Body posture recognition based on the raw accelerometry data

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February 24, 2020

OUTLINE

- WEARABLE ACCELEROMETERS
- RAW ACCELEROMETRY DATA
- DEVICE PLACEMENT
- METHODS FOR:
  - SITTING VS. STANDING
  - WALKING
- APPLICATIONS
- CONCLUSIONS

WEARABLE ACCELEROMETERS – WHY?

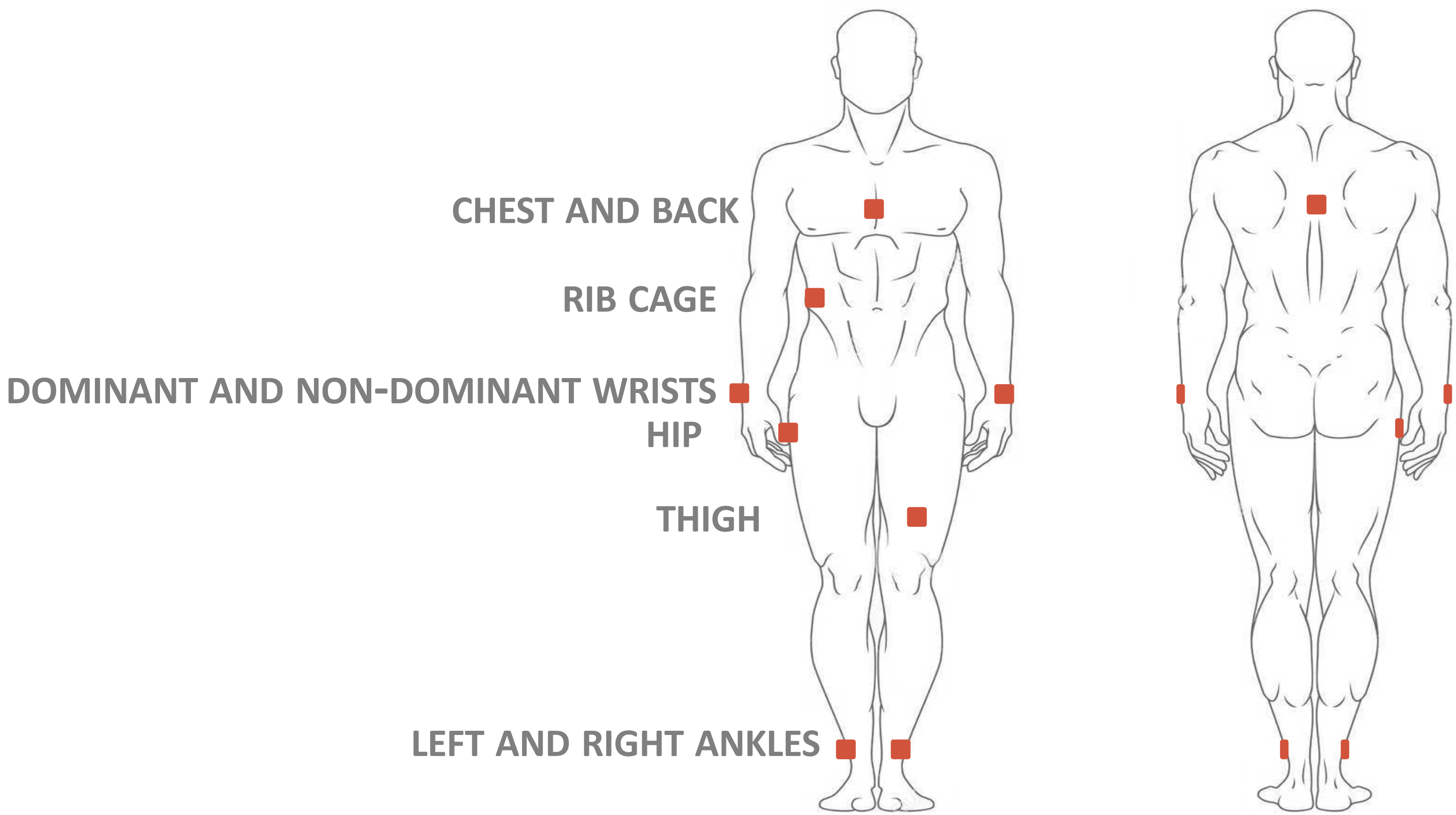
WHY?

- THEY ARE OBJECTIVE
- THEY ARE EASY TO WEAR
- THEY ARE CHEAP
- THEY MEASURE ACTIVITY AT A RESOLUTION HUMANS CANNOT REPORT
- THEY PROVIDE REPRODUCIBLE PROXY MEASUREMENTS

THUS...

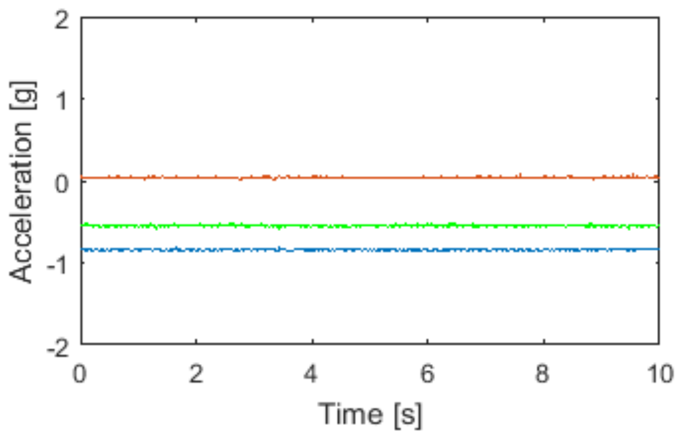
- THEY GAINED ACCEPTANCE IN LARGE OBSERVATIONAL STUDIES AND CLINICAL TRIALS

WEARABLE ACCELEROMETERS – WHERE?

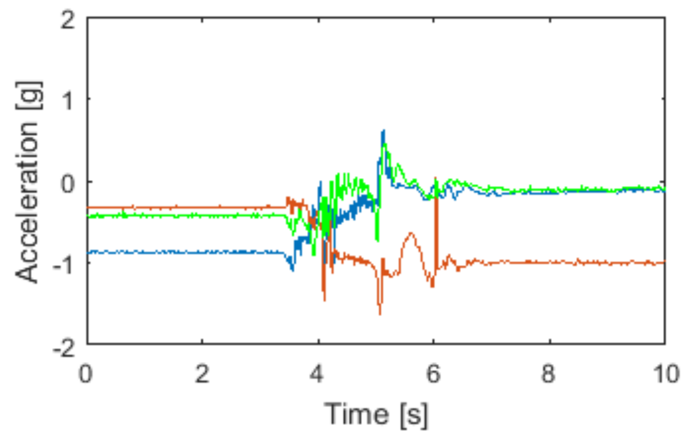


WEARABLE ACCELEROMETERS – WHAT?

