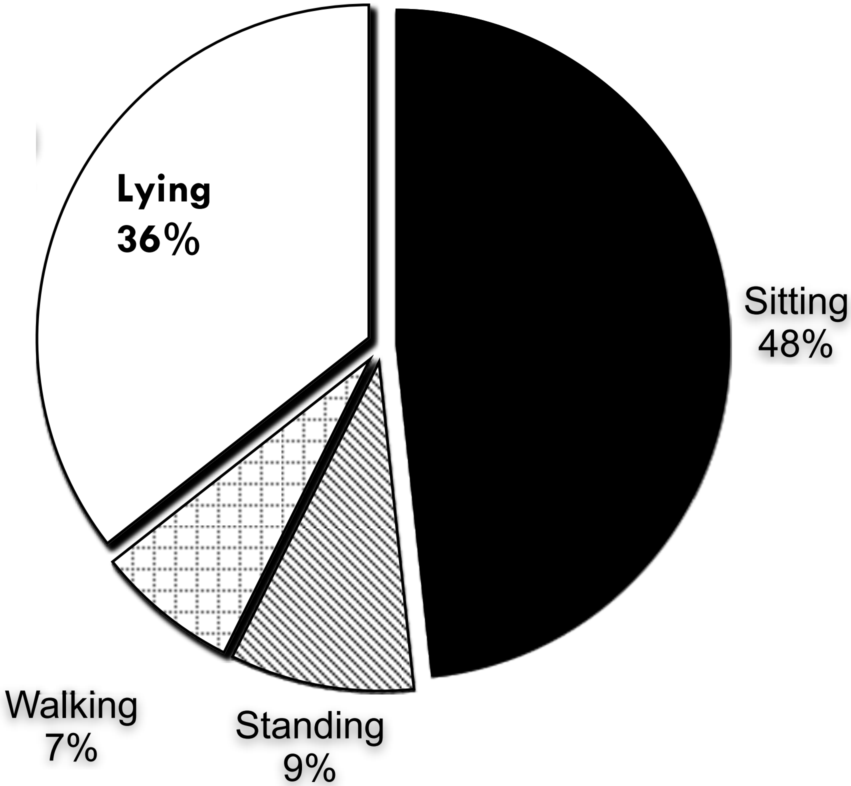




Salarian et al. (2007), IEEE-TBME, Massé et al. Journal of NeuroEngineering and Rehabilitation (2015)

12 hours of physical activity

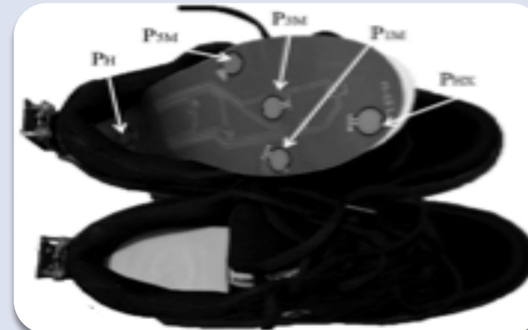




Instrumented shoes: Gait or Activity

Weenk et al. IEEE TNRSE, 2015

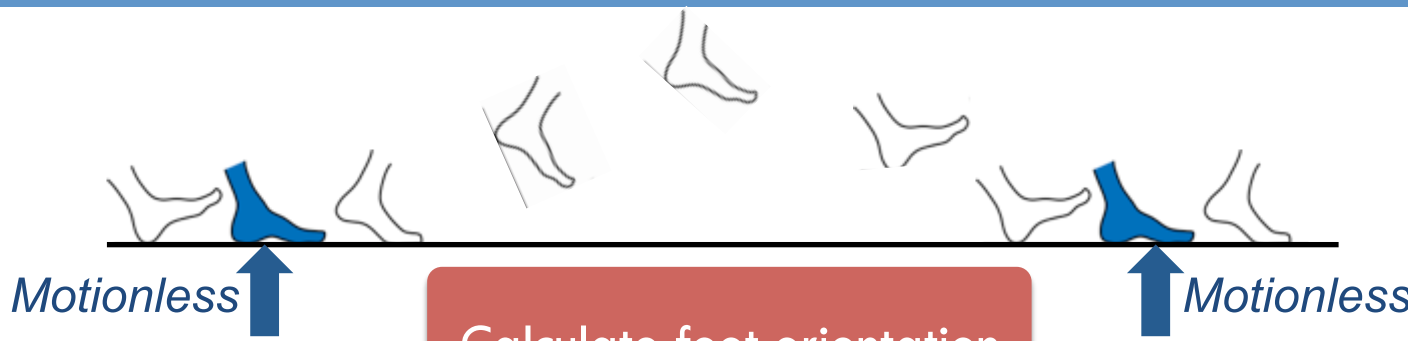
Mariani et al. J. Biomech, 2010



Tang and Sazonov, IEEE JBHI 2014

IMU + Ultrasound	IMU	FSR + Accelerometer
Gait Analysis	Gait Analysis	Activity classification

Gait parameters



Calculate foot orientation

↓

Calculate the inertial acceleration

↓

Double integration with constraints → foot position

Stride velocity
Stride length

Error ≈ 1.3 ± 6.5 %

Foot clearance

Error ≈ 7.5 ± 8.4 %

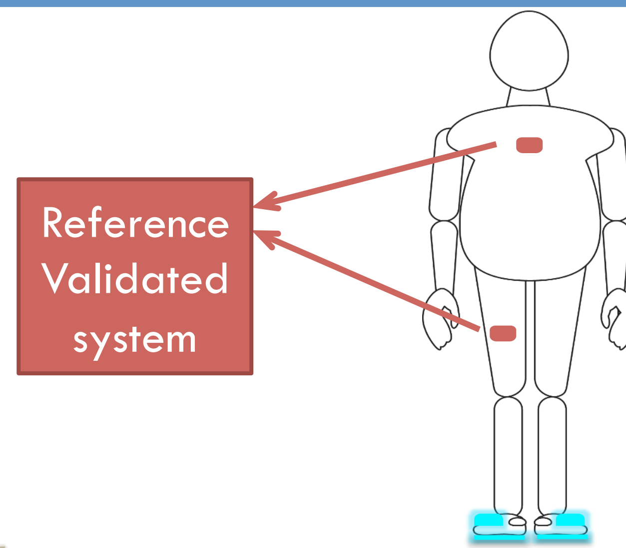
Turning angle

Inter-cycle variability

Mariani B. et al., J. Biomech, 2010

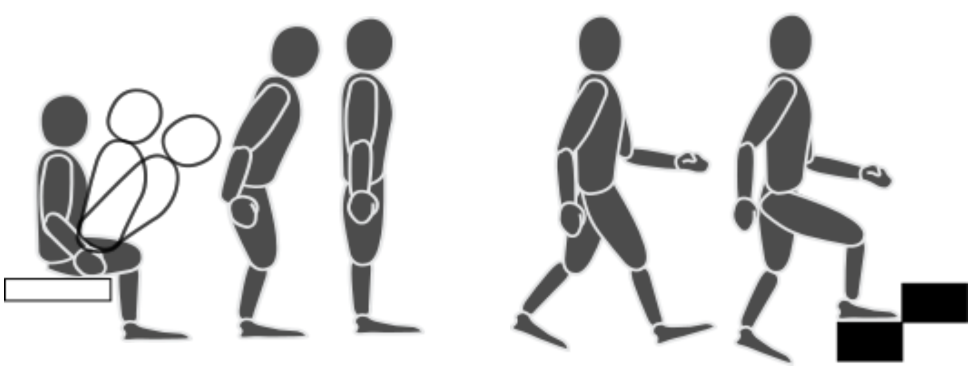
Instrumented shoes: Gait and Activity

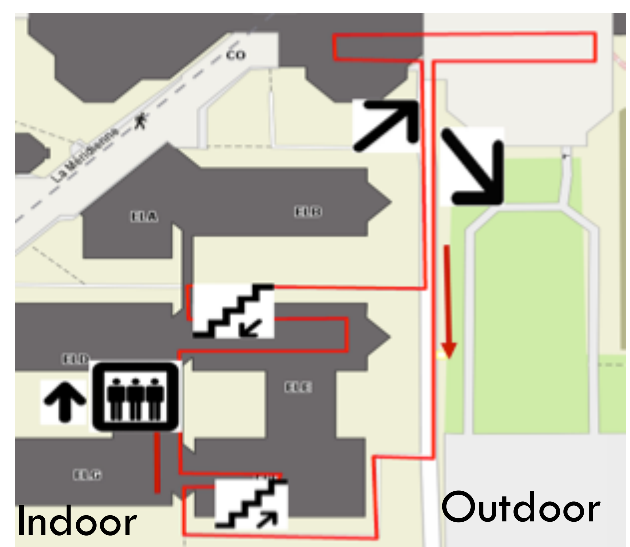
- IMU+ Barometric sensors+ foot Pressure sensors
- 10 elderly, healthy subject>65 years
- Predefined track (~700m)
- 4 hour of daily activity



IMU: Physilog, GaitUp, CH

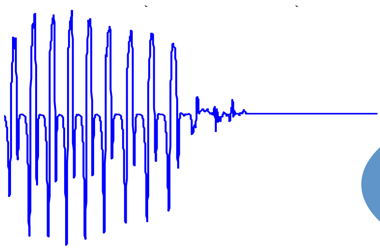
Insole: IEE, LU





Moufawad ElAchkar et al. Gait& Posture 2016

Algorithms for activity classification



Data

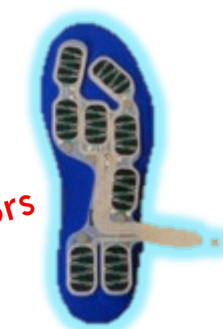
Step detection

- Locomotion
  - Body elevation
    - Stairs 0.98 / 0.89
    - Elevator 0.78 / 0.90
    - Ramps 0.96 / 0.94
- Non-locomotion
  - Body weight
    - Sit (<th) 1 / 0.96
    - Stand (>th) 0.99 / 0.96

