Fragmentation: overview and applications

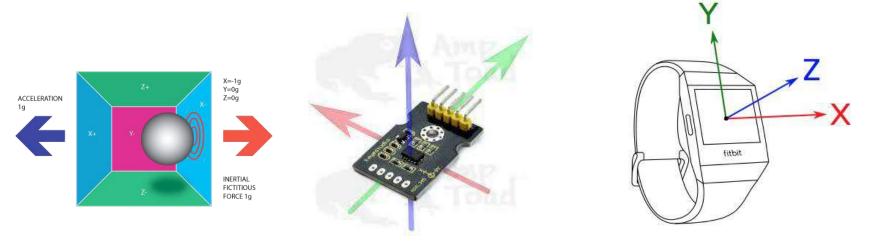
Vadim Zipunnikov, PhD

Department of Biostatistics

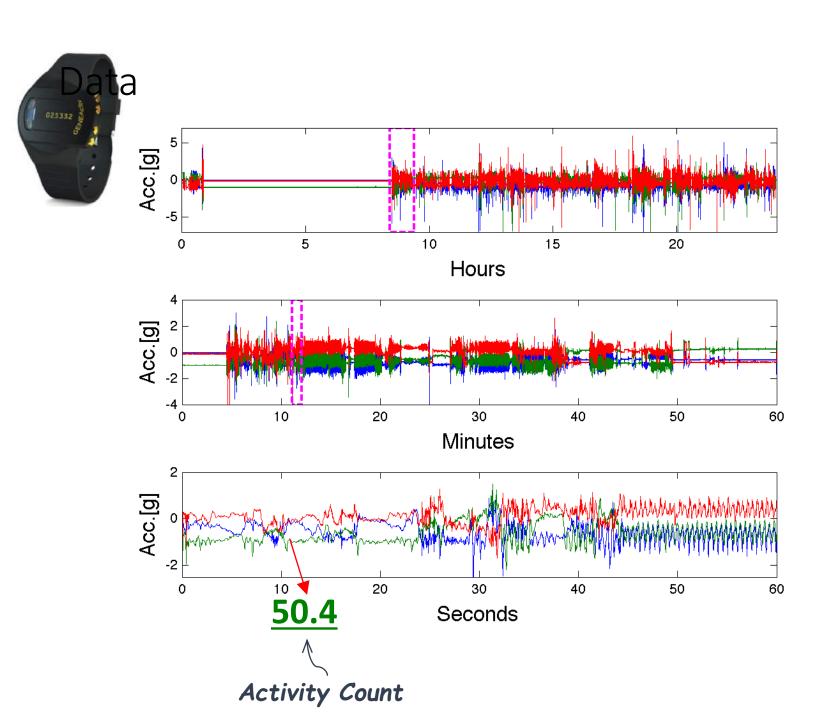




Accelerometers

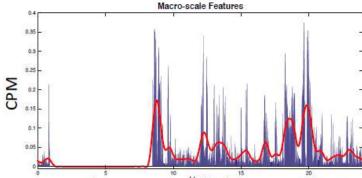


- Detects acceleration in three orthogonal planes
- https://www.youtube.com/watch?v=irjG9Y4NGnE

