Comparison of accelerometry-based physical activity measures

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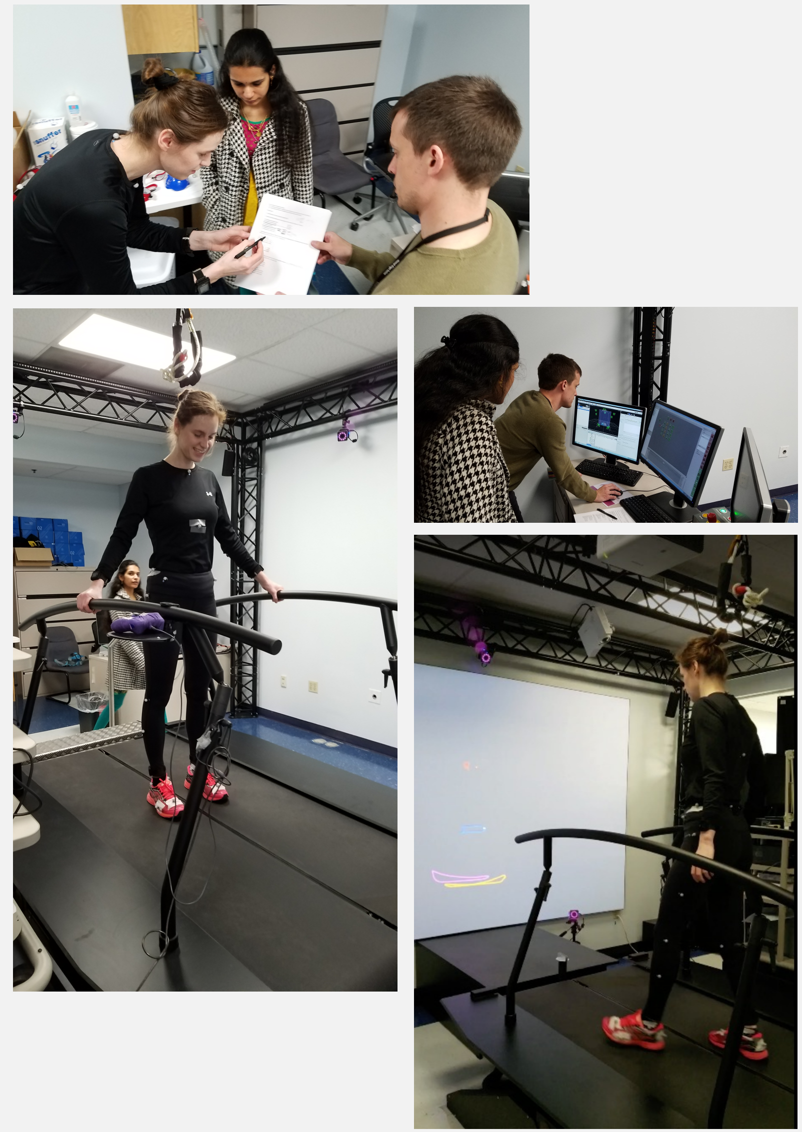
About

- Postdoctoral researcher at Onnela Lab (Harvard University -- Biostatistics)
    - Missing data imputation and uncertainty quantification for sensor data
    - Wearable devices and smartphone data to quantify: (a) ALS disease progression, (b) behavior patterns in population with suicidal thoughts
- Formerly: PhD candidate at Wearable and Implantable Technology (WIT) lab (Johns Hopkins University -- Biostatistics)
    - Accelerometry data
    - Power estimation in complex settings

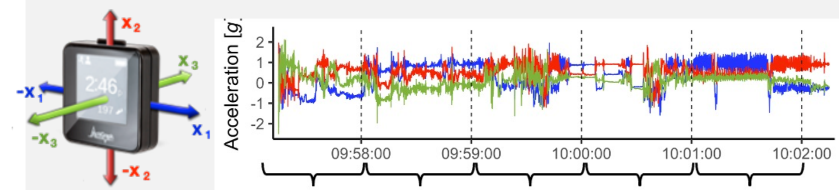


Motivation

- Summary measures of raw accelerometry data are commonly used in health research[1]
- Widely-used: ActiGraph activity counts (AC)
  - Until Feb 2022: proprietary measure; 20,000+ works with AC published
  - Feb 2022: AC algorithm published[2]
- Recently, other statistics have been proposed to aggregate raw data: MIMS, ENMO, MAD, AI[3]