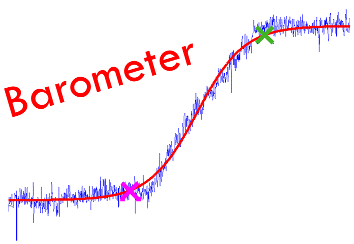
Sensitivity, Precision

Gyroscope

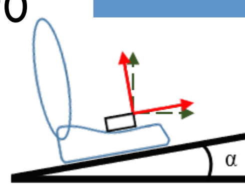
Force sensors

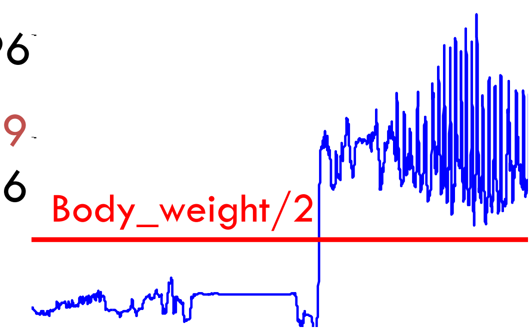


Barometer



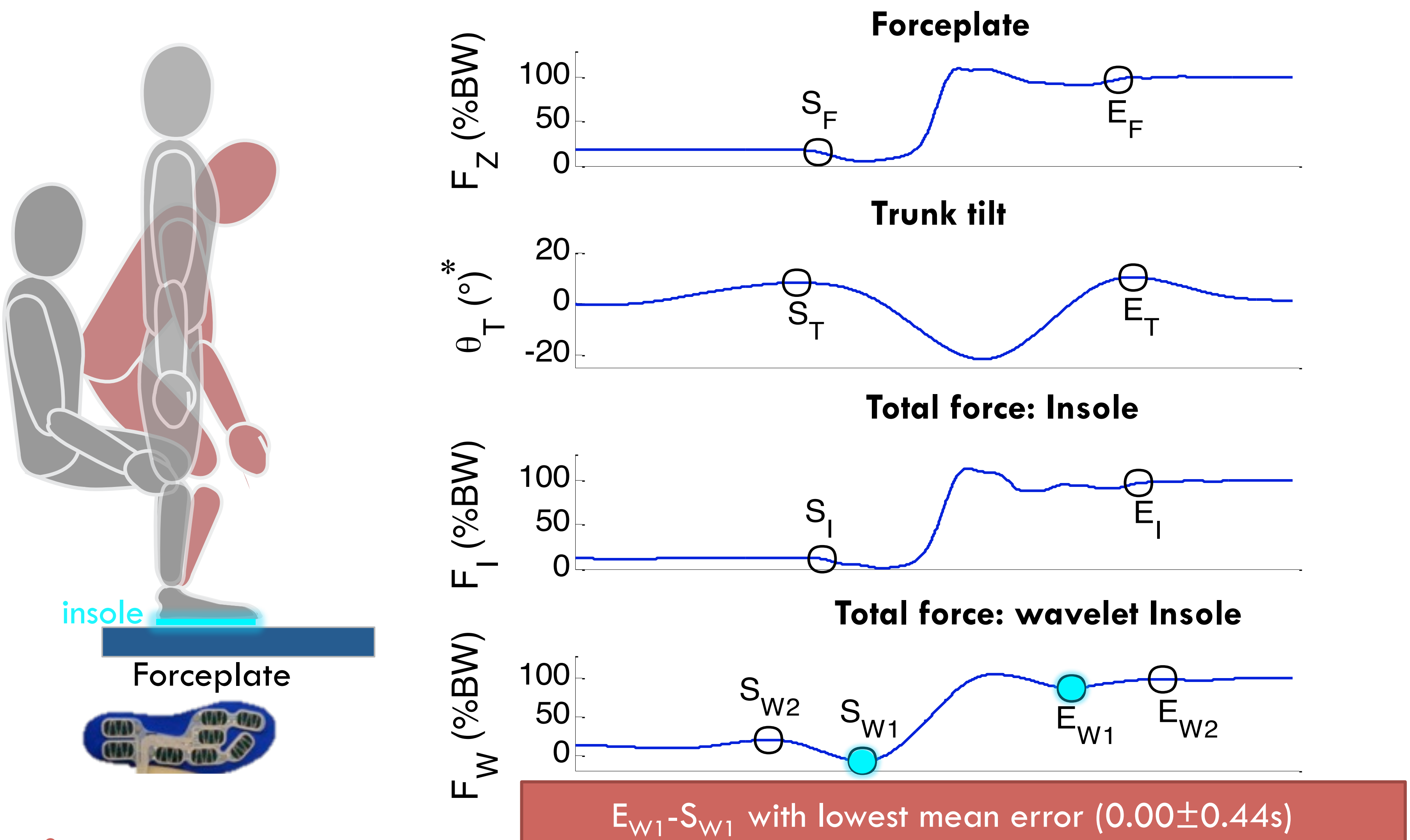
Accelerometer





Moufawad El Achkar et al., Gait & Posture, 2016

Transition duration: in lab validation



Submitted to IEEE transactions on Biomedical Engineering, * Najafi et al. IEEE TBME, 2002