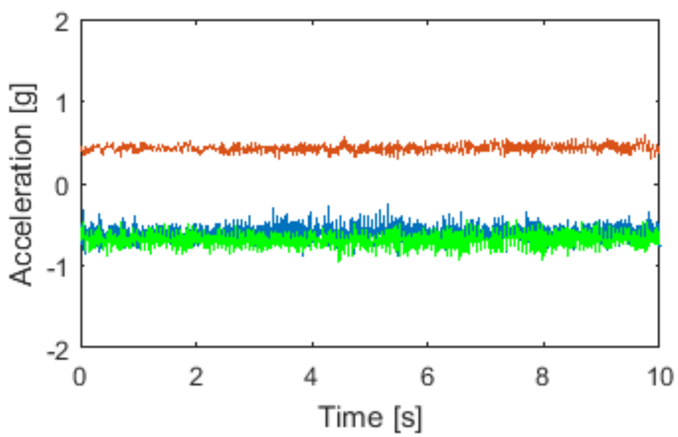
RESTING



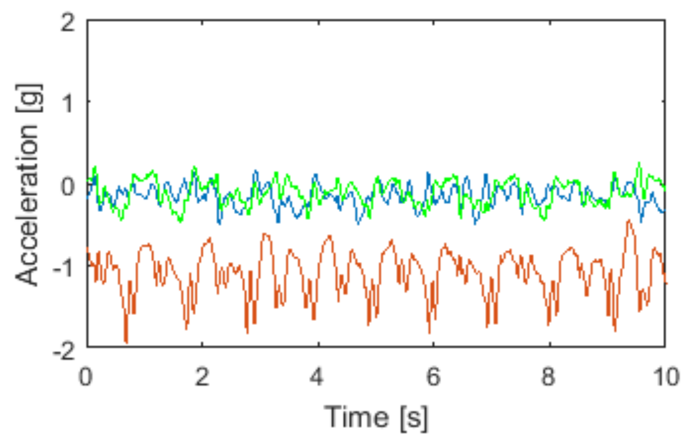
STANDING UP



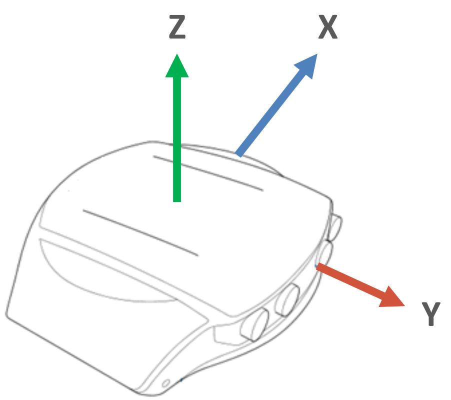
DRIVING

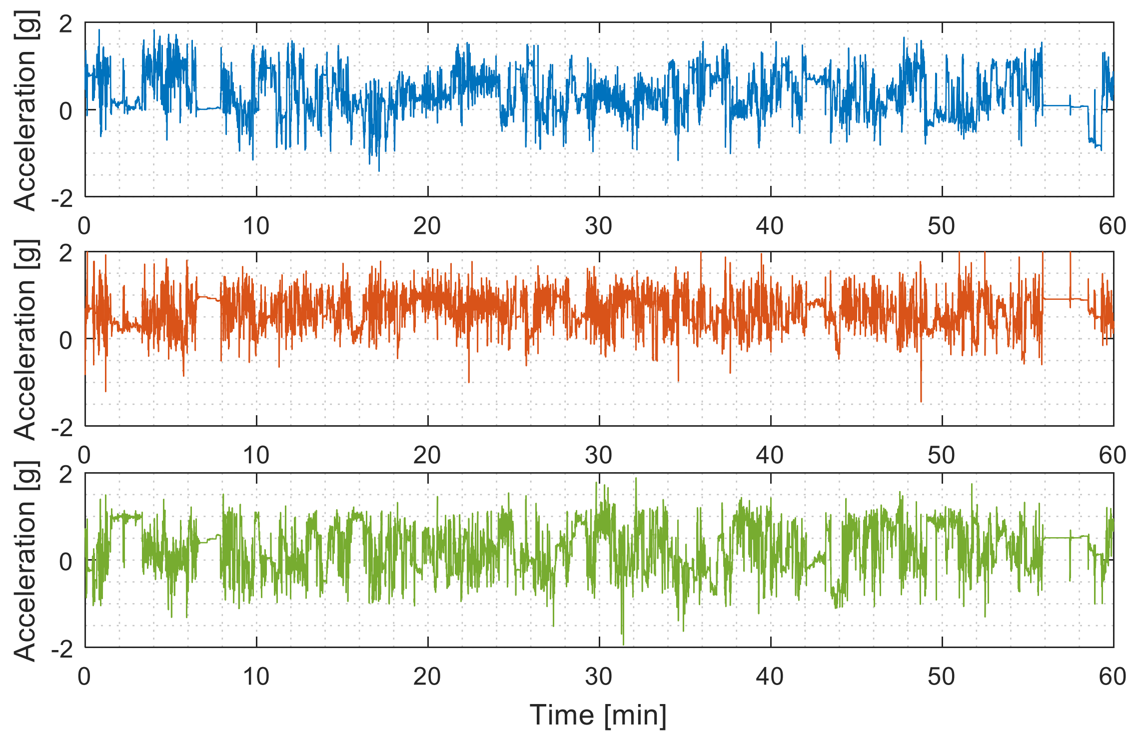


WALKING

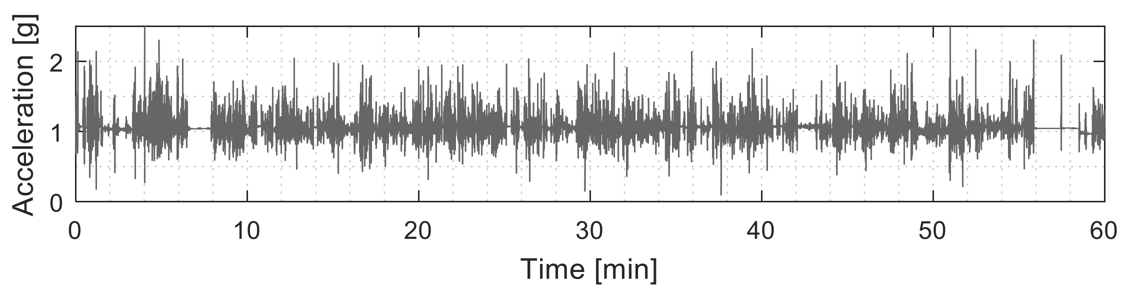


WEARABLE ACCELEROMETERS – WHAT?





$$vm\,(t) = \sqrt{\left(x(t)\right)^2 + \left(y(t)\right)^2 + \left(z(t)\right)^2}$$



ACTIVITY AND WALKING RECOGNITION METHODS

TYPICALLY USED METHODS

- THRESHOLD ON VECTOR MAGNITUDE
- FOURIER TRANSFORM
- ARTIFICIAL INTELLIGENCE (BLACK BOX) APPROACHES
- PROPRIETARY ALGORITHMS LIKE ACTIVPAL

COMMON SHORTCOMINGS:

VALIDATED ONLY IN LABORATORY CONDITIONS

ACCURACY IS STRONGLY SUBJECT-DEPENDENT

ACCURACY IS STRONGLY SENSOR PLACEMENT-DEPENDENT

SILVER STANDARD

*"The behavior was measured using an **activPAL**, an inclinometer- based activity monitor which **can directly identify periods of sitting/lying, standing and stepping**."*

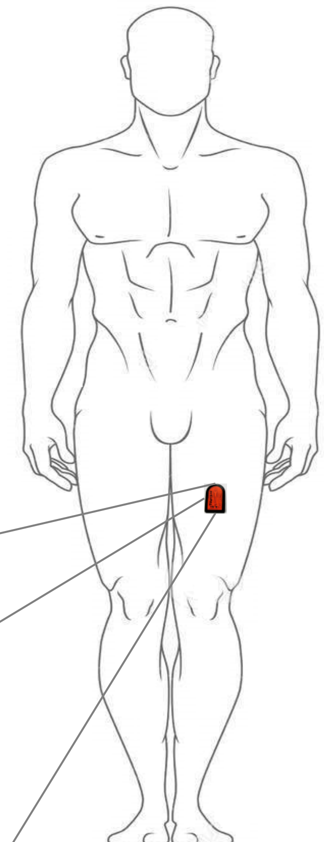
Source:

Gibson et al., An examination of objectively-measured sedentary behavior and mental well-being in adults across week days and weekends, PLOS ONE, 2017