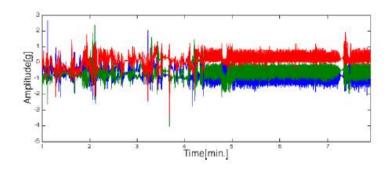


Macro- and Micro-scale

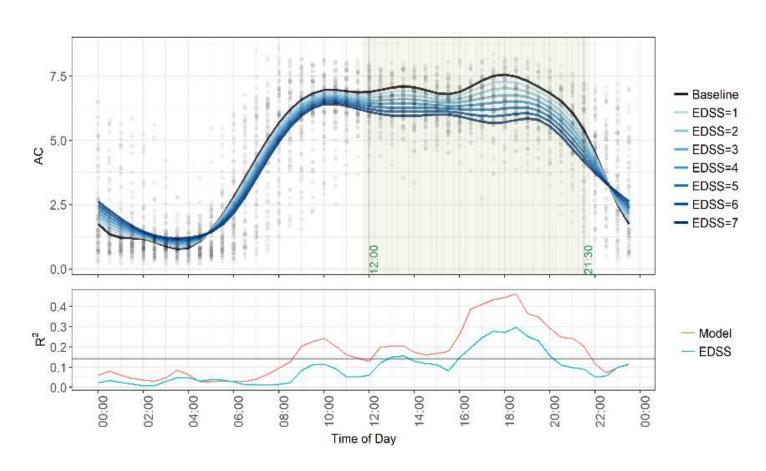
Macro-scale – summarized data (1 minute intervals)



• Micro-scale – raw accelerometry data collected (10Hz+)



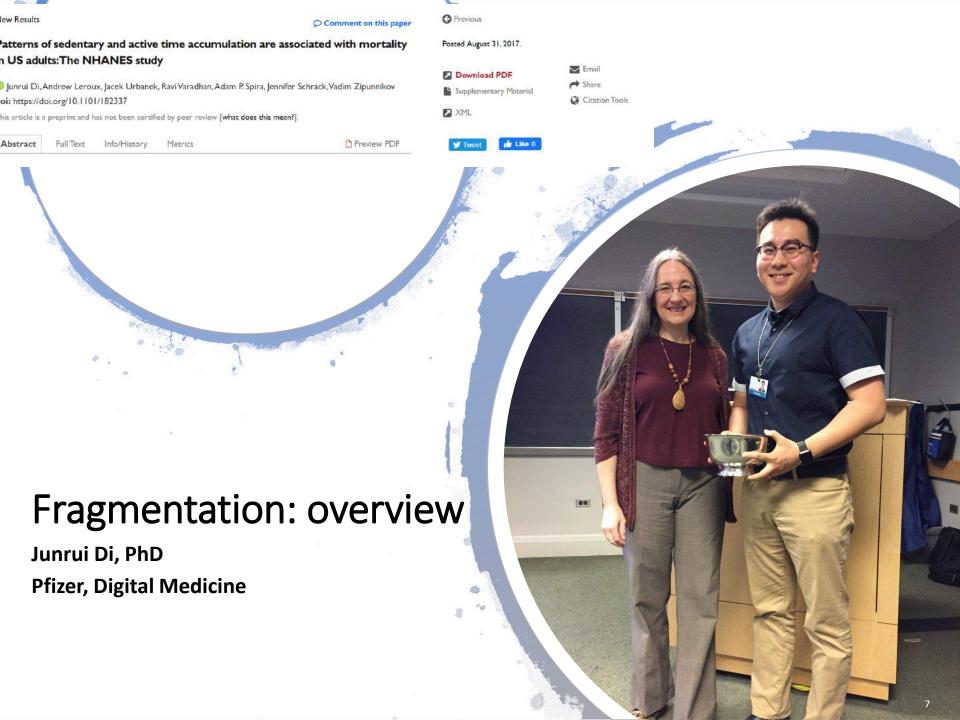
Disability in Multiple Sclerosis



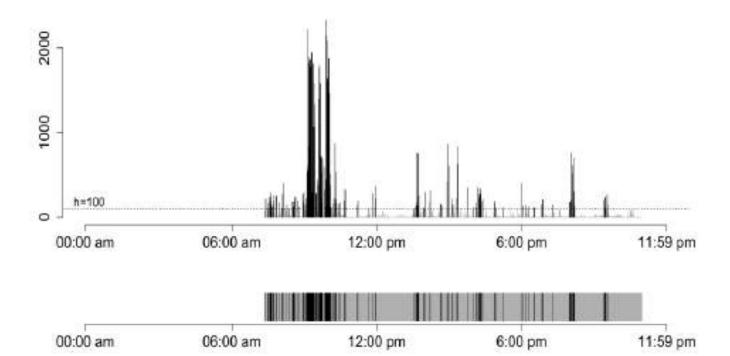
Fragmentation: overview

Junrui Di, PhD Pfizer, Digital Medicine





Fragmentation



Motivation: Sedentary Behavior Sedentary Behavior

10 5.5 0.5

- Time spent in a day
 - Sedentary E.g. sitting, driving, reading
 - Active = LIPA + MVPA
 - light physical activity (LIPA) e.g. walking
 - moderate to vigorous activity (MVPA) e.g. exercise
- Sedentary behavior is a risk factor for a wide range of diseases and comorbidities.