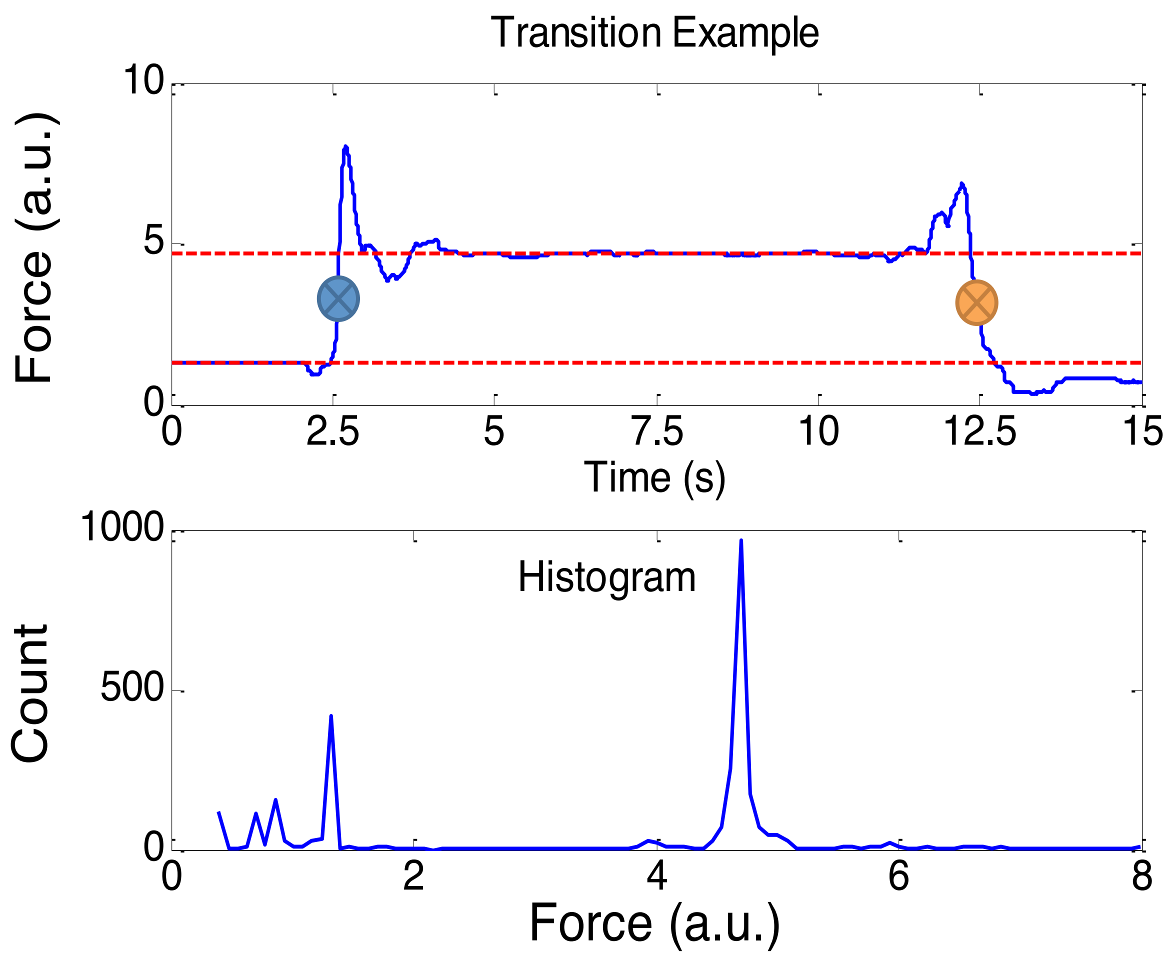
Transition detection in daily life

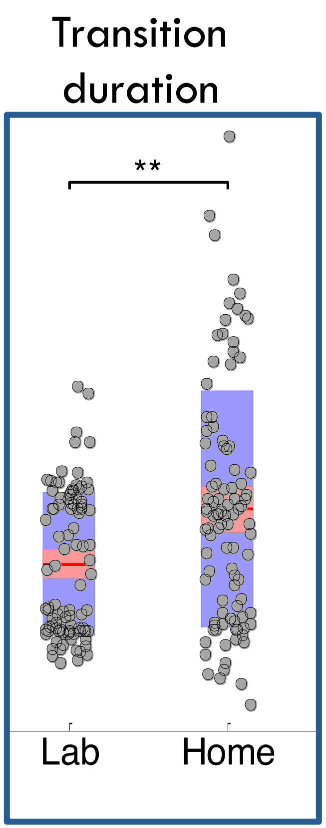
Histogram

Max/min Levels

Midcross

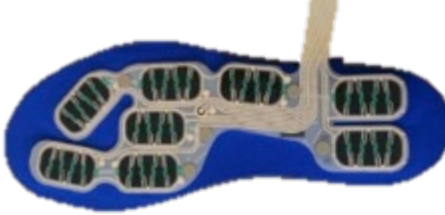
Transition



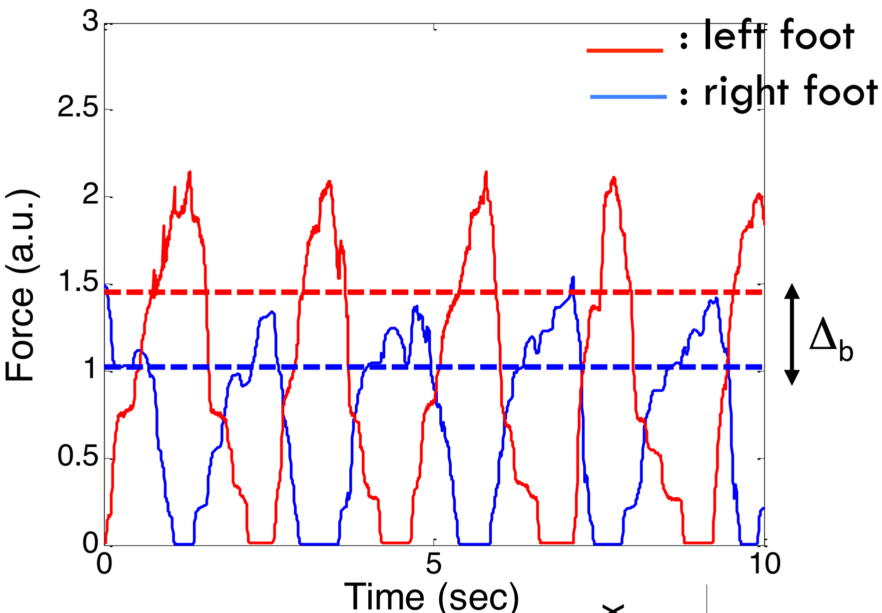


Sensitivity: 0.90, Precision: 0.93

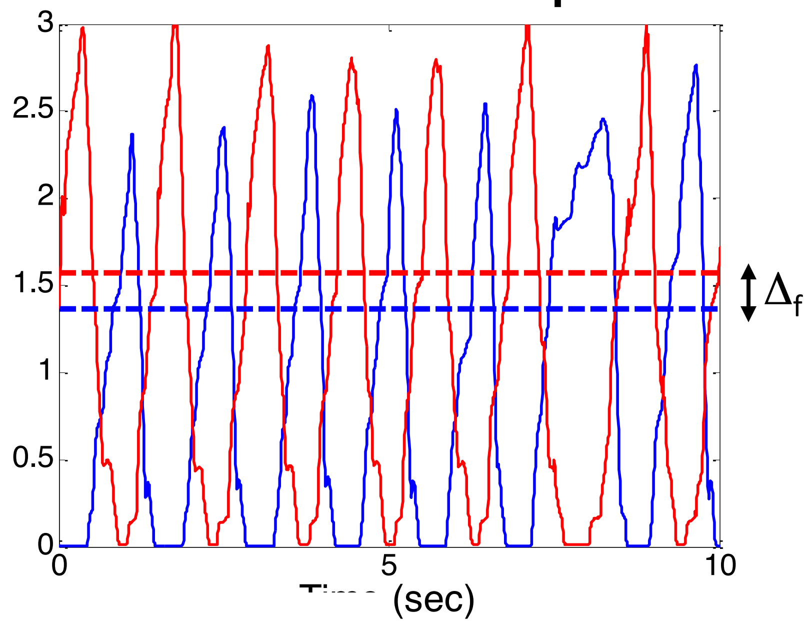
Foot loading during walking

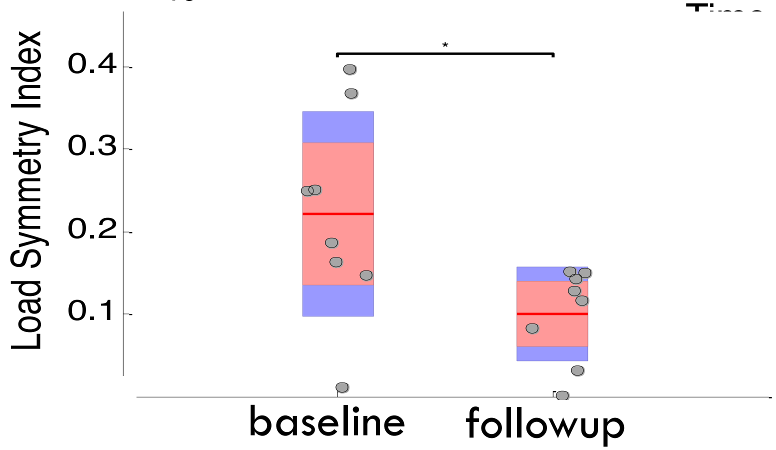


Baseline



Follow-up

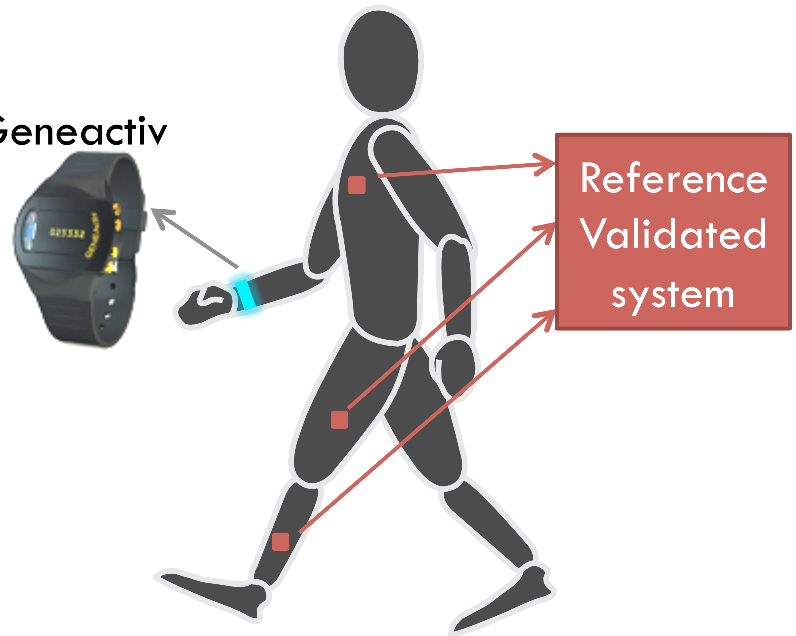




Moufawad El Achkar et al., EPFL thesis, 2016

Wrist sensors: activity classification

- Mostly based on machine learning
  - Support vector machine with time-frequency features: accuracy 85% *
  - **75% correct** activity intensity classification, **99% correct** locomotion time**
  - Validated in laboratory
- In field validation using IMU reference system***
  - N=20
  - 1 day of activity life
  - Features derived from:
    - Arm postures and patterns
    - Statistical, temporal frequency domain
- Locomotion periods classification
  - Accuracy of 99%
  - Sensitivity of 85%
  - Specificity of 99%



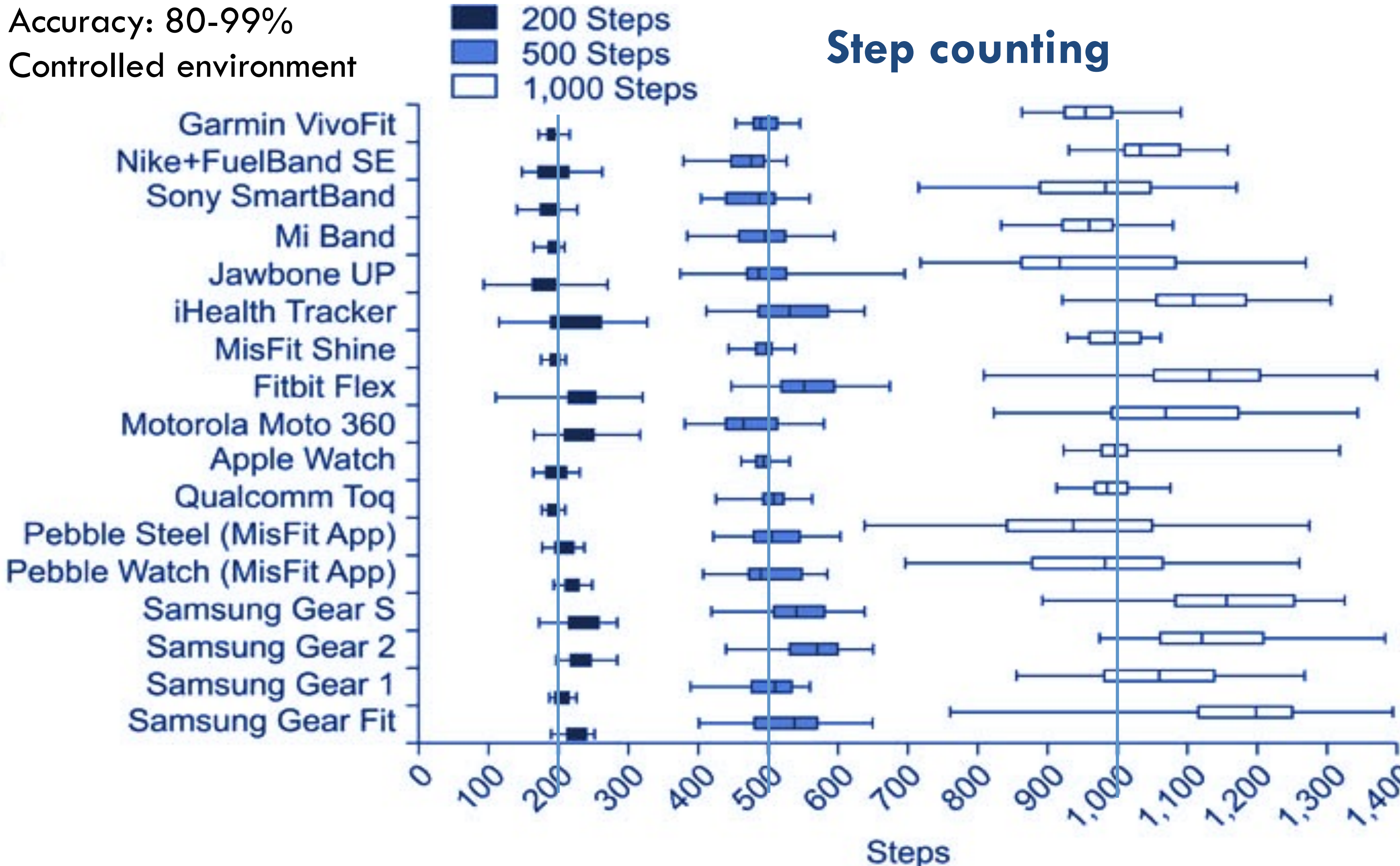
*Mannini et al. Med.Sci.Sports&Exercise, 2013, **Staudenmayer et al. J Appl Physiol, 2015, ***Hasler, Master Thesis, 2016

Step counters

Accuracy: 80-99%

Controlled environment

Step counting

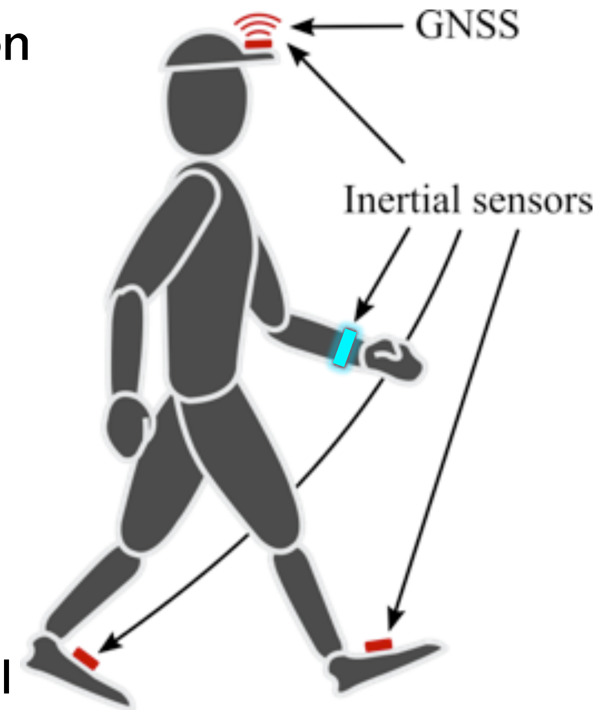


El-Amrawy et al. Healthc Inform Res. 2015

Wrist sensor: speed and cadence estimation

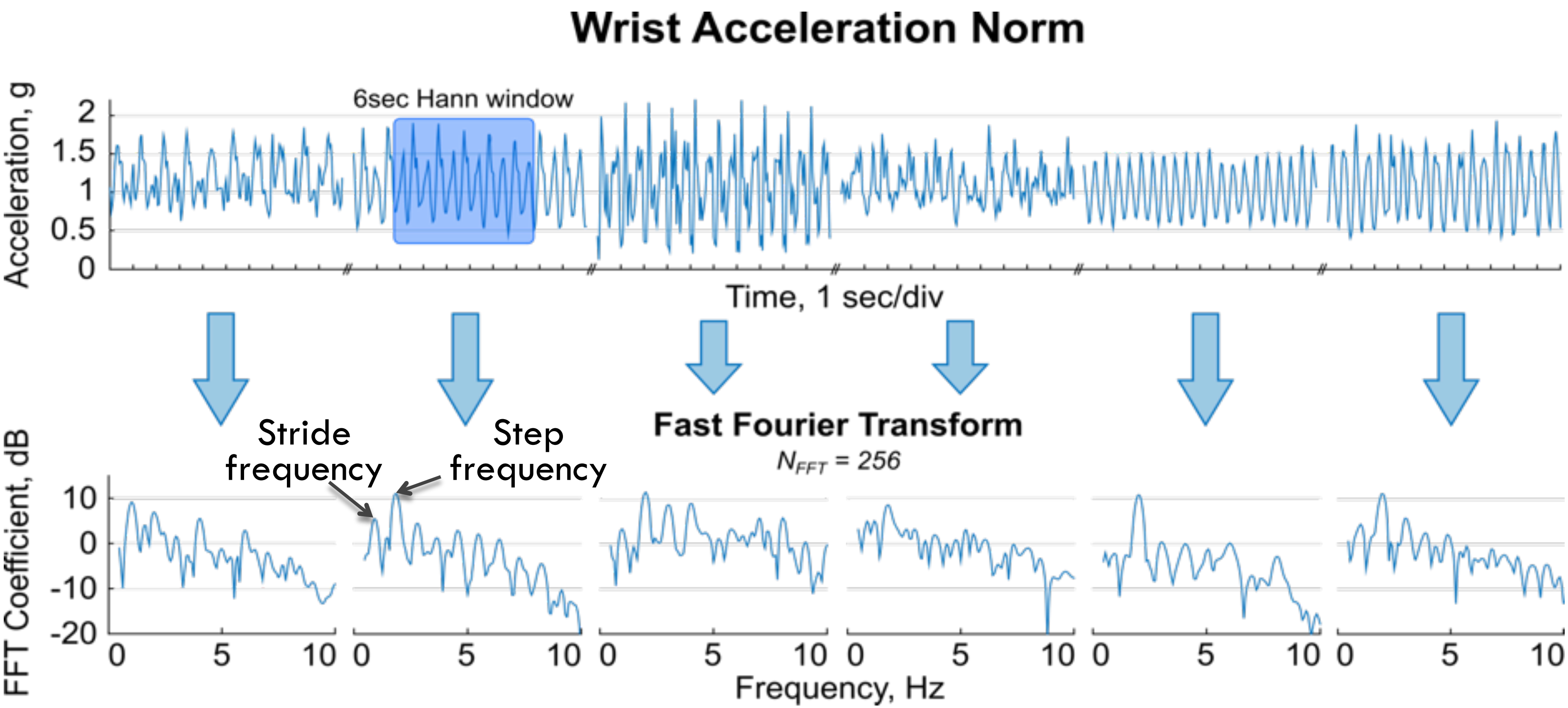
- Challenges
  - "Random" arm movement
    - other than locomotion related movement
  - High drift in integral of arm acceleration
    - no motion less period to reset drift
  - Error in step detection