"The activPAL monitor is a valid tool for measuring time spent sitting/lying, standing, and walking, *and total count of sit-to-stand and stand-to-sit transitions along with step counts in slow and normal walking…"*

Source:

Aminian & hinckson, Examining the validity of the activPAL monitor in measuring posture and ambulatory movement in children,
International Journal of Behavioral Nutrition and Physical Activity, 2012



OUR AIMS

WE WANT OUR METHODS TO BE:

- ✓ **UNIVERSAL:**
  - AUTOMATIC
  - SUBJECT INDEPENDENT
  - DEVICE INDEPENDENT
  - SENSOR PLACEMENT INDEPENDENT
- ✓ **ROBUST:**
  - APPLICABLE TO LARGE POPULATION

Sitting vs. Standing

Estimation of body posture based on wrist-worn devices

Upright vs. sedentary position

Compared with silver standard (activPAL)

Compared with the Sedentary sphere approach

(Rowlands AV, Olds TS, Hillsdon M, et al. Assessing sedentary behavior with the GENEActiv: introducing the sedentary sphere. Med Sci Sports Exerc. 2014;46(6):1235-47.)

SEDUP

SedUp algorithm

Inputs: $y(t)$ – accelerometry signal from the selected axis , τ – window size (expressed in number of seconds), f_s – sampling frequency, β_0, β_1, β_2 – logistic regression coefficients,Δ – threshold.

Output: $\widehat{z(t)}$ – binary indicator of standing.

Step 1: For $t = 1,2, \ldots$ estimate the standard deviation σ(t) of the signal $y(t)$ in the interval $[t - f_s/2, t + f_s/2]$.
Step 2: Obtain the smoothed version of σ(t) for each interval τ, called $S(t)$.
Step 3: Obtain the median of y(t) for each interval τ, called $M(t)$.
Step 4: Predicted $\widehat{z(t)} = 1$ if $\text{logit}(\Delta) < \beta_0 + \beta_1 \cdot M(t) + \beta_2 \cdot S(t)$.

STUDY AT THE UNIVERSITY OF PITTSBURGH

Population:

N = 51 (26 women) enrolled in the
Development Epidemiologic Cohort Study (DECOS)

Age: between 70 and 90 (median = 78, SD = 5.68),

BMI: between 20.5 and 37.9 (median 25.9, SD = 3.91)

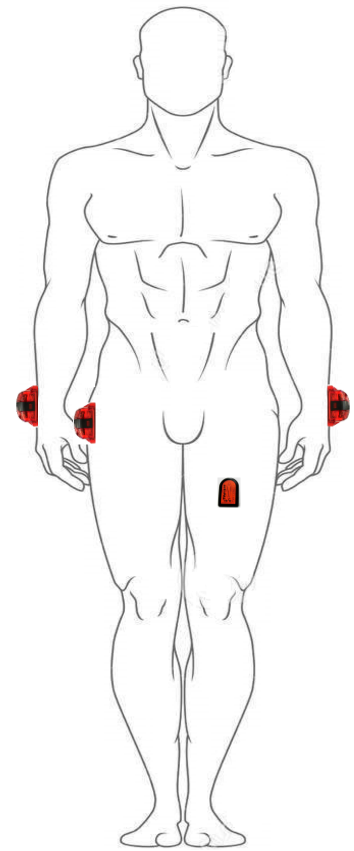
Data:

Free-living data collected for 7 days

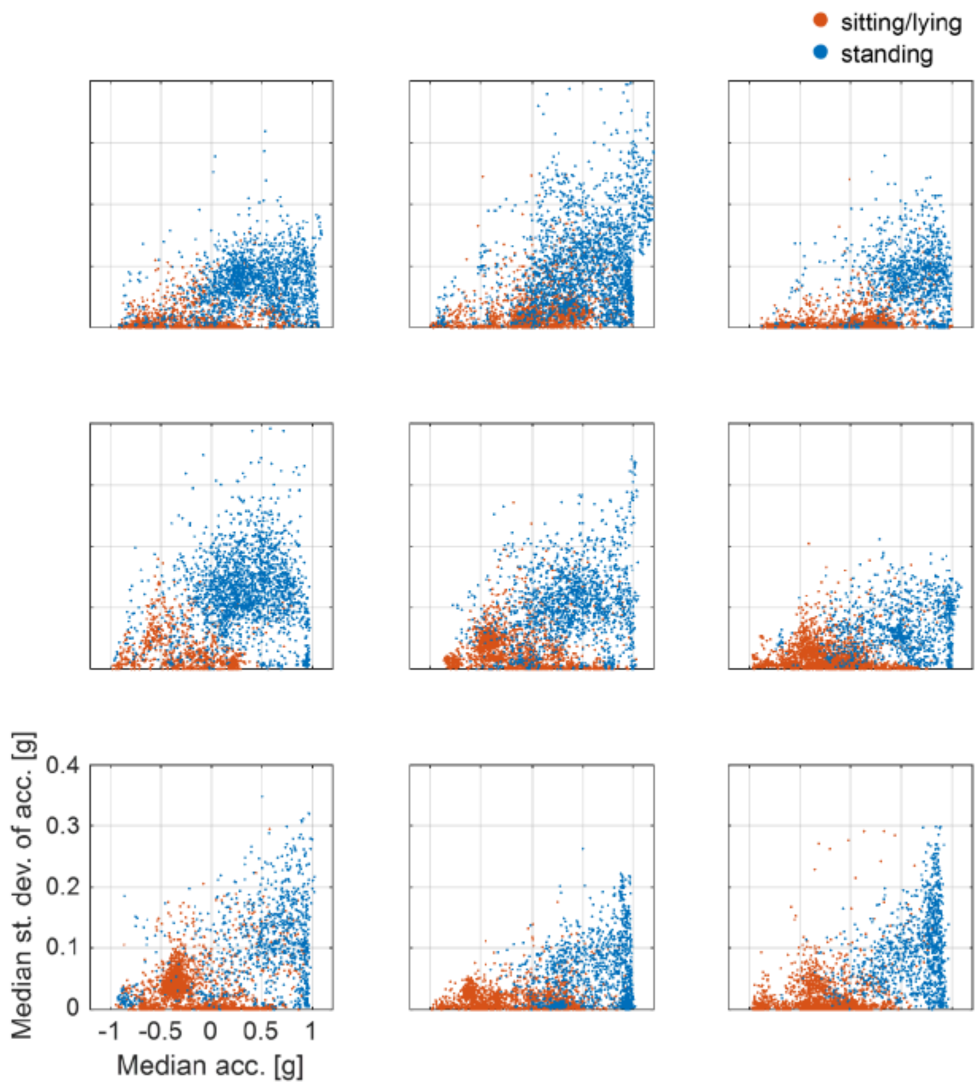
left and right wrists: ActiGraph GT3X+ (80Hz)

hip: ActiGraph GT3X+ (80Hz)