BLSA BALTIMORE LONGITUDINAL STUDY OF AGING — AC
biobank uk — ENMO
nhats National Health & Aging Trends Study, how daily life changes as we age — AC
nhanes National Health and Nutrition Examination Survey — MIMS
NHANES most recent release (cohorts 2011-2012, 2013-2014)

- Comparability to previously published research is unknown



1min-level measure	Based on
ActiGraph AC	Sum of resampled, bandpass-filtered, rescaled, thresholded, down-sampled $x_m(t)$; then aggregated across axes $m = 1,2,3$
MIMS	AUC of interpolated, extrapolated, bandpass-filtered $x_m(t)$; then added across axes $m = 1,2,3$
ENMO	Mean of $r(t)$ vector magnitude from pre-calibrated raw data $[x_1(t), x_2(t), x_3(t)]$
MAD	Mean amplitude deviation of $r(t)$ vector magnitude
AI	Variance of $x_m(t)$ at 1 s-level averaged across axes $m = 1,2,3$; summed up at 1 min-level

1: Karas et al. 2019
2: Neishabouri et al., 2022
3: MIMS: John et al., 2019; ENMO: van Hees et al., 2013; MAD: Vähä-Ypyä et al., 2015; AI: Bai et al., 2012

Summary of contributions

Data from ~700 participants in the Baltimore Longitudinal Study on Aging (BLSA), each monitored for a week with a wrist-worn PA sensor

1. Summarized raw data at minute-level: ActiGraph AC, MIMS, ENMO, MAD, AI

2. Quantified association between AC and other measures marginally and conditionally on age, sex and BMI

3. Harmonized minute-level AC with other measures via one-to-one mapping

4. Evaluated the harmonization mapping, derived cut-points of MIMS, ENMO, MAD, AI that correspond to established AC cut-points

Measures derivation

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Challenges

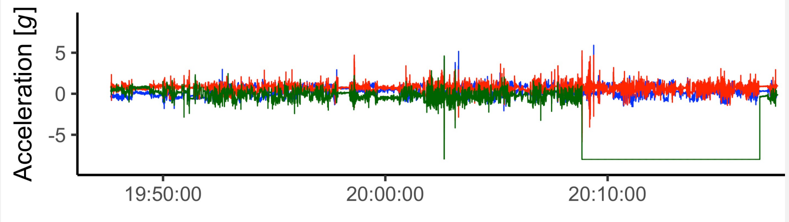
- Large volume of raw accelerometry data needs quality check
  - 700 participants x 7 days x 1440 minutes x 60 seconds x 80 obs./s x 3 sensor axes = 101,606,400,000 (one hundred billion+)

Methods

- Adapted raw data quality flags from recently published NHANES protocol
- Implemented flags to detect acceleration spikes, values at the sensor's dynamic range

Results

- Flagged cases of raw measurements



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Results (cont.)

- Developed SummarizedActigraphy R package with unified interface to summarize raw data at minute-level: AC and open-source MIMS, ENMO, MAD, AI

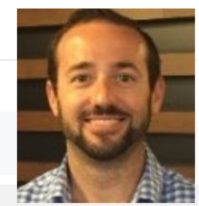
SummarizedActigraphy Package:

The goal of `SummarizedActigraphy` is to provide functions for reading Actigraphy data and turn it into `SummarizedExperiment` s.