- In field validation
- Protocol
  - N=22
    22 👨, 7 👩,
    39±11 years
  - 4.7 km
  - Normal
  - Level, inclined
  - Tar, grass, gravel
  - Urban, rural
  - Constraints: Cellphone, obstacle, bag, hand in pocket



- Reference: GNSS and foot sensors

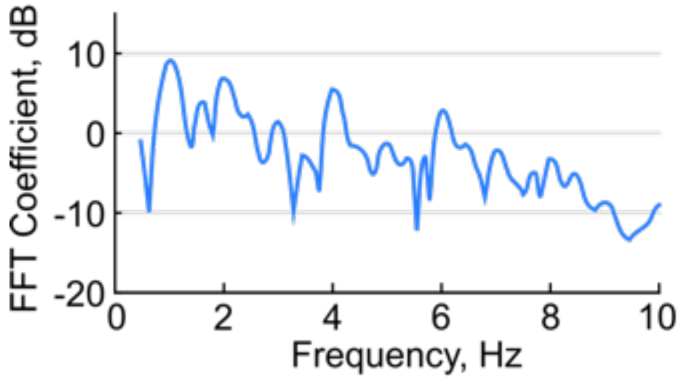
Methods – Cadence extraction



Methods: cadence estimation

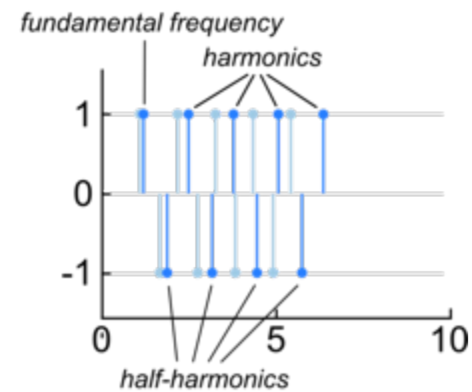
Fast Fourier Transform

Hann window, 6 seconds



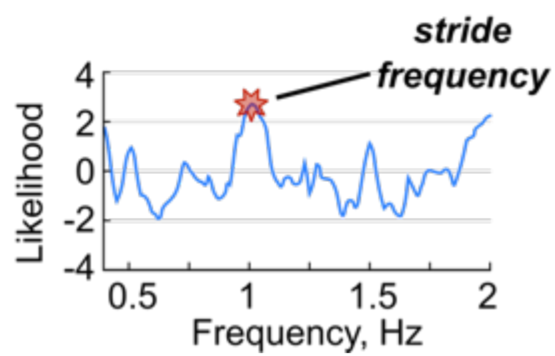
Convolution

sweep 0.4-2Hz

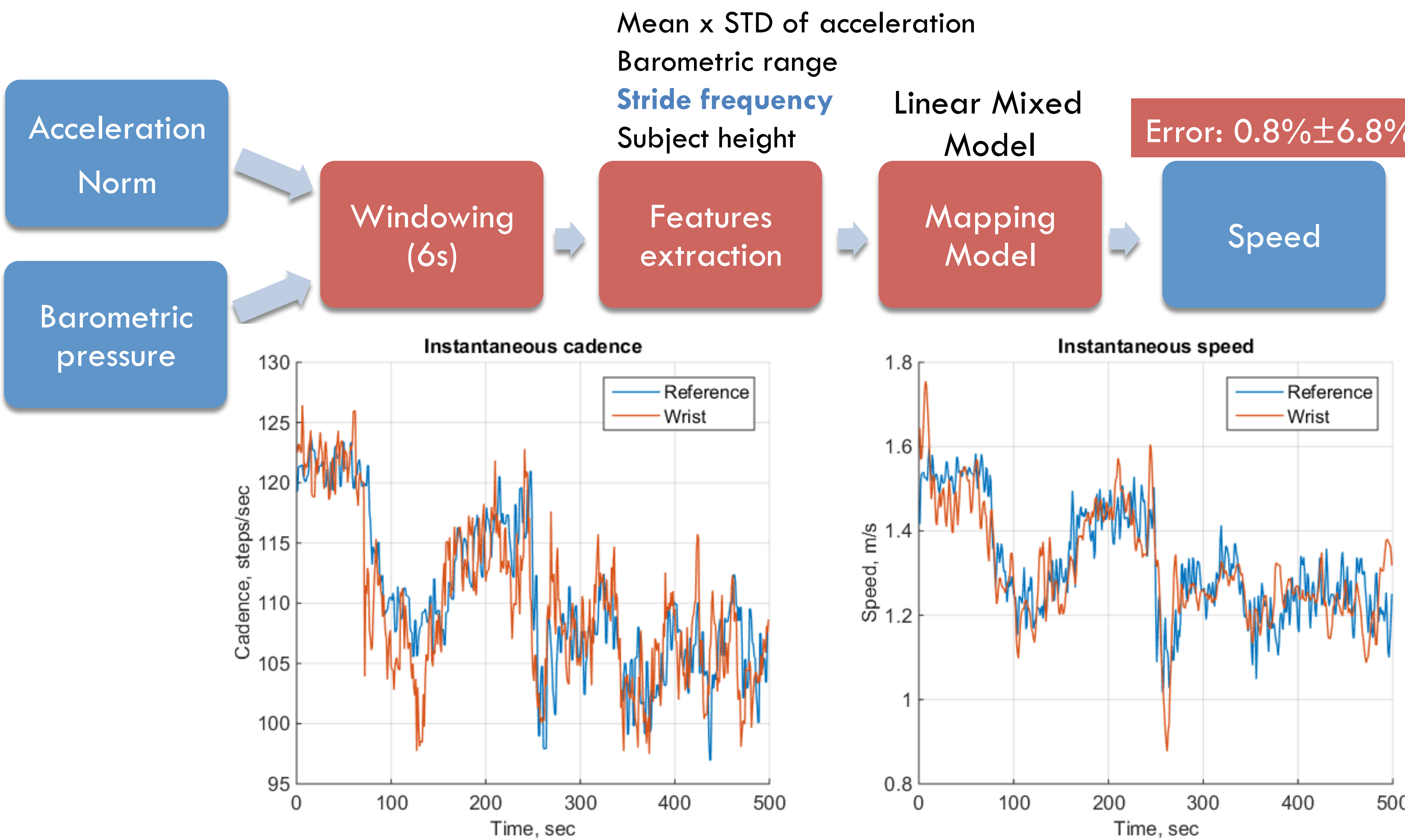


Cadence Likelihood

0.01Hz resolution



Speed estimation



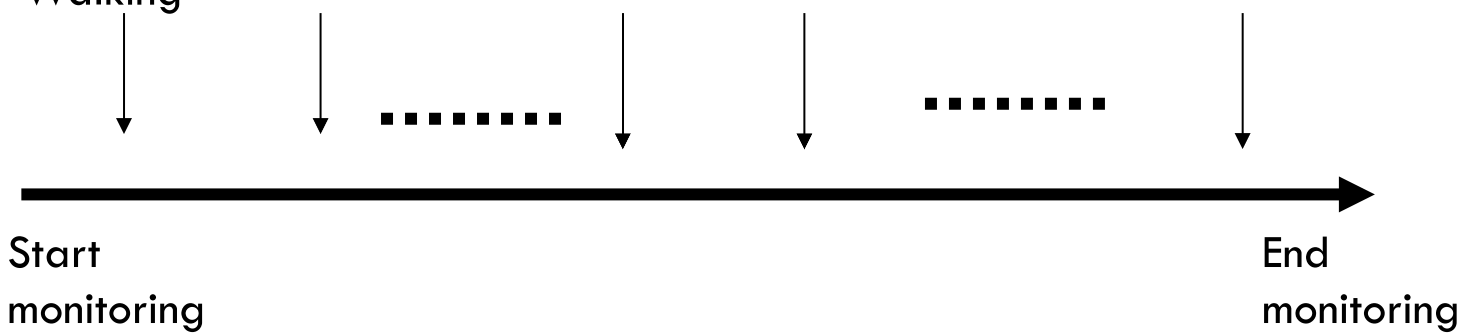
PA patterns/time-series: the concept

- Representation of how **PA parameters** evolve with the **time**

Type:
- Sitting/lying
- Standing
- Walking

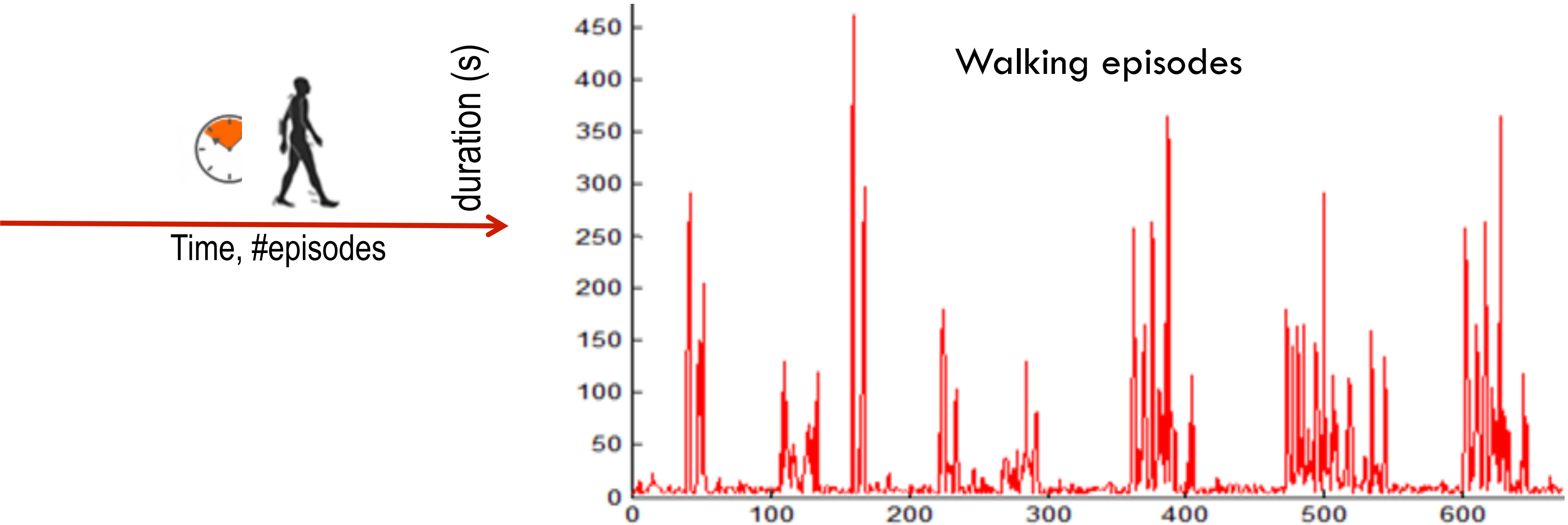
Intensity:
- Trunk acceleration
- Gait features (speed, cadence)