 Quantified as absolute duration or proportion of waking hours spent in sedentary state.

Statistical Framework

Nonparametric

Metrics	Interpretation	Definition	Estimation
AAC (μ)	average duration	Edi	<u>T</u>
nAAC ($^*\mu$)	normalized average	Ed _i ∗ d	T = dn
Gini (g)	normalized variabilit	$\frac{E d_i-d_j }{2\mu}$	$\frac{\sum_{ij} d_i - d_j }{2n \sum_t d_t}$
AH (\bar{h})	average hazard	$h(t) = \frac{F'(t)}{1 - F}$	$\frac{t}{h} = \frac{1}{m} \sum_{t \in \mathcal{D}} \hat{h}(t)$
Systematic Deri	vation	I_{ψ} (I	$\hat{F}) = \int_0^{*d} \psi(\hat{F}(t)) dt$
AAC	$\hat{\mu} = \int_0^* d(1 - \hat{F}(t)) dt$	it	
nAAC	$\hat{\mu} = \frac{1}{d} \int_0^t (1 - \hat{F}(t)) dt$		
Gini	$\hat{g} = \frac{1}{\hat{\mu}} \int_0^{*d} \hat{F}(t) (1 - \hat{F}(t)) dt$		
АН	$\bar{h} = \frac{1}{*d} \int_0^* \frac{d}{t} \frac{\hat{f}(t) - \hat{f}(t-1)}{1 - \hat{f}(t-1)} dt$		

Between-State Transition Probabilities

Assumption: two state system (sedentary (S) and active (A))

 $P_S = Pr(x_t = 0)$: proportion of time spent sedentary

 $P_A = Pr(x_t = 1)$: proportion of time spent active

0, 1 for sedentary and active bout respectively, x_t is the type of bout

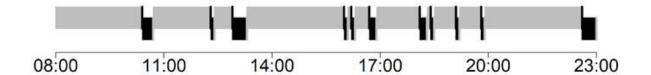
Between-state transition probabilities

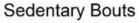
ASTP =
$$Pr(x_{t+1} = 0 | x_t = 1)$$

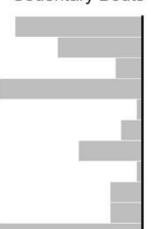
SATP = $Pr(x_{t+1} = 1 | x_t = 0)$

Estimation

$$\widehat{\text{SATP}} = \frac{n_A}{T_A} = 1$$
/average active bout $\widehat{\text{SATP}} = \frac{n_S}{T_S} = 1$ /average sedentary bout n_A , n_S : total number of active and sedentary bouts T_A , T_S : total number of active and sedentary time





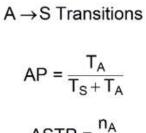


 $S \rightarrow A$ Transitions

$$SP = \frac{T_S}{T_S + T_A}$$

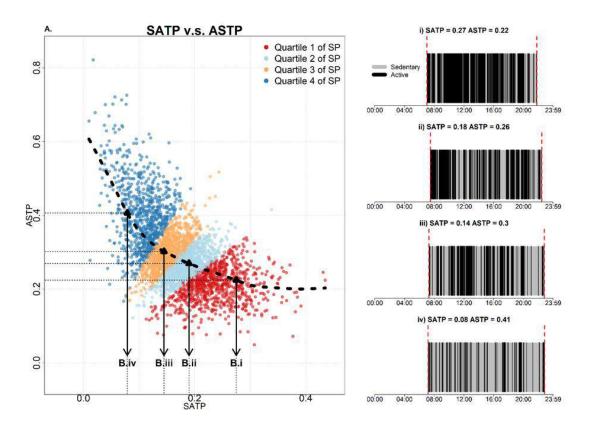
$$SATP = \frac{n_S}{T_S}$$

Active Bouts



$$ASTP = \frac{n_A}{T_A}$$

Properties and Intuitions for ASTP and SATP



Grey background: active state
White background: sedentary state

Figure 2. ASTP and SATP stratified by quartiles of total daily sedentary proportions (P_s).