Installation

You can install `SummarizedActigraphy` from GitHub with:

```
# install.packages("remotes")
remotes::install_github("muschellij2/SummarizedActigraphy")
```



John Muschelli

Measures comparison

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Methods

- Linear regression with subject-specific correlation between measures as an outcome

Results

- All correlations between AC and other measures large (mean r ≥ 0.87) and especially MIMS and AI (mean r ≥ 0.97)
- Significant but small of age, sex and BMI

	Unadjust. model	Model adjusted for: age, BMI, sex			
	Intercept	Intercept	Age	BMI	Sex (is male)
Response var.	Coef. est. (se)	Coef. est. (se)	Coef. est. (se)	Coef. est. (se)	Coef. est. (se)
corr (AC, MIMS)	0.988 (0.0002)	0.988 (0.0017)	< 0.001 (<0.0001)	< 0.001 (<0.0001)	-0.002 (0.0005)*
corr (AC, ENMO)	0.867 (0.0018)	0.887 (0.0138)	-0.001 (0.0001)*	0.001 (0.0004)	> -0.001 (0.0037)
corr (AC, MAD)	0.913 (0.0013)	0.892 (0.0099)	< 0.001 (0.0001)	0.001 (0.0003)*	-0.010 (0.0026)*
corr (AC, AI)	0.970 (0.0007)	0.962 (0.0050)	< 0.001 (< 0.0001)	< 0.001 (0.0001)*	-0.010 (0.0013)*

Table. "*" symbol is used to denote model coefficients (excluding intercept) for which the corresponding p-value was <0.05.

Measures harmonization

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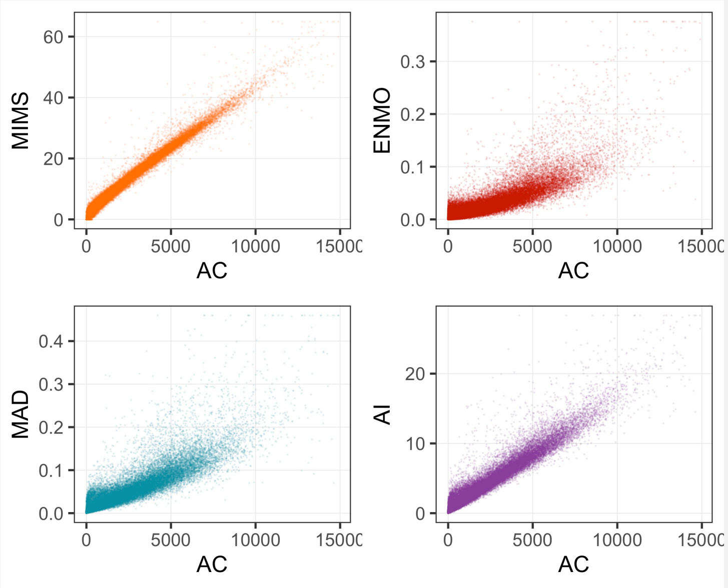
Challenges

- Estimate the relation between pairs of minute-level measures $(x_{ij}(t), y_{ij}(t))$ e.g., $(AC_{ij}(t), MIMS_{ij}(t))$ as a smooth function f while accounting for correlation structure (i-th participant, j-th day, t-th minute)

- Volume of minute-level data = 700 participants x 7 days x 1440 minutes = 7,056,000



1% of the data

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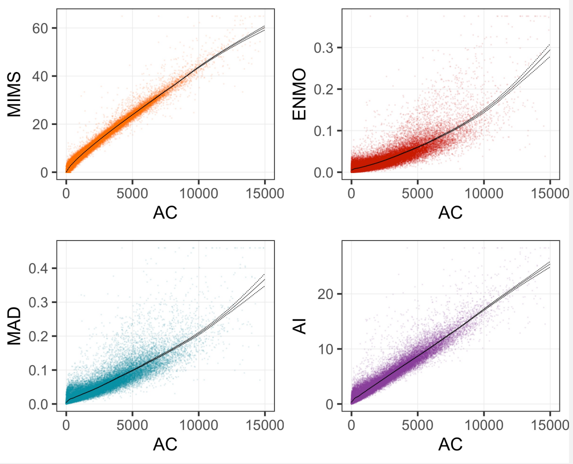
Methods