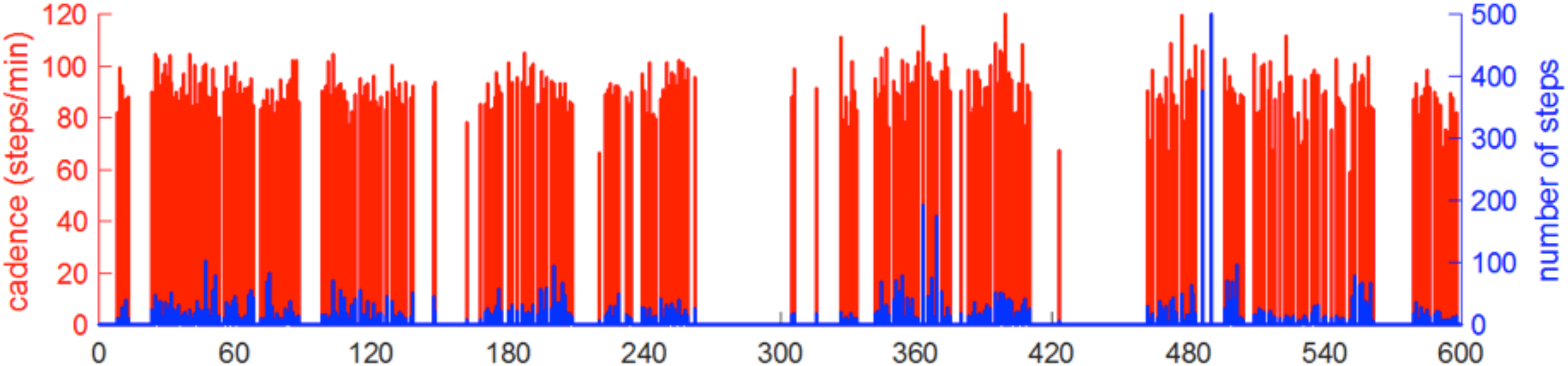
Duration:
- Continuous walking



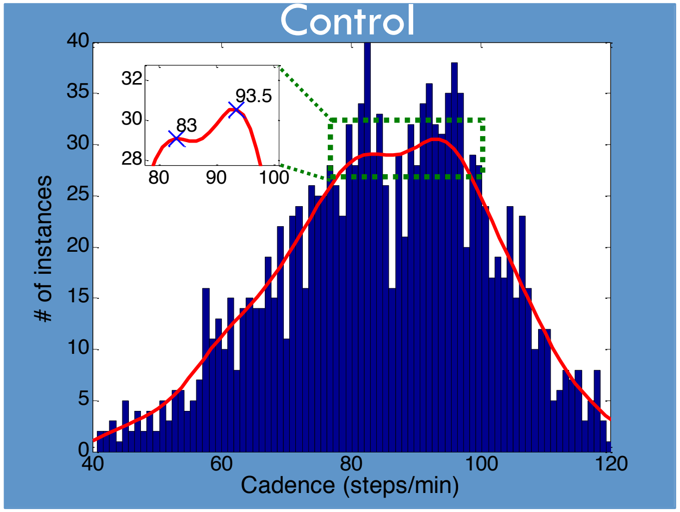
- **Hypothesis: time evolution captures ‘behavioral features’**

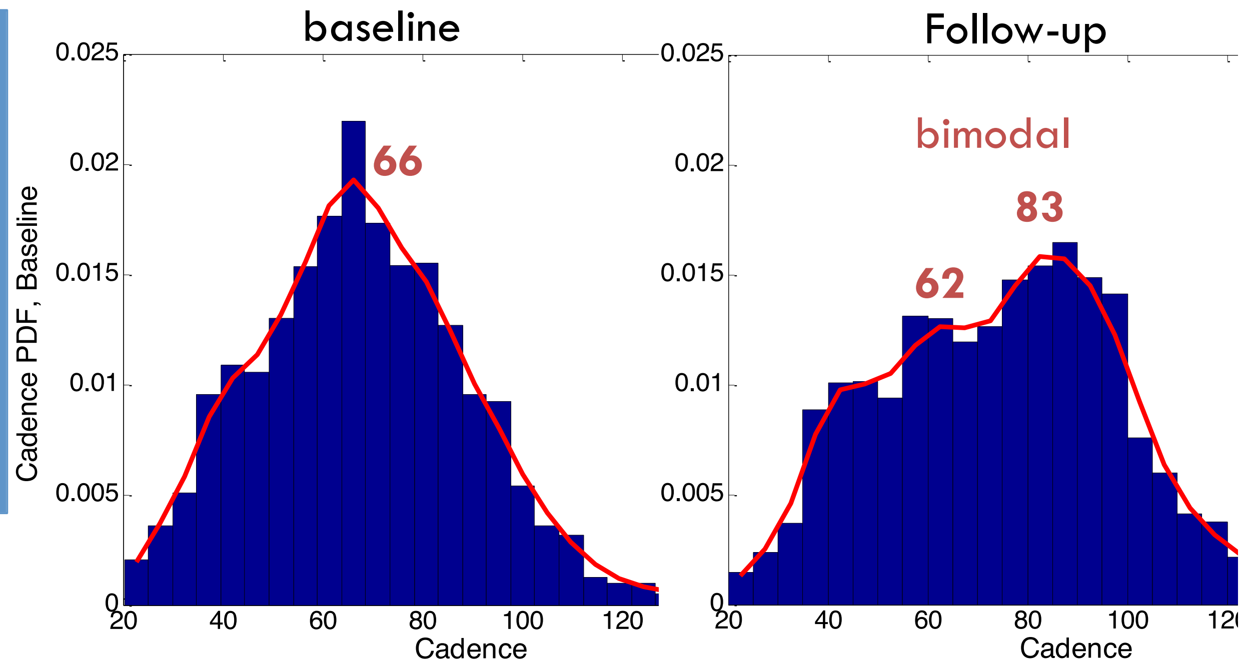
PA patterns/time-series: univariate





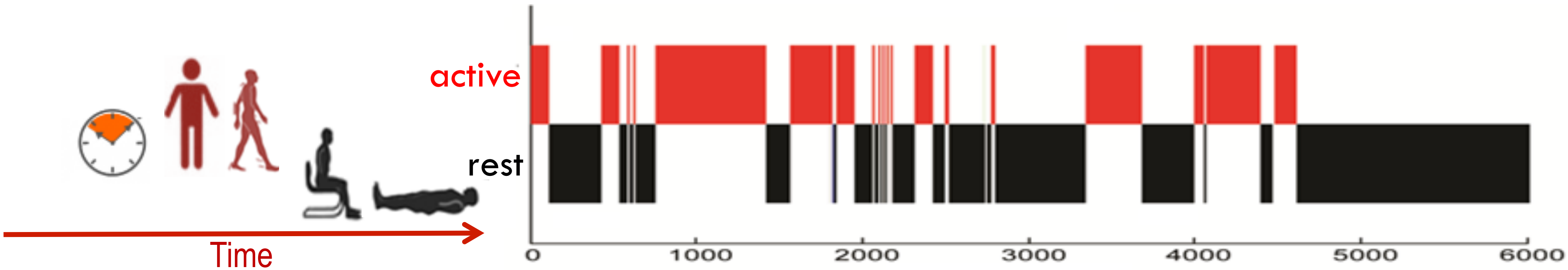
Post-surgery hip fracture patients (69-93 years): Cadence distribution in real-life (N=8, 1day)



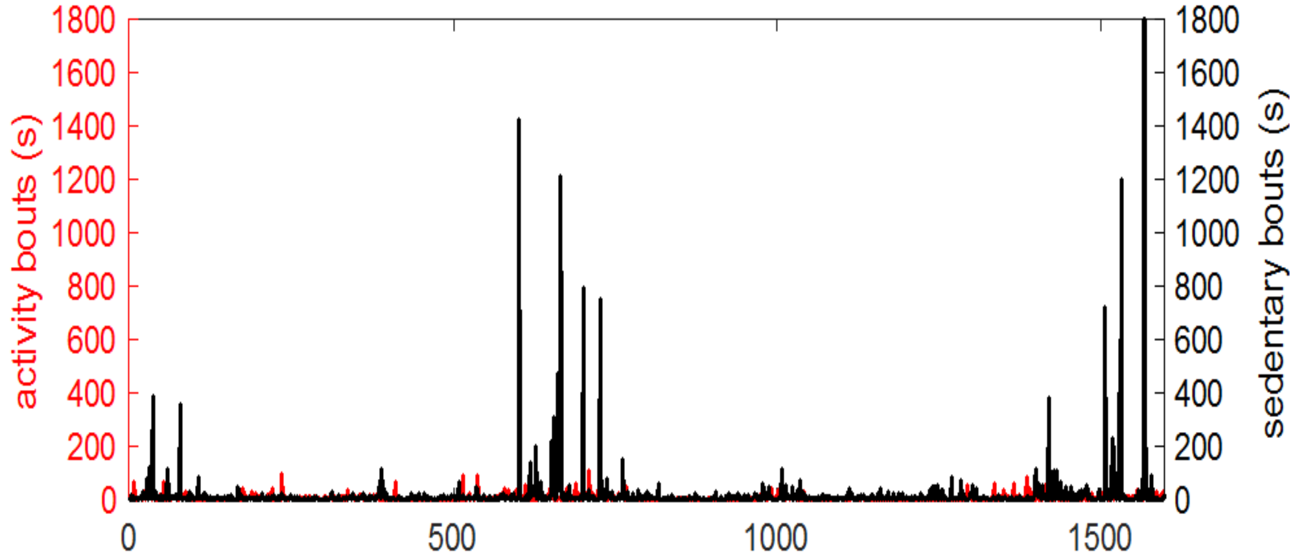


Maximum duration (sec)	52±18	78±35
Cadence (steps/min)	65±8	73±5
Velocity (m/s) mean	0.31±0.11	0.38±0.09
Heel Clearance (cm)	15±5/20±7	17±3/22±4
Tinetti	17±2	21±1

PA patterns/time-series: bivariate

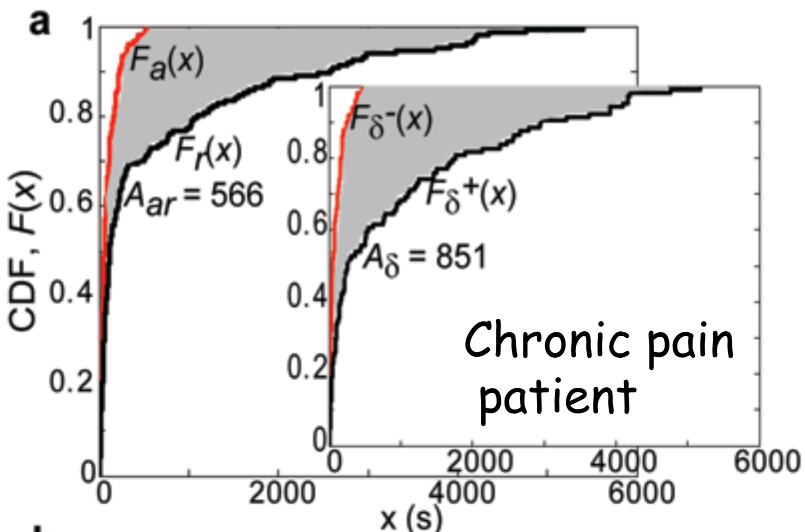


- How rest and activity happen during daily life
  - Short rest after long walk (healthy condition, deficit rest)
  - Long rest after short walk (disease condition, excess rest)