thigh: activPAL 3 (20Hz) treated as silver standard



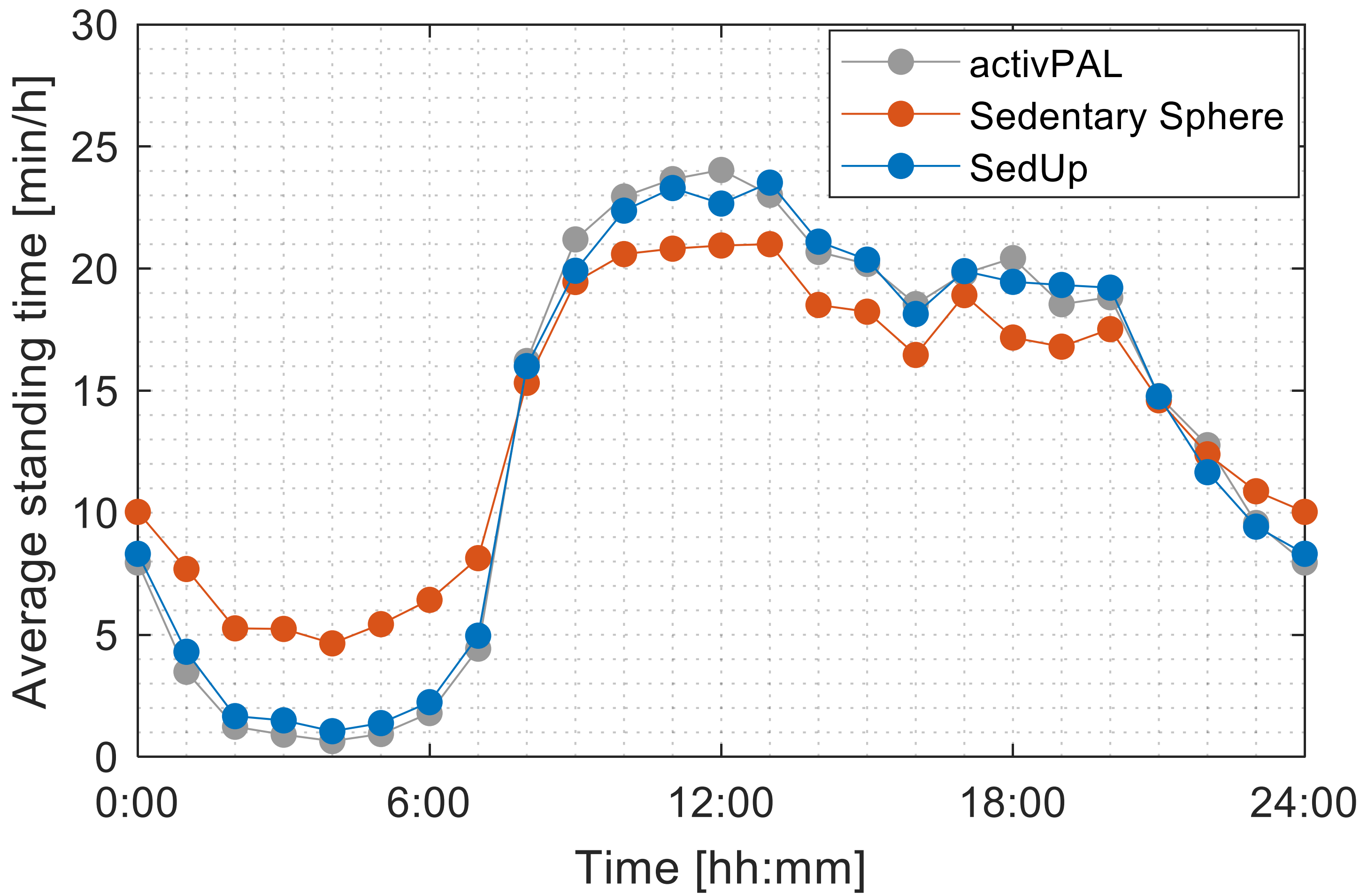
DATA


sitting/lying
standing
Median st. dev. of acc. [g]
0.4
0.3
0.2
0.1
0
-1
-0.5
0
0.5
1
Median acc. [g]

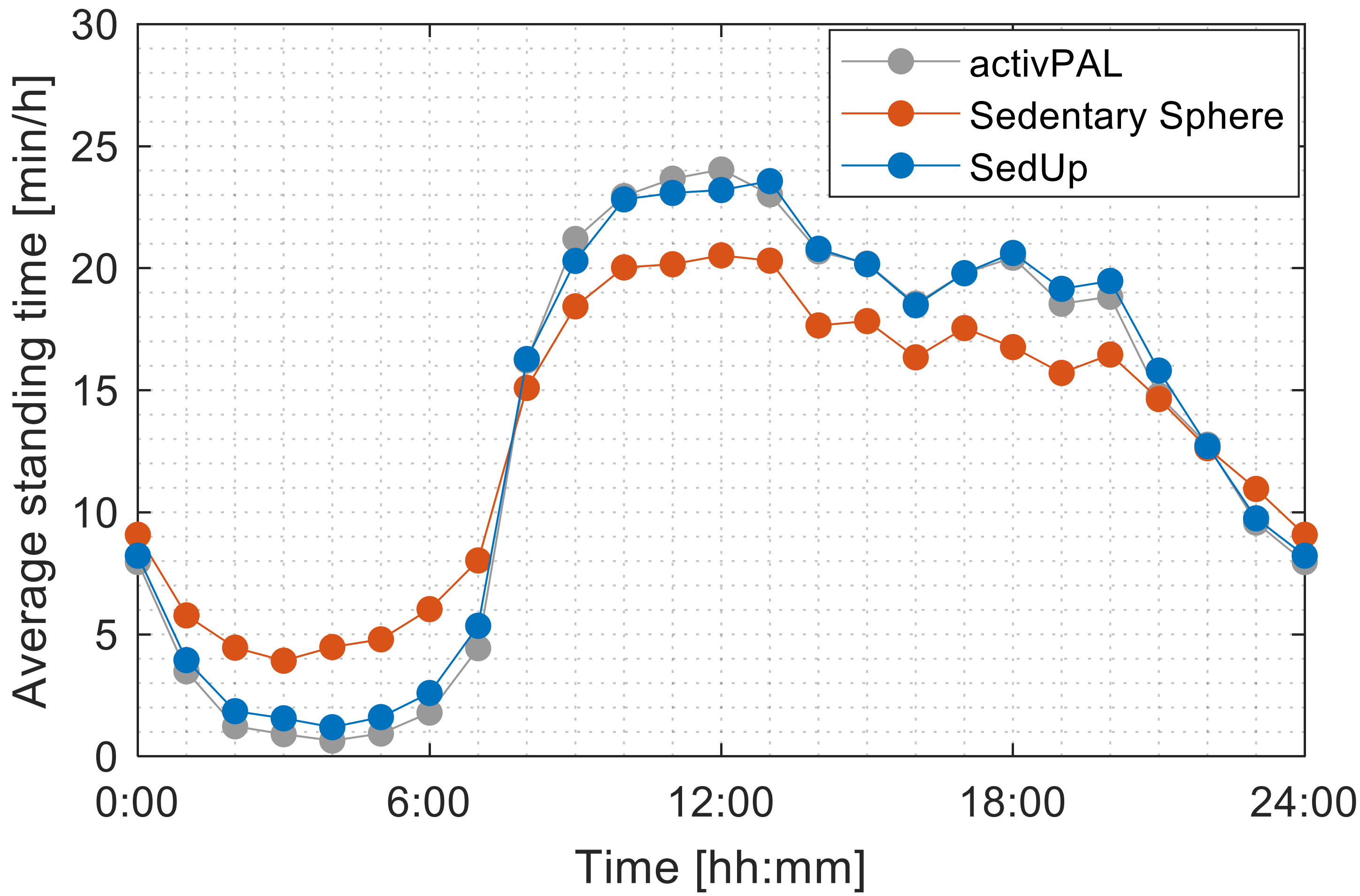
RESULTS

Method		Left wrist							Right wrist						
		SedUp						SS	SedUp						SS
Window [s]		15	30	45	60	75	90	-	15	30	45	60	75	90	-
TPR	Median	0.79	0.81	0.83	0.83	0.84	**0.83**	**0.66**	0.82	0.83	0.84	0.85	0.86	**0.86**	**0.65**
TNR	Median	0.90	0.90	0.91	0.91	0.91	**0.91**	**0.85**	0.91	0.92	0.92	0.93	0.93	**0.93**	**0.88**
MAPE [%]		13.3	13.0	12.7	12.6	12.6	**12.5**	**18.2**	15.7	15.3	15.2	15.0	15.1	**15.1**	**19.5**
MPE [%]		4.1	4.5	3.7	3.4	3.5	**2.9**	**4.1**	5.3	4.6	5.6	4.3	4.5	**4.5**	**6.7**

RESULTS (LEFT WRIST)



RESULTS (RIGHT WRIST)



SedUp conclusions

Estimation of body posture based on wrist-worn devices

Extraction of 2 simple features (median & SD)

Classification via logistic regression

Low Bias when compared with ActivPal

Better TPR and TNR when compared to the Sedentary Sphere

WALKING RECOGNITION METHOD

- PROPOSED ALGORITHM IS BASED ON THE **CONTINUOUS WAVELET TRANSFORM (CWT)**

$$C(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \cdot \psi\left(\frac{t-b}{a}\right) dt$$

a IS A FREQUENCY SCALE AND b IS A TIME SHIFT.