Results of Survival Models for ASTP and SATP

Final	HR	Beta	P value
ASTP	1.33 (1.18, 1.50)	0.29 (0.17. 0.41)	<0.0001
SATP	0.47 (0.27, 0.80)	-0.76 (-1.30, -0.23)	0.005
Low P _S	0.21 (0.10, 0.45)	-1.56 (-2.30, -0.81)	<0.0001
High P _s	ref	ref	
SATP Low P _s	2.71 (1.53, 4.81)	1.00 (0.43, 1.57)	0.0006

- Two behavioral strategies of reducing sedentary time: prolonging active bouts and breaking sedentary bouts.
- Benefits of prolonging active bouts exist regardless of overall sedentary time.
- Only for those who are extremely sedentary, there is an benefit of reducing their total sedentary time via more frequent breaking their sedentary bouts.

Quantifying the Varying Predictive Value of Physical Activity Measures Obtained from Wearable Accelerometers on All-Cause Mortality over Short to Medium Time Horizons in NHANES 2003–2006

Lucia Tabacu 1,*, Mark Ledbetter 20, Andrew Leroux 3, Ciprian Crainiceanu 4 and Ekaterina Smirnova 50

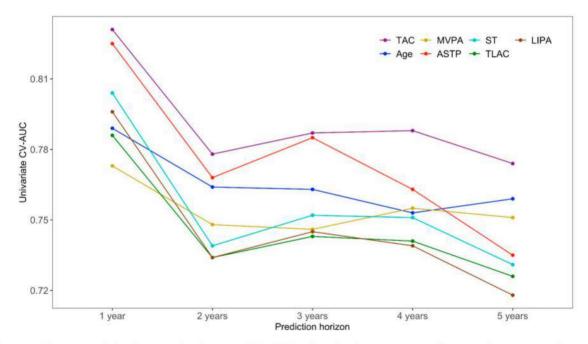


Figure 1. The cross-validated area under the curve (CV-AUC) values for the top seven predictors in the univariate five-year all-cause mortality logistic regression models across one- to five-year mortality prediction horizons. The x-axis corresponds to the prediction horizon and the y-axis is the CV-AUC (higher indicates better prediction performance).

Article

Quantifying the Varying Predictive Value of Physical Activity Measures Obtained from Wearable Accelerometers on All-Cause Mortality over Short to Medium Time Horizons in NHANES 2003–2006

Lucia Tabacu 1,*, Mark Ledbetter 20, Andrew Leroux 3, Ciprian Crainiceanu 4 and Ekaterina Smirnova 500

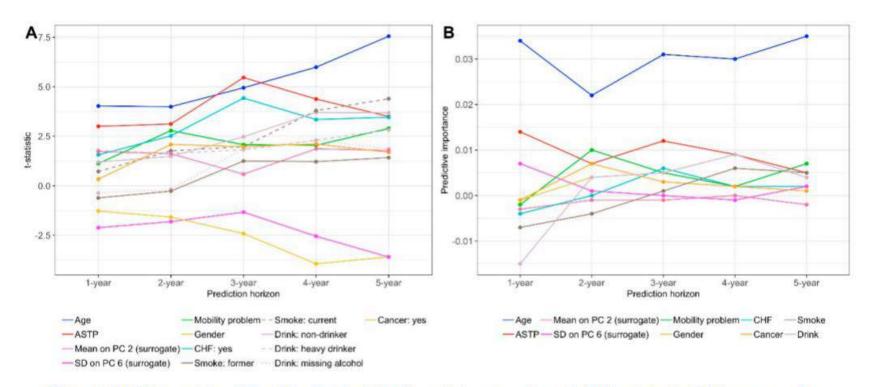


Figure 2. (**A**) The t-statistic values of the combined model coefficients in each prediction horizon. Each line corresponds to a t-statistic coefficient value (y-axis) as a function of the horizon prediction model (x-axis). (**B**) Predictive importance of each variable in the combined model measured by the difference between the CV-AUC of the full combined model and the combined model without that variable across prediction horizons.