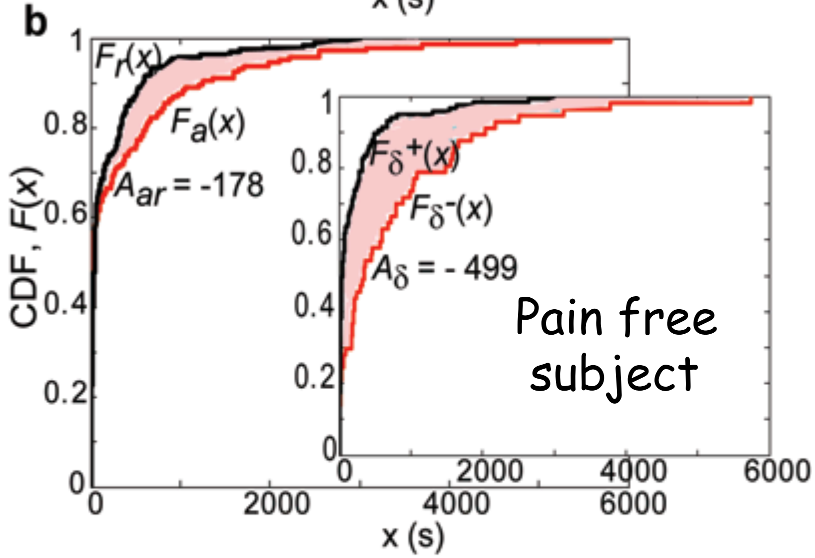


Relationship between successive activity and rest periods and their distribution over the day time?

Rest/activity distribution of PA patterns



- Chronic pain
  - More short activity/ more long rest
  - More excess in rest

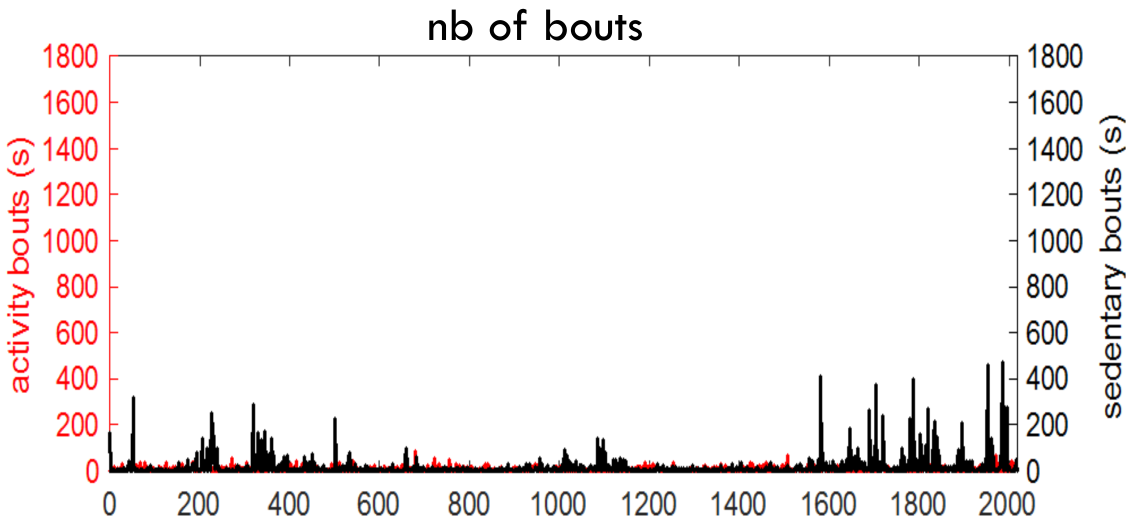


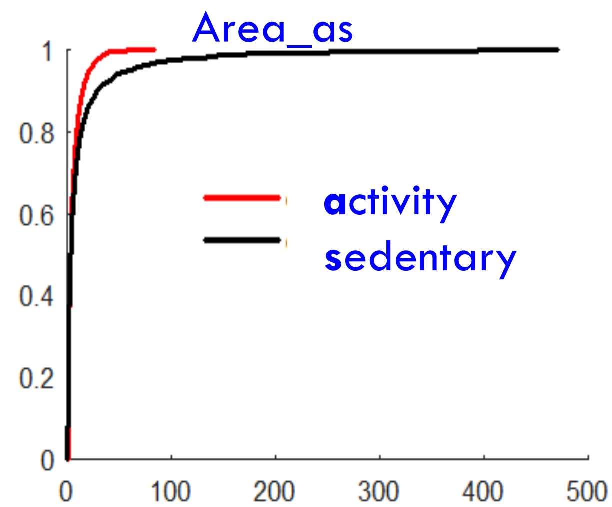
- Pain free
  - More long activity/more short rest
  - More deficit in rest

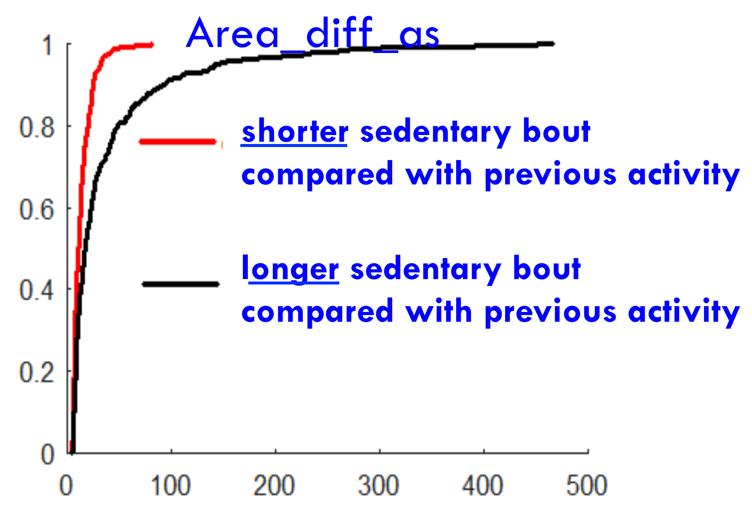
Metrics (A): statistical distance (area) between Cumulative Density Function (CDF)

A. Paraschiv-Ionescu, Aminian et al., Scientific Reports, 2013

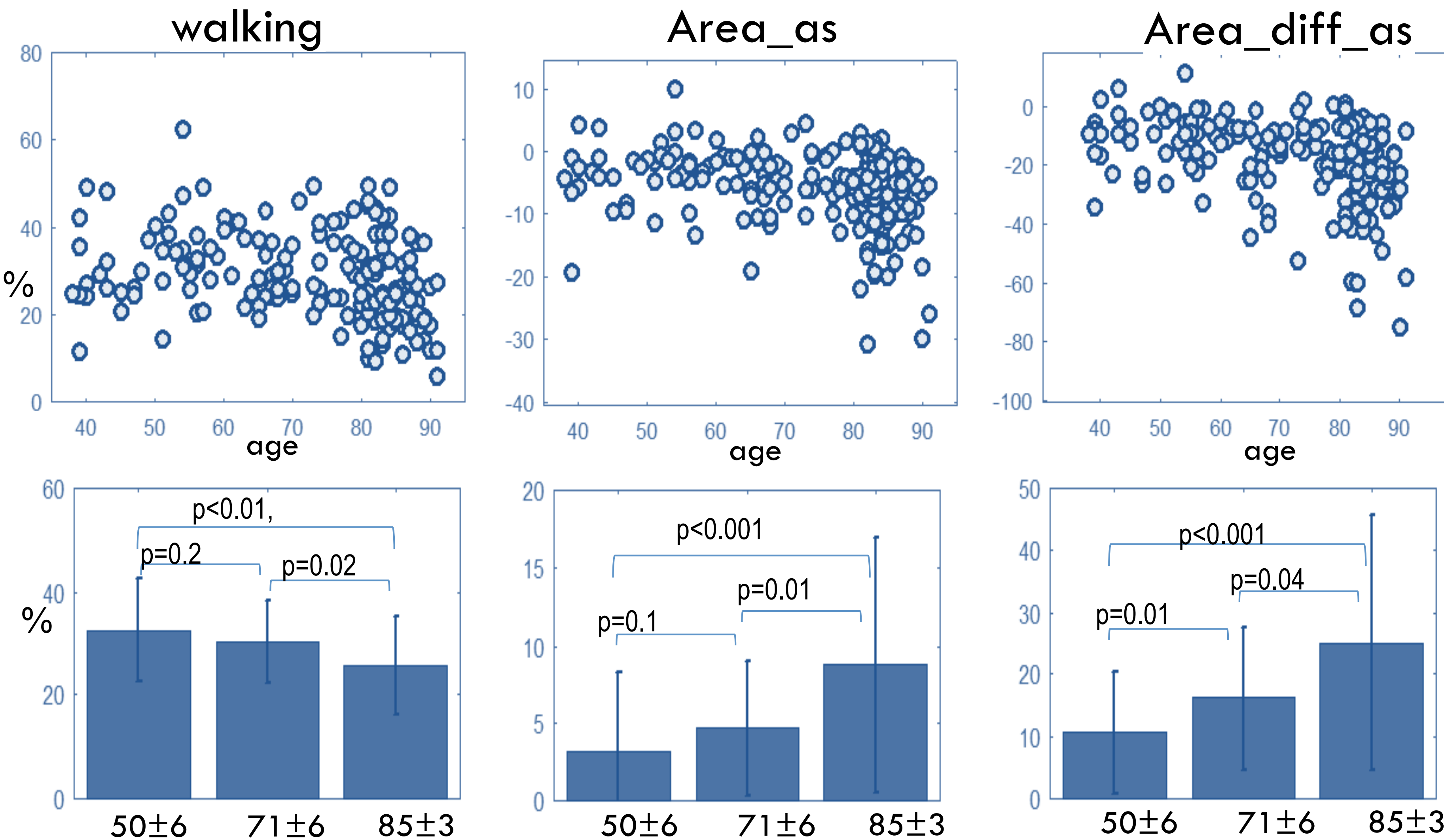
Bivariate patterns: *Activity-Sedentary*