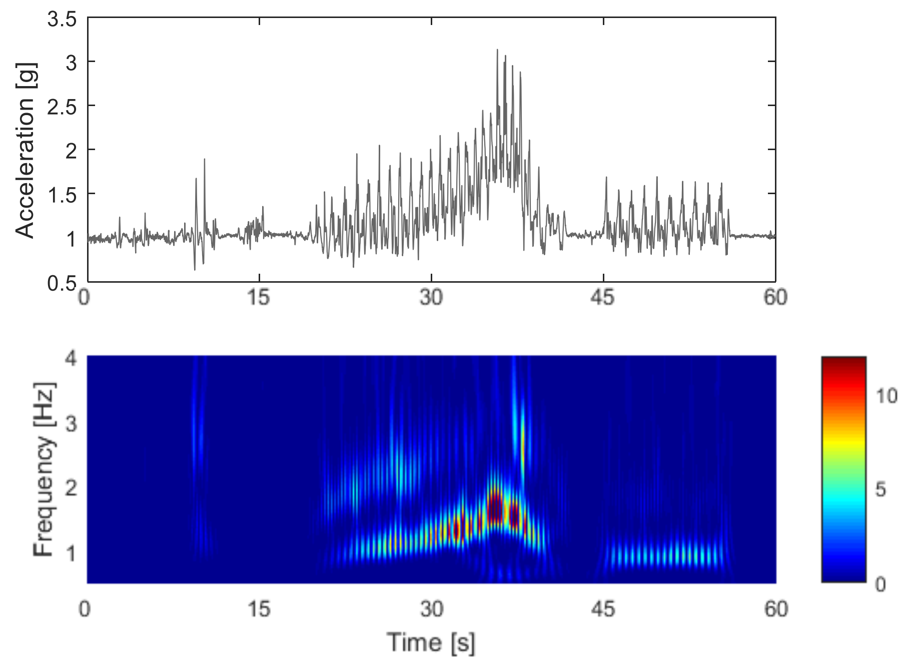
- **CWT DECOMPOSES THE ORIGINAL TIME SERIES SIGNAL** INTO A SET OF SCALED TIME-SHIFTED VERSIONS OF A 'MOTHER' WAVELET ψ.

- OBTAINED WAVELET COEFFICIENTS REPRESENT THE SIMILARITY BETWEEN A SPECIFIC WAVELET FUNCTION CHARACTERIZED BY FREQUENCY AND TIME-SHIFT AND A LOCALIZED SECTION OF THE SIGNAL.

- **WAVELET COEFFICIENTS ARE MAXIMIZED** WHEN A PARTICULAR FREQUENCY MATCHES THE FREQUENCY OF THE OBSERVED SIGNAL AT A PARTICULAR TIME POINT.

WALKING

Walking interval	Start of walking	Walking duration	Walking speed
1	~ 9 s	~ 1.2 s	Constant
2	~ 19 s	~ 22 s	Changing
3	~ 45 s	~ 11 s	Constant



PROPOSED METHOD

ALGORITHM BASED ON CWT

INPUT: x(t) - vector magnitude of tri-axial accelerometry signal, ψ - mother wavelet (e.g. Morlet), $f_{min} = 1$Hz, f_{max} = 2.5Hz, δ - threshold.

OUTPUT: y(t) - binary walking indicator

STEP 1. Transform the signal x(t) to time-frequency domain $C(t, f)$ using CWT with the selected wavelet ψ.

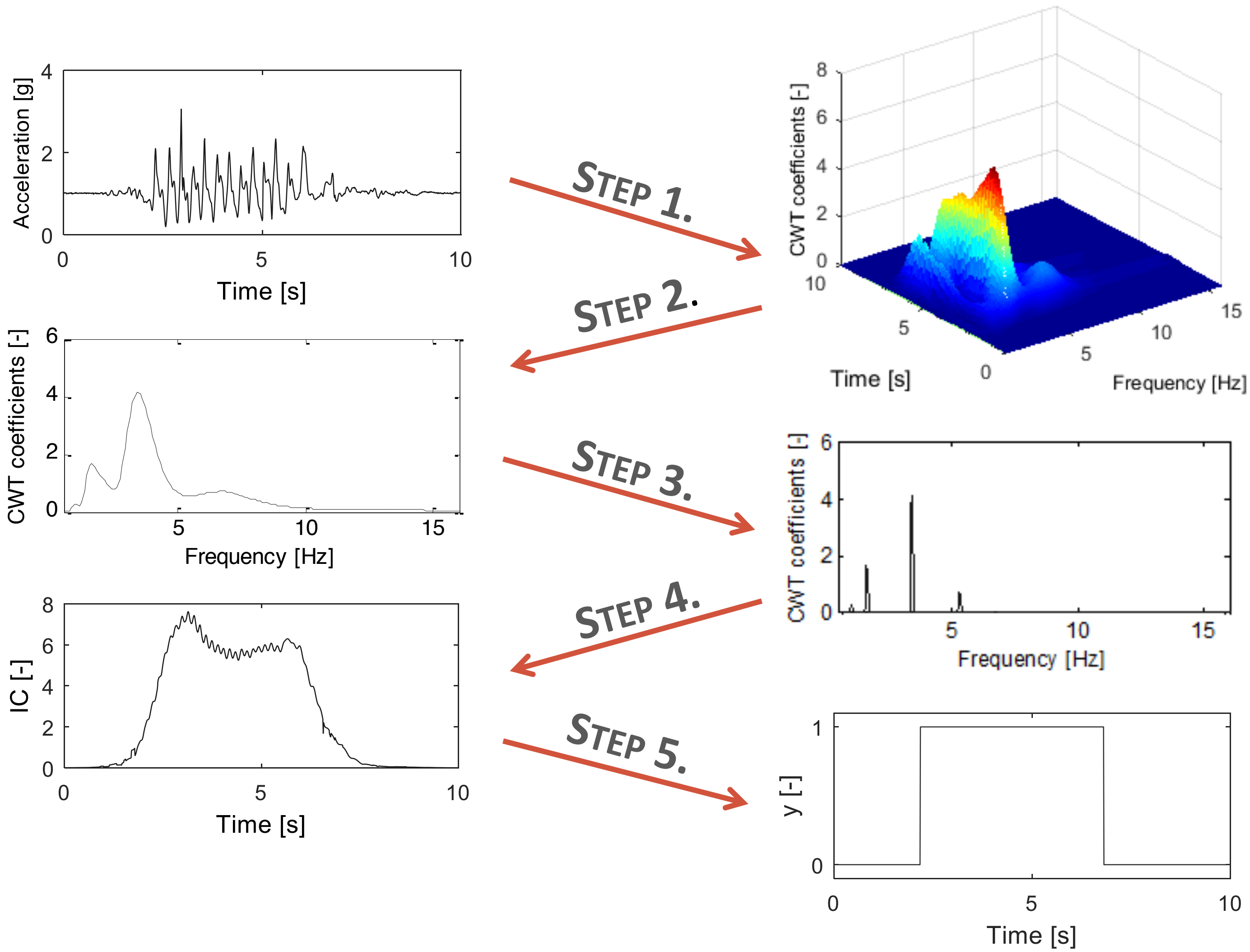
STEP 2. For each time *t* obtain a frequency representation $C(f)$.

