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Normalization and extraction of interpretable metrics from raw accelerometry data: Supplementary Materials

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S1. More on the analysis of association with health outcomes

We conduct an exploratory data analysis on 34 subjects from the LifeMeter study who had at least three complete days of accelerometer recordings. Subjects were instructed to wear the device for about 4-5 days in the free-living environment, except when they were taking a shower, swimming, or sleeping. During these times the device was taken off and placed on a table. Demographic information was collected for every subject. We investigate the possible association of Time Active mean (TAM), Activity Intensity Mean (AIM), Time Active Variability (TAV) and Activity Intensity Variability (AIV) with several different covariates: Marital Status (Marstat), Sex, Self-Reported General Health (SRH), Quality of Life (QOL), Age, Education (Edu) and Weekend. The age range of the 34 subjects (25 females: Sex= 1) was between 59 to 80, with a mean age of 68.9. Marital status is labeled as: married, separated, divorced, widowed, never married; "married" is the baseline category. Education, SRH and QOL are all treated as 0/1 variables. For

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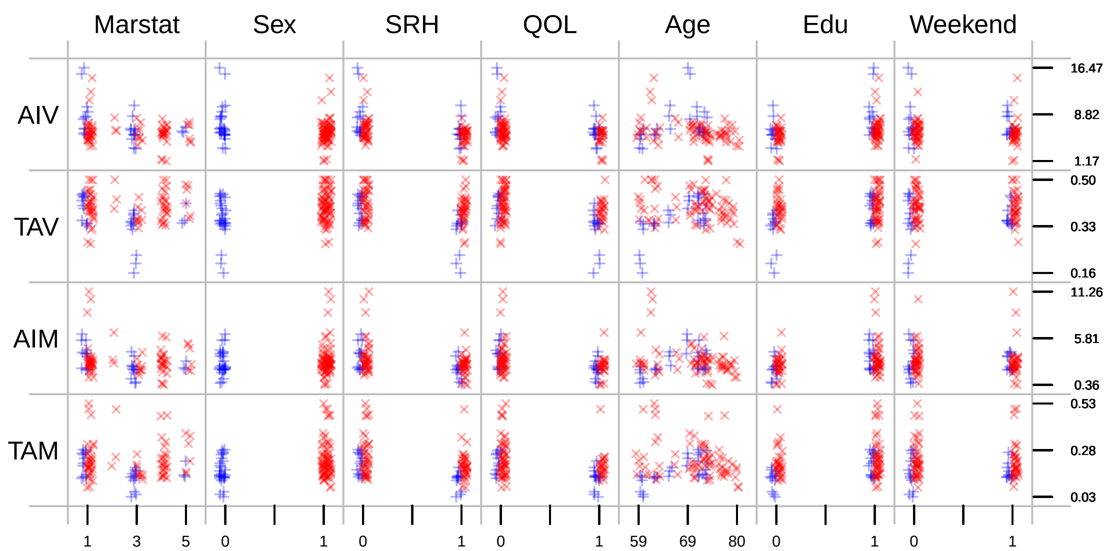

Fig. S1. 7 different covariates (Marital Status, Sex, Self-reviewed Health, Quality of Life, Age, Education and Weekend) plotted with 4 outcomes (Time Active Mean, Activity Intensity Mean, Time Active Variability and Activity Intensity Variability). The values of covariates are slightly jittered to better reflect their relationship with the outcomes. Male and female subjects are illustrated in blue and red cross-hairs, respectively.

education, 0 stands for having gone to high school or less (20 subjects) and 1 stands for having gone to some college or more (14 subjects). For SRH and QOL, 1 is for overall poor ratings (18 subjects for SRH and 21 for QOL) and 0 is for overall good ratings (16 subjects for SRH and 13 for QOL); "weekend" is 1 for a weekend day and zero otherwise.

Figure S1 displays the measurements for each of three days plotted versus covariates. Male and female subjects are depicted in blue and red, respectively. We started by fitting four models, each for a different outcome: TAM_{ij}, AIM_{ij}, TAV_{ij}, and AIV_{ij}. Here $i = 1, 2, \ldots, 34$ are subjects and $j = 1, 2, 3$ are days. Models were fit using generalized estimating equations with an exchangeable assumption for days within subject. Several significant predictors were identified from all or some of the models: Sex (women were found to have longer time active and higher variability in intensity), Age (older individuals had lower activity intensity mean and variability), SRH (worse health status was associated with less activity) and being divorced (was associated with less activity). The weekend effect was not found to be significant (p-value > 0.5) in this data set.

The high correlation (0.71) between SRH and QOL may indicate over-adjustment for measures of self-reported quality of life. Thus, we refit four simpler models: one with SRH and the other with QOL. The coefficients and their p-values are shown in Table S1. Results indicate that: a) SRH and being divorced (Marstat= 3) are both significantly associated with all activity outcomes; b) a worse SRH is associated with lower TAM, AIM, TAV and AIV; and c) being divorced is associated with lower TAM, AIM, TAV and AIV. Age was found to be weakly associated with TAM and AIM, implying that there may be a significant decrease of average time active and activity intensity with age. We further quantify associations for women, as there were only 9 men in the sample. Results in Table S1 confirm both the negative effect of worse SRH and of being divorced. We found a significant association between age and all 4 outcomes, indicating that, as age increases, both the activity level and variability decreases. Women who were never married tend to spend more time being active and exhibit a higher variation in time active. Similar results were found when SRH was replaced with QOL.

S2. More on the validation of Activity Intensity

In this section, we compare AI associated with normal walking and brisk walking in the two lab sessions discussed in Section 4.1. We chose two replicates of brisk walking from two lab sessions for 10 subjects. Figure S2 and Figure S3 display the raw data and corresponding AI for Subjects 3106 and 3208. In both figures, the first two rows display raw acceleration and AI for normal walking, whereas the following two rows correspond to brisk walking. The raw signals of brisk walking exhibit larger amplitude, which leads to a larger AI, at least on average. The probability density functions for AI in Figure S2 and Figure S3 indicate these difference, with the curves associated with brisk walking being shifted to the right indicating larger average AI compared to

Coefficients	Estimate	p-value		Coefficients