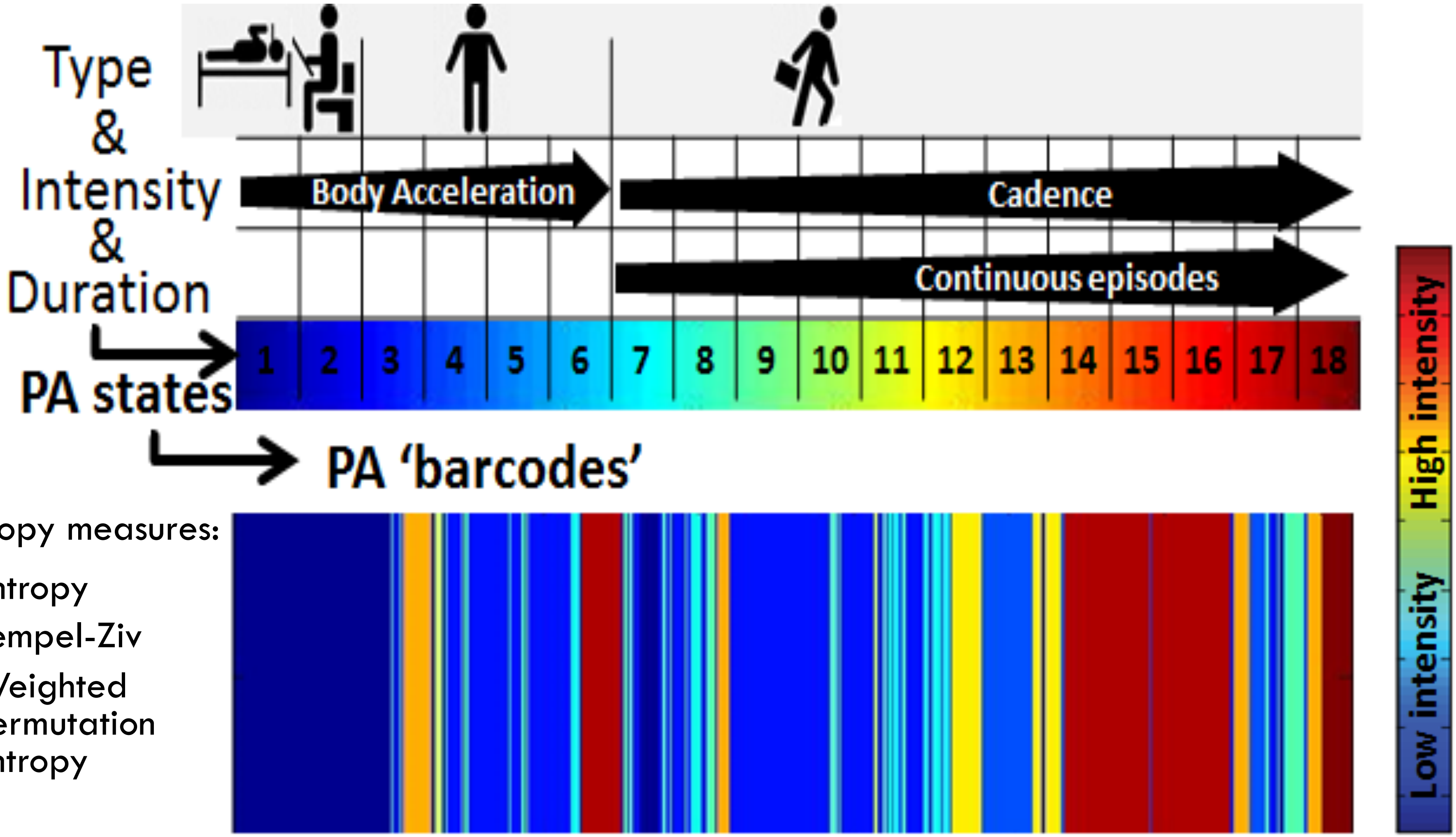




inChianti datset: N=183, 4days, 8h/day



Multivariate patterns: *barcode complexity*

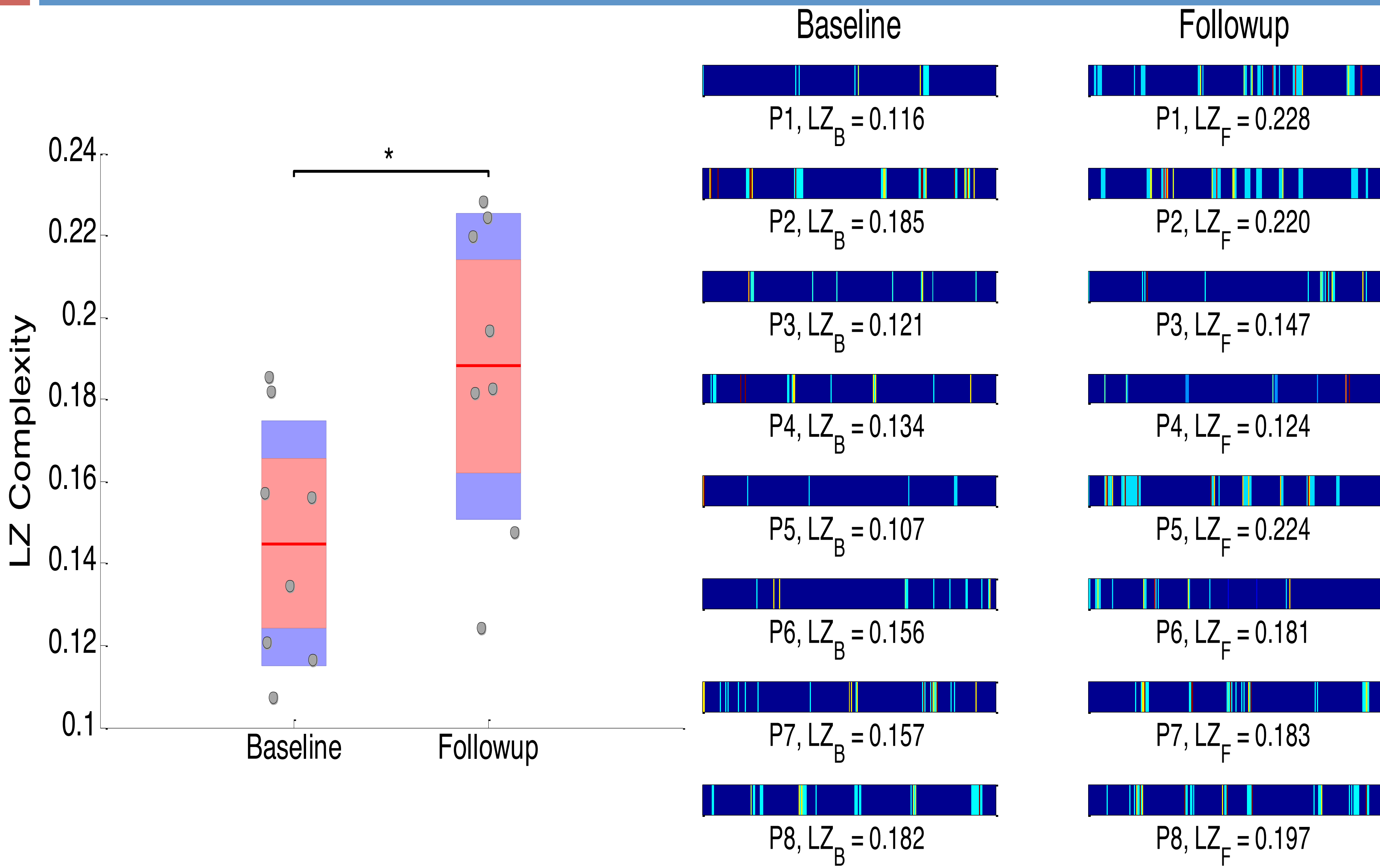


Entropy measures:

- Entropy
- Lempel-Ziv
- Weighted Permutation Entropy

Paraschiv-Ionescu et al. (2012) , PLoS ONE

Post-surgery hip fracture patients (69-93 years): barcode complexity (N=8, 1day)



Data collection and protocol

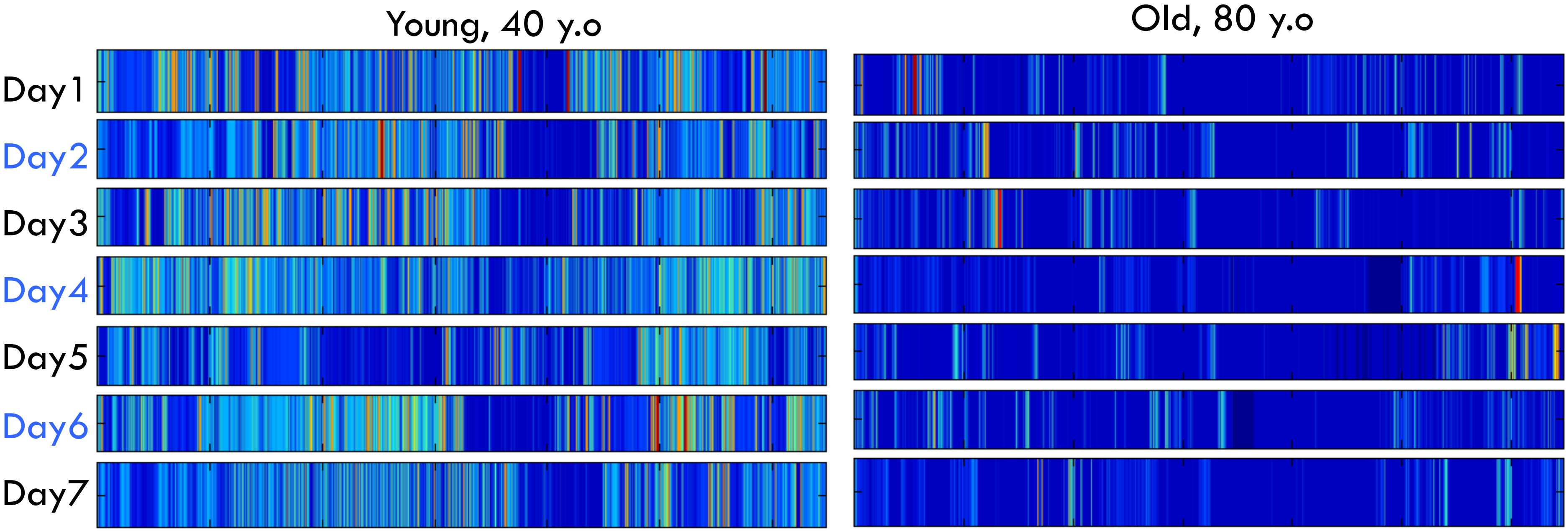
- Subjects: N=254
- Age: 41-98 y.o
- Smartphone recording:

  7 days, 9hours/day
- Activity **states & Barcodes:**
  - **type:** lying/sedentary, active, gait
  - **intensity:** activity counts, cadence
  - **duration:** walking (gait) bouts
  - **18 states barcodes**