STEP 3. Compute partial area under $C(f)$ for each value of f_j, where *j* = 1, 2, 3 and f_1 is from f_{min} to f_{max}.

STEP 4. For each *t* identify frequency *f* for which $IC(t, f) = \sum_{i=1}^{3} C_i\,(f)$ is maximized.

STEP 5. Walking is predicted $\left(\widehat{y(t)} = 1\right)$ for all times *t* when $IC(t, f) > \delta$.

WALKING



Acceleration [g]
Time [s]
STEP 1.
CWT coefficients [-]
Time [s]
Frequency [Hz]
STEP 2.
CWT coefficients [-]
Frequency [Hz]
STEP 3.
CWT coefficients [-]
Frequency [Hz]
STEP 4.
IC [-]
Time [s]
STEP 5.
y [-]
Time [s]

STATISTICAL ANALYSIS

- WE USED ACTIVPAL MEASUREMENTS AS A **SILVER STANDARD** FOR WALKING.
- WE ESTIMATED OPTIMAL SUBJECT-SPECIFIC THRESHOLDS δ_i AS A POINT AT WHICH **F-SCORE** MEASURE WAS MAXIMIZED.
- **F-SCORE** IS A MEASURE OF A TEST'S ACCURACY. IT TAKES INTO ACCOUNT BOTH SENSITIVITY AND POSITIVE PREDICTED VALUE DEEMPHASIZING TRUE NEGATIVE PREDICTIONS, WHICH IN THE CASE OF WALKING (SMALL FRACTION OF DAILY ACTIVITY), COULD CONSTITUTE A MAJORITY OF PREDICTIONS.
- A **UNIVERSAL THRESHOLD** δ WAS DEFINED AS THE MEDIAN OF SUBJECT-SPECIFIC THRESHOLDS.

STUDY AT THE UNIVERSITY OF PITTSBURGH

POPULATION:

N = 51 (26 WOMEN) ENROLLED IN THE DEVELOPMENT EPIDEMIOLOGIC COHORT STUDY (DECOS)

AGE: BETWEEN 70 AND 90 (MEDIAN = 78, SD = 5.68),

BMI: BETWEEN 20.5 AND 37.9 (MEDIAN 25.9, SD = 3.91)

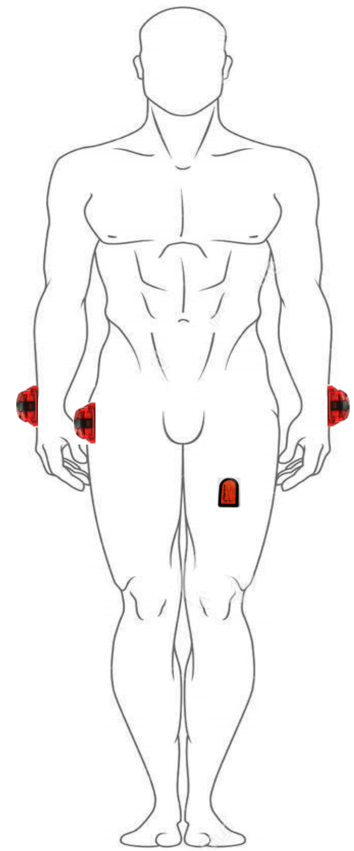
DATA:

FREE-LIVING DATA COLLECTED FOR 7 DAYS

LEFT AND RIGHT WRISTS: ACTIGRAPH GT3X+ (80HZ)

HIP: ACTIGRAPH GT3X+ (80HZ)

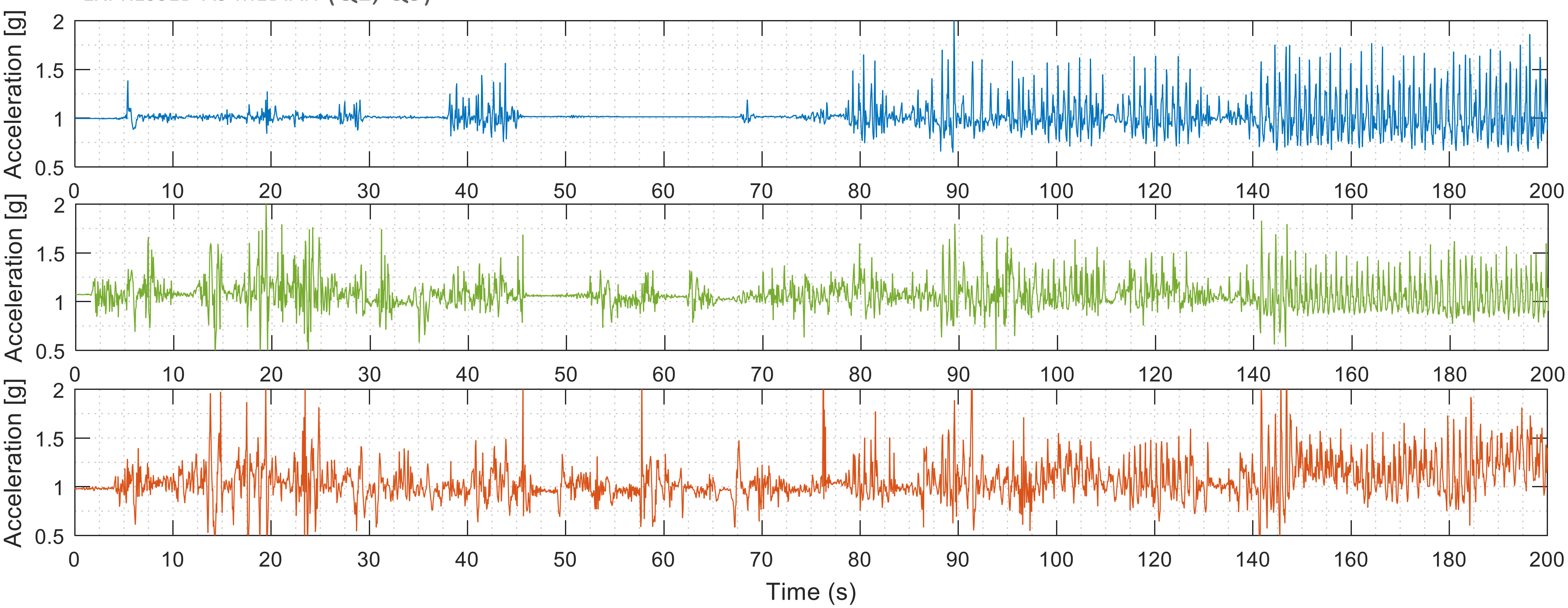
THIGH: ACTIVPAL 3 (20HZ) TREATED AS SILVER STANDARD