- Estimated f via additive model $y_{ij}(t) = f(x_{ij}(t)) + \varepsilon_{ij}(t)$, assuming independence; 95 % CI via case-bootstrap
- Used $\hat{f}$ to define one-to-one mapping

Results

Black solid line: $\hat{f}(AC)$, dashed lines: 95% CI



AC cut-offs and mapped values of MIMS, ENMO, MAD, AI

	AC cut-off	MIMS fitted	ENMO fitted	MAD fitted	AI fitted
1	1853	10.558	0.022	0.039	3.620
2	2860	15.047	0.033	0.057	5.273
3	3940	19.614	0.046	0.078	7.025

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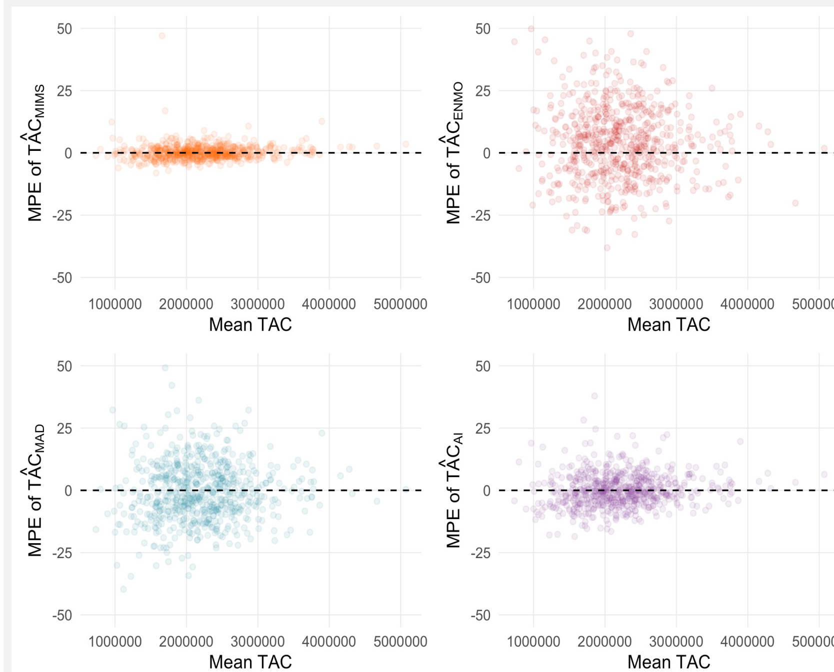
Methods

- Evaluated $\hat{f}$ in tasks of: (a) estimating total AC, (b) classifying a minute into active vs non-active

Results

Mean percentage error (MPE) in estimating total activity counts (TAC) from MIMS, ENMO, MAD, AI, arranged according to the participant's average TAC.



Summary and resources

Summary

- Correlations between minute-level AC and other measures all large (mean rho ≥ 0.87), especially for MIMS and AI (mean rho ≥ 0.97)
- Harmonization mapping allows translation of established AC cut-offs for separating activity intensity levels

Resources

- Open-access paper[1], all R code analyses and results on GitHub[2]
- SummarizedActigraphy R package[3], blog post demonstrating how to use[4].

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Computing minute-level summary measures of physical activity from raw accelerometry data in R: AC, MIMS, ENMO, MAD, and AI

Jul 10, 2021 · 12 min read

In this post, we:

- use dataset "Labeled raw accelerometry data captured during walking, stair climbing and driving" that is freely available on PhysioNet;
- derive four minute-level summary measures of physical activity – AC, MIMS, ENMO, MAD, AI – from raw accelerometry data using `SummarizedActigraphy` R package;
- summarize minute-level summary measures across walking and driving activities.