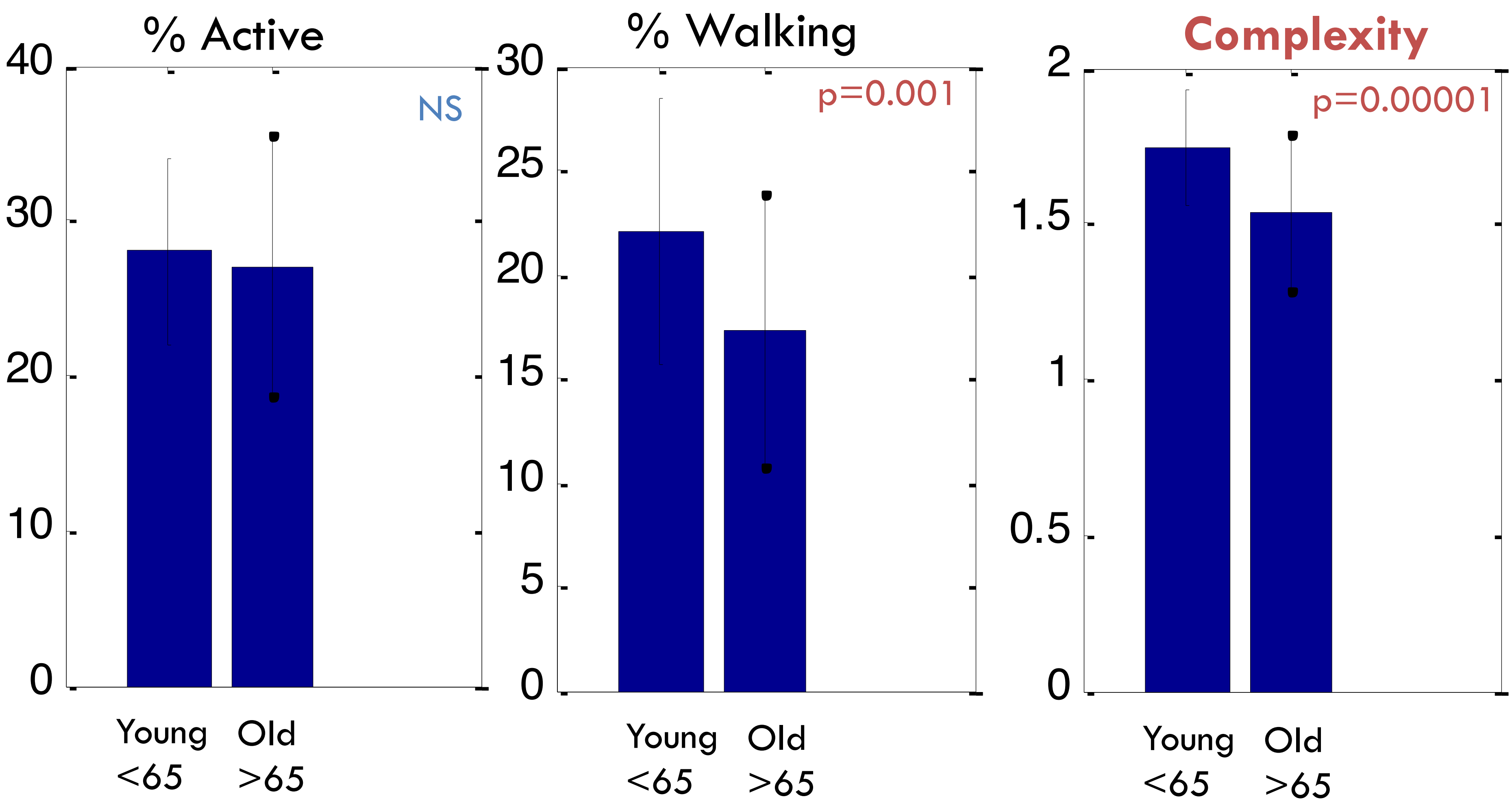
European Commission
Information Society and Media

http://farseeingresearch.eu

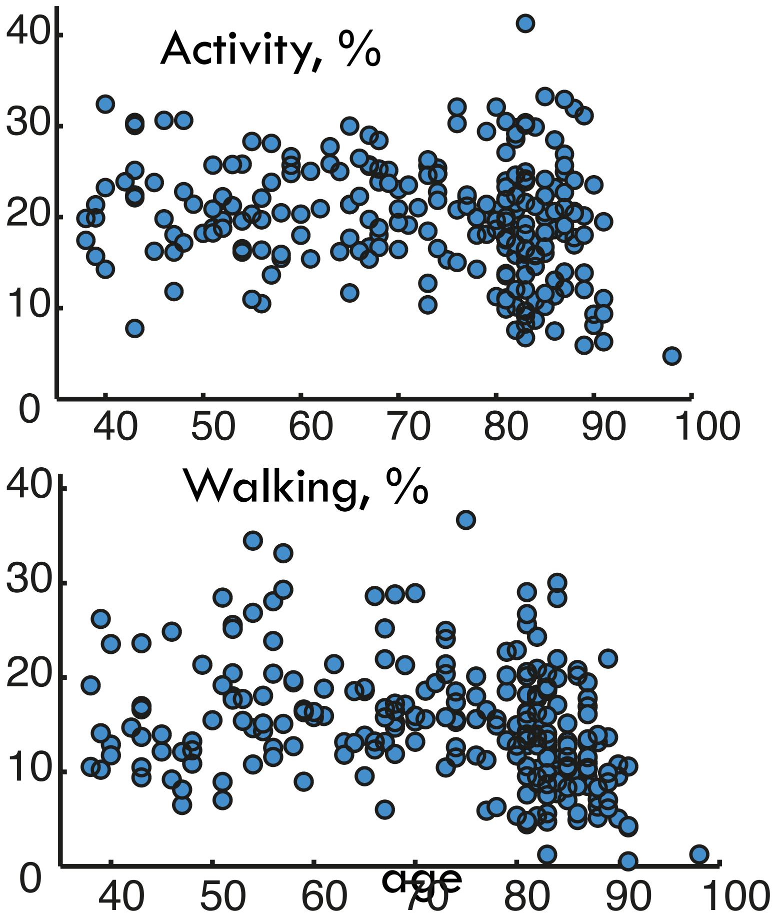
Young vs. old barcodes



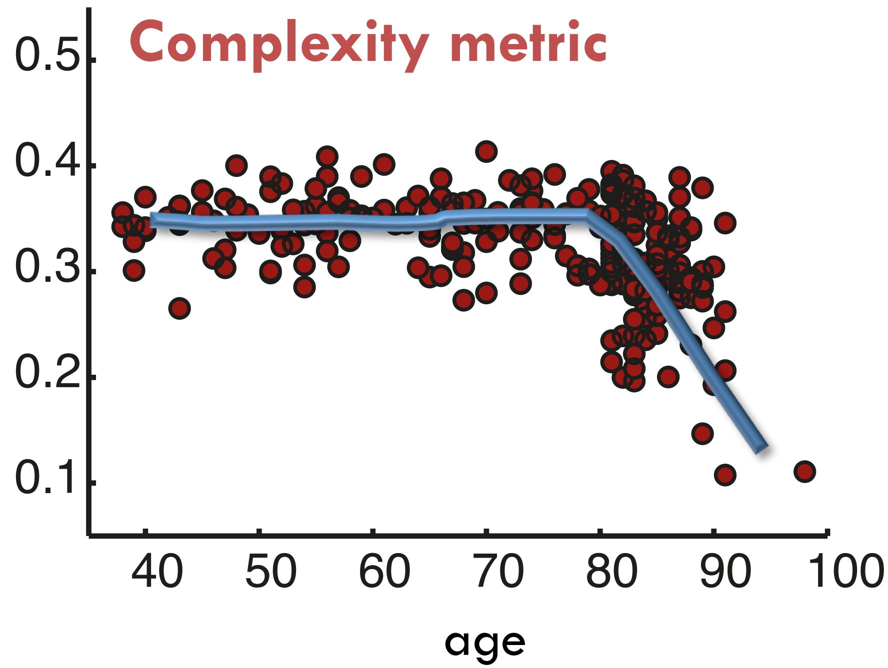
Standard vs complexity metrics



Activity metrics vs. age



No clear relationship

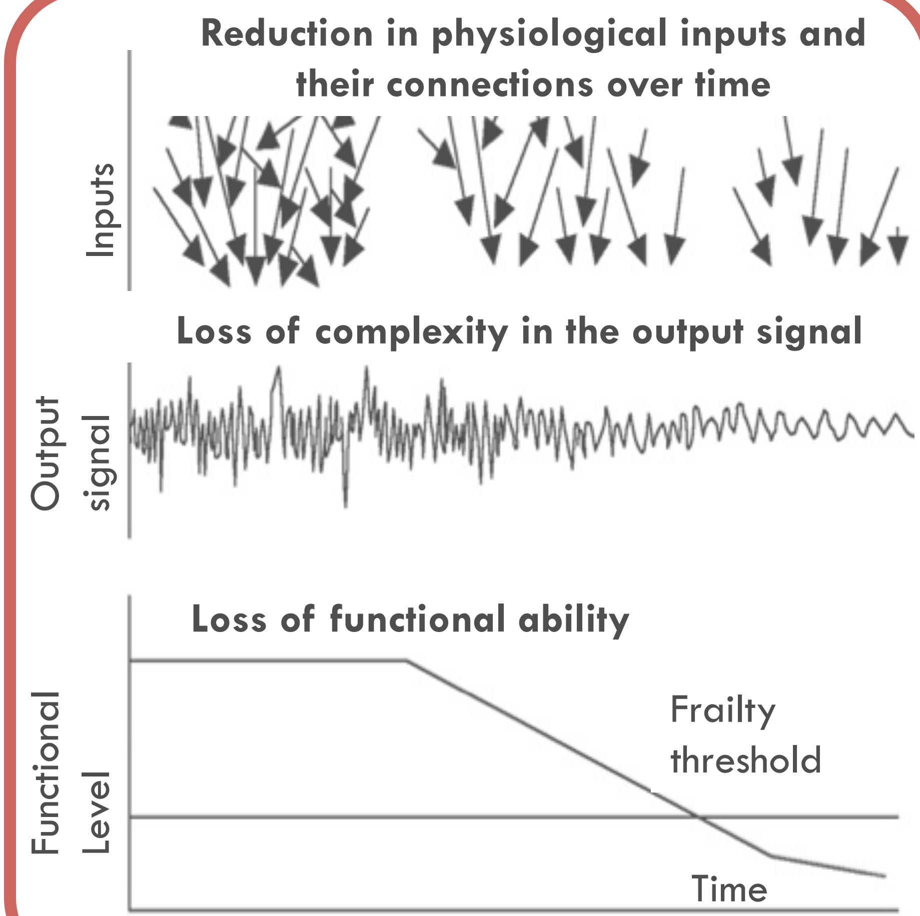


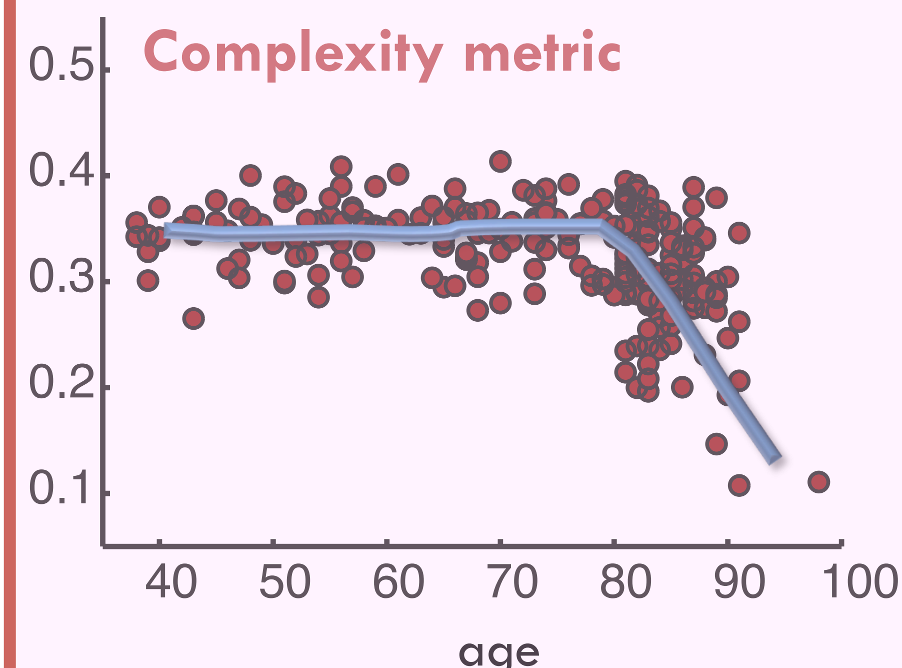
Plateau then drop just before 80 years (~ 75)

Frailty threshold

Lipsitz - Science's SAGE KE, 2004

from Physiology *to* Movement complexity





PA complexity seems to support
The concept defined by Lipsitz

Conclusions

- Physical behavior is a good marker of quality of life
- Physical behavior can be measured objectively with sensors embedded in wearables:
  - Gait, activity profile, complexity
  - field measurement

- Main perspectives
  - Mobile health: support medical decision, personalization
  - Behavior monitoring: physical-social interaction
  - Active coaching: monitor and suggest how to progress

- Challenges
  - Usability
  - Adherence and safety
  - Data protection