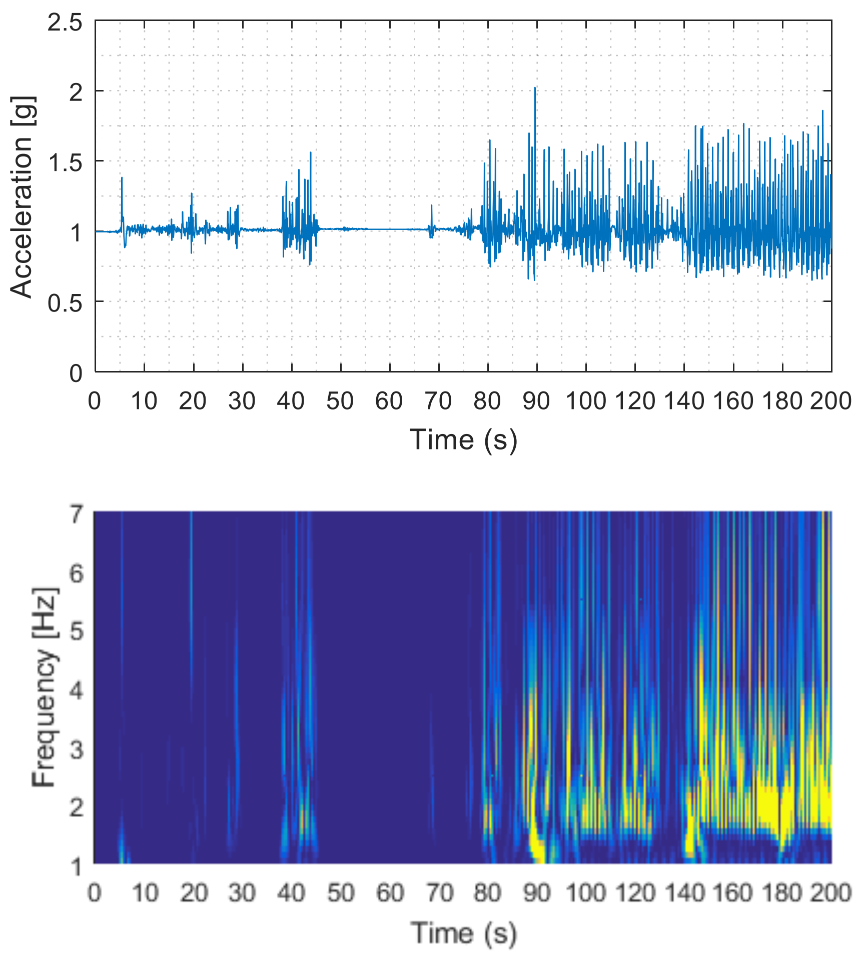
RESULTS

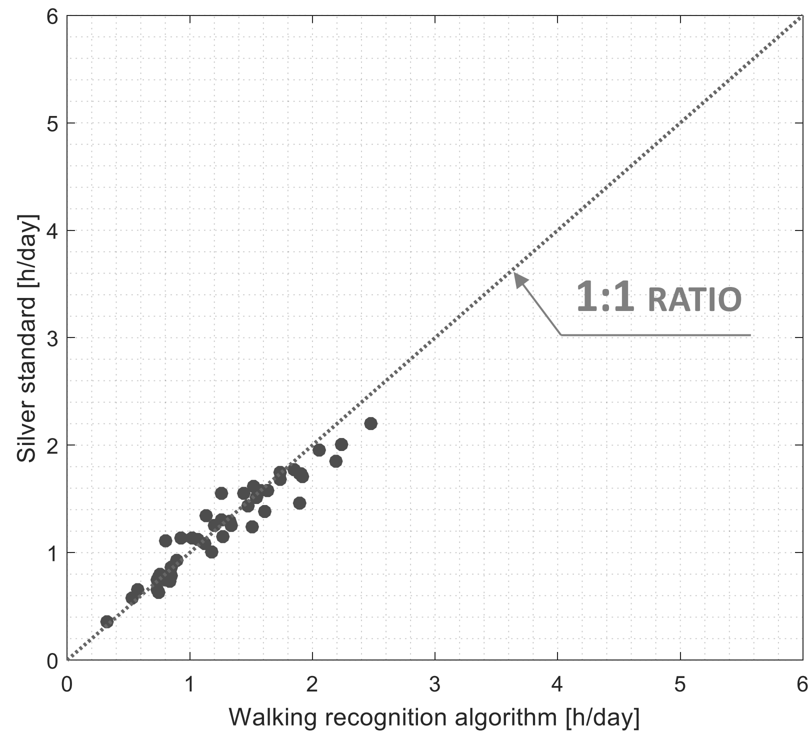
	HIP	LEFT WRIST	RIGHT WRIST
THRESHOLD*	0.008 (0.007, 0.010)	0.024 (0.018, 0.037)	0.028 (0.022, 0.042)
F1 SCORE	0.830 (0.806, 0.861)	0.610 (0.530, 0.656)	0.541 (0.481, 0.626)
TRUE POSITIVE RATE	0.843 (0.795, 0.889)	0.747 (0.642, 0.810)	0.711 (0.610, 0.807)
TRUE NEGATIVE RATE	0.990 (0.985, 0.993)	0.941 (0.927, 0.976)	0.937 (0.920, 0.958)

*EXPRESSED AS MEDIAN (Q1, Q3)