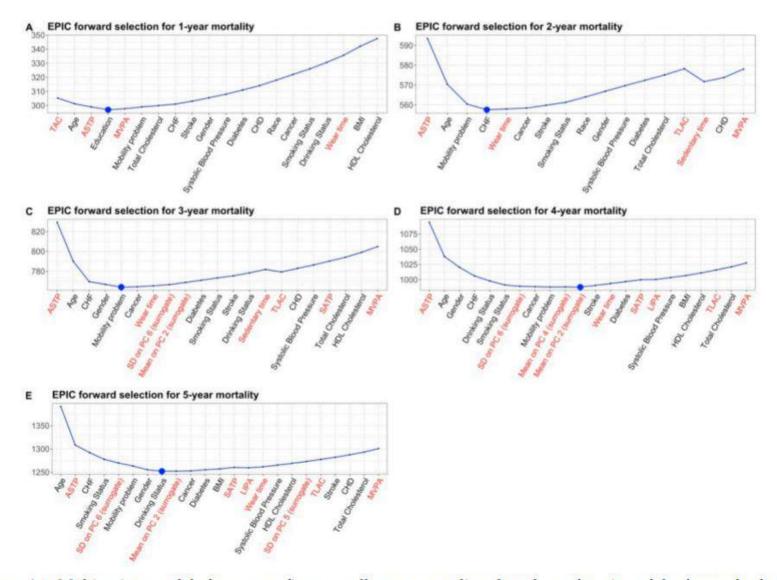
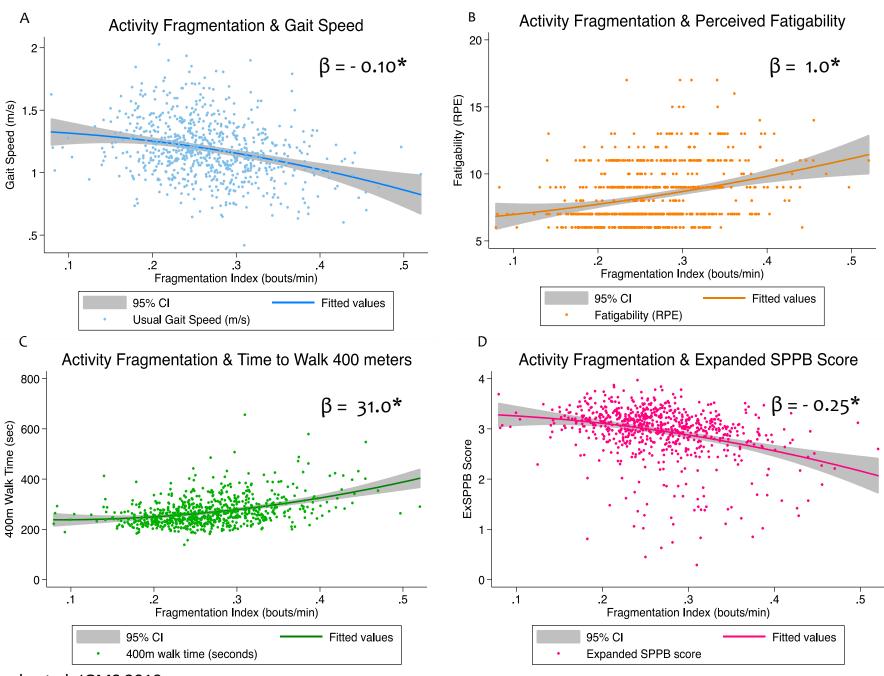


Figure A1. Multivariate models for one- to five-year all-cause mortality plotted as a function of the forward selection procedure. Accelerometry predictors are shown in red on the horizontal ax-is. NHANES Pooled Cohorts Study, United States, 2003–2006.