1: Karas et al. 2022; https://mhealth.jmir.org/2022/7/e38077
2: https://github.com/muschellij2/blsa_mims
3: https://github.com/muschellij2/SummarizedActigraphy
4: https://martakarass.github.io/post/2021-06-29-pa_measures_and_summarizedactigraphy/

Considerations for raw accelerometry data collected with large smartphone studies

Smartphones

- Broadly adopted and used
- Allow data collection using one's existing personal device

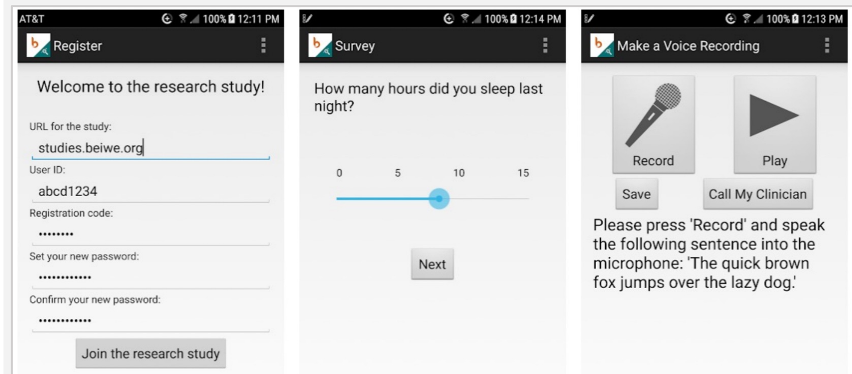
“Active data”

- Taking surveys, contributing audio diary entries, carry out cognitive assessments

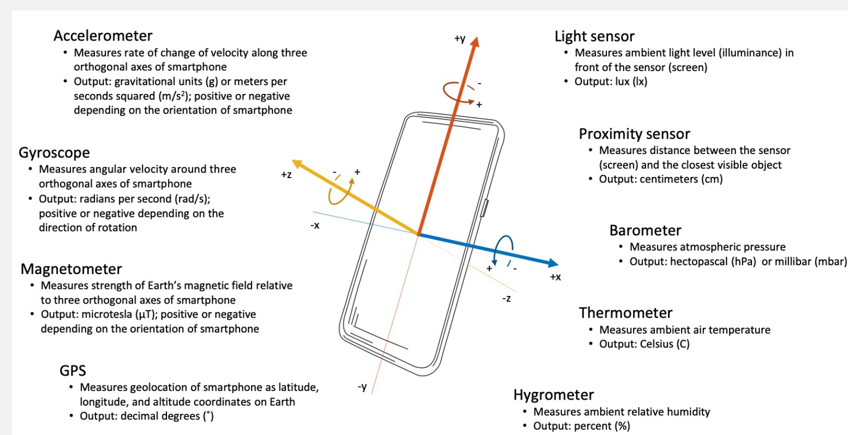
“Passive data”

- From smartphone sensors (e.g., accelerometer data) and smartphone logs (e.g., screen activity logs)
- Can be generated by the device passively, pose no burden on the participant

Smartphone app, a part of the **Beiwe research platform** (Harvard University, Onnela Lab) to collect smartphone sensor and usage data in clinical and non-clinical studies



Straczkiewicz et al. (2021). Overview of standard smartphone sensors



Considerations for raw accelerometry data collected with large smartphone studies (cont.)

Smartphone monitoring of population self-injurious thoughts and behaviors

- Intensive longitudinal study:
  - ~400 participants
  - 6 months of continuous smartphone data collection
- Smartphone raw accelerometer data
  - Collection alternated between 10 sec on-cycle (data collected) and 10 sec an off-cycle (data not collected)
- Summarize raw accelerometer data to
  - Quantify movement at minute & day scale
  - Tell whether smartphone is with a person
  - Help validate other data (e.g., phone usage patterns at night)

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Activity Index (AI; Bai et al., 2012)

- Straightforward definition
- Fast to compute (does not require extensive data preprocessing)
- Defined on 1 sec-level => can be easily adopted for our data collected in 10 sec on/off cycles
- Demonstrated high correlation with widely used ActiGraph AC

Thank you!


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