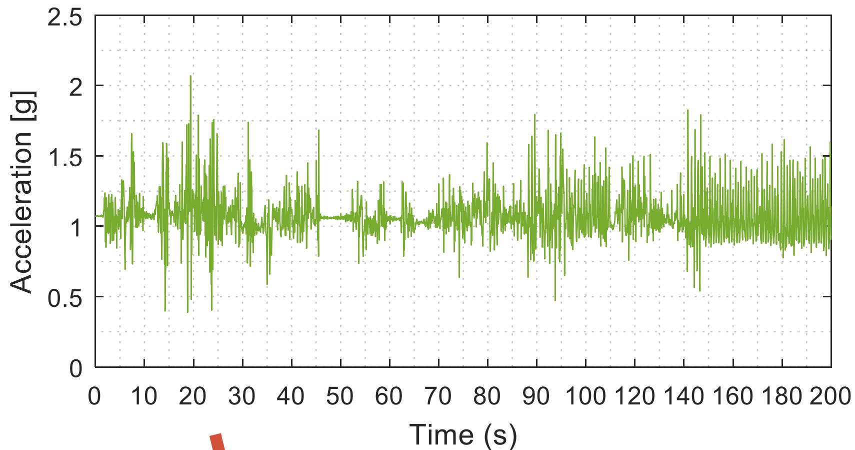


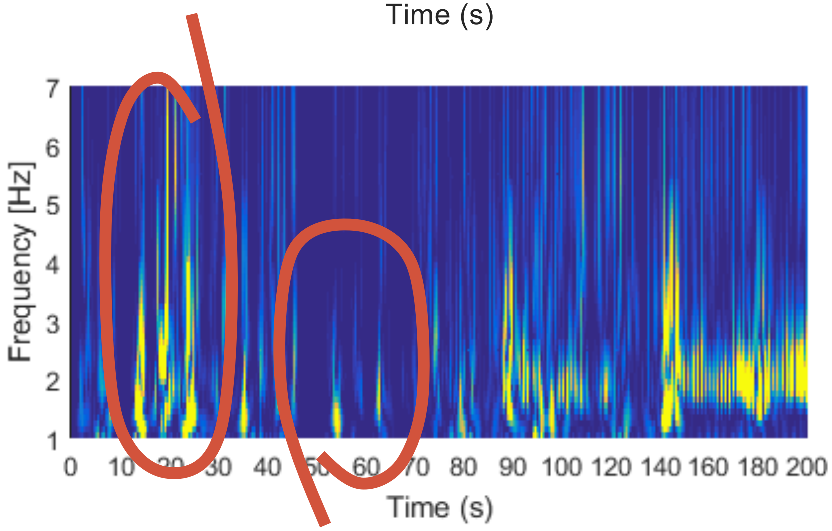
SENSOR ON THE HIP

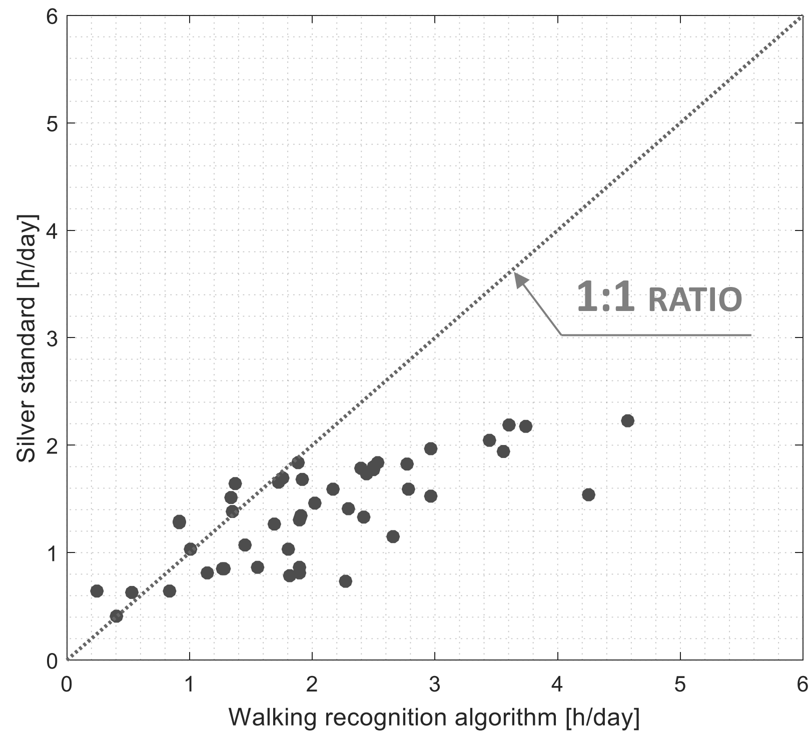




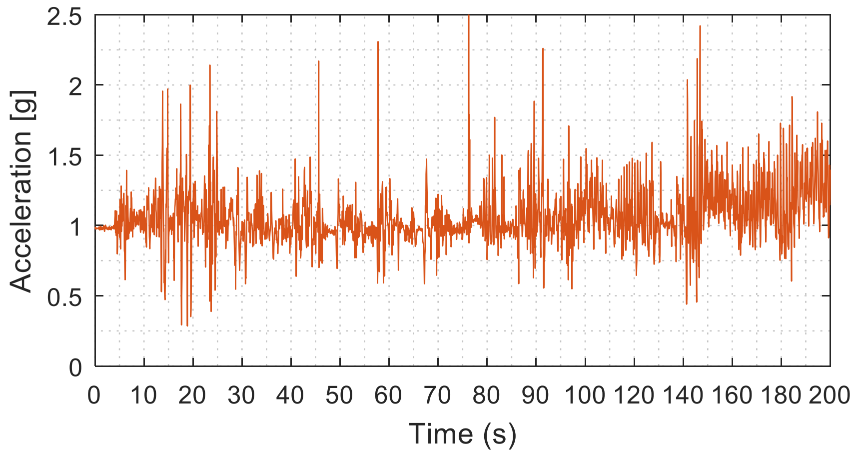
SENSOR ON THE LEFT WRIST

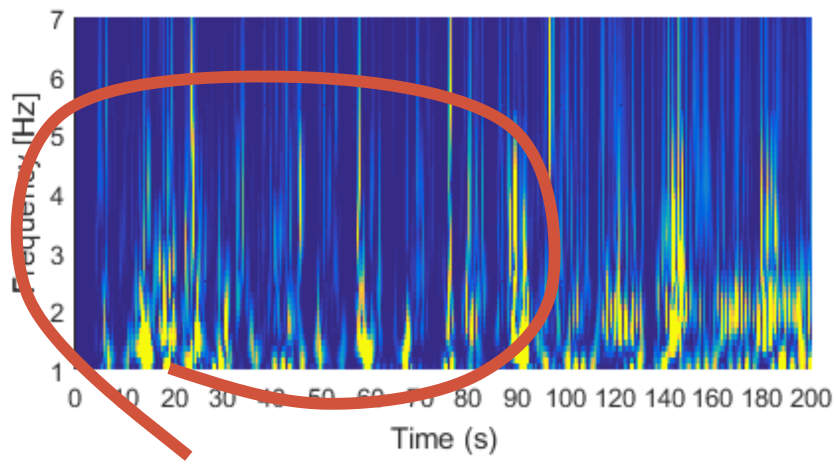


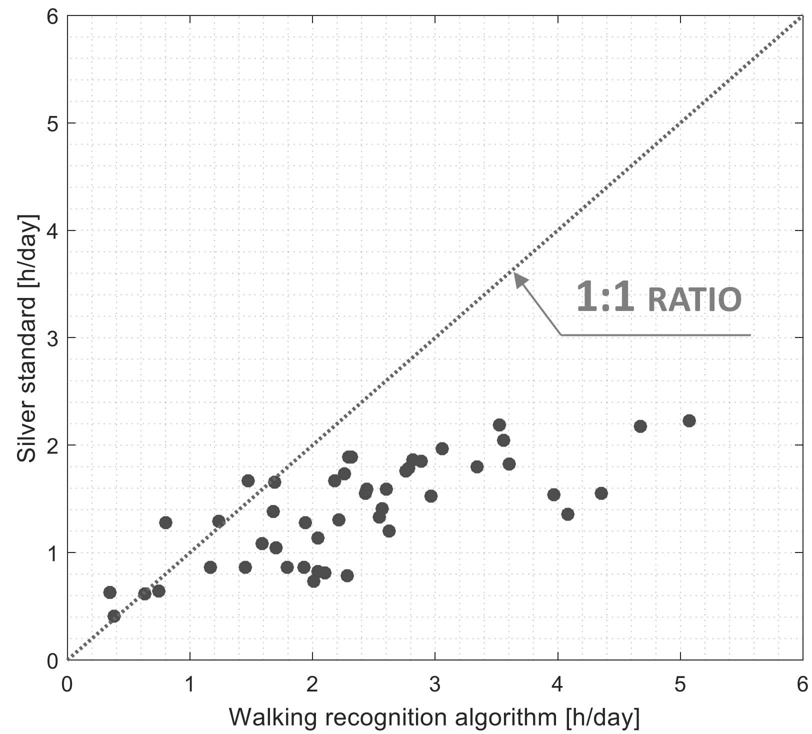




SENSOR ON THE RIGHT WRIST







WALKING ALGORITHM CONCLUSIONS

- DEVELOPED A METHOD THAT IS **SENSITIVE TO PERIODIC DEVIATIONS** FROM A LONG TIME AVERAGE FOR **AS LONG AS THE PERSON IS WALKING.**

- USED **CWT**:
  - GOOD TIME RESOLUTION FOR HIGH-FREQUENCY COMPONENTS
  - GOOD FREQUENCY RESOLUTION FOR LOW-FREQUENCY COMPONENTS
  - **CLOSELY RESEMBLES WALKING**

- THE RESULTS SHOWED:
  - **HIGH ACCURACY** FOR CLASSIFICATION ACTIVITIES WHEN DATA WERE **COLLECTED ON THE HIP**
  - **FOR WRIST-WORN SENSORS WALKING TIME WAS OVERESTIMATED**

COLLABORATORS

- **Harvard University**
  - **Marcin Straczkiewicz, PhD**
- **University of Pittsburgh**
  - **Nancy Glynn, PhD**
- **Johns Hopkins University**
  - **Ciprian Crainiceanu, PhD**
  - **Jacek Urbanek, PhD**
  - **Vadim Zipunnikov, PhD**

Thank you