Schrack, et al, JGMS 2019



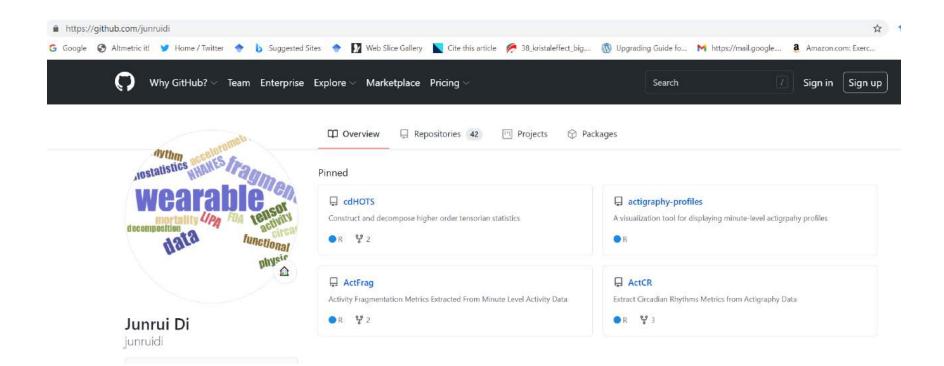
Original Investigation | Geriatrics

Association of Total Daily Physical Activity and Fragmented Physical Activity With Mortality in Older Adults

Amal A. Wanigatunga, PhD, MPH; Junrui Di, PhD; Vadim Zipunnikov, PhD; Jacek K. Urbanek, PhD; Pei-Lun Kuo, MD, MPH; Eleanor M. Simonsick, PhD; Luigi Ferrucci, MD, PhD; Jennifer A. Schrack, PhD

Table 3. Hazard Ratios for Total Activity, Activity Fragmentation, and Time Spent in Various Bout Lengths^a

	Hazard Ratio (95% CI)			
<mark>Variable</mark>	Model 1 ^b	Model 2 ^c	Model 3 ^d	
Total physical activity, h/d	0.88 (0.74-1.03)	0.86 (0.72-1.03)	0.87 (0.73-1.03)	
Activity fragmentation ^e	1.60 (1.13-2.26)	1.74 (1.19-2.54)	1.49 (1.02-2.19)	
Activity spent in bouts, %f				
<5 min	1.35 (1.09-1.66)	1.40 (1.12-1.76)	1.28 (1.01-1.61)	
5-10 min	0.89 (0.54-1.49)	0.88 (0.51-1.49)	0.99 (0.58-1.69)	
≥10 min	0.78 (0.64-0.96)	0.76 (0.61-0.985	0.81 (0.65-1.01)	



Joint work with

- Jennifer Schrack, JHU
- Jacek Urbanek, JHU
- Amal Wanigatunga, JHU
- Adam Spira, JHU,
- Jiawei Bai, JHU
- Ciprian Crainiceanu, JHU
- Ellen Mowry, MD
- Kate Fitzgerald, MD
- Kathy Zackowski, PhD OT
- Jennifer Keller, PT, MS
- Fan Tian, MS
- Jeff Goldsmith, Columbia University
- Mike Xiao, NIMH
- Lisa Reider, JHU

- Junrui Di, Pfizer
- Lei Huang, Google
- Daisy Zhu, Johns Hopkins University
- Yu Du, Eli Lilly
- Ximin Li, Johns Hopkins University
- Kathleen Merikangas, NIMH
- Haochang Shou, University of Pennsylvania
- Rahul Ghosal, JHU
- Vijay Varma, NIA
- Luigi Ferrucci, NIA
- Paul Rosenberg, Psychiatry
- Amber Watts, University of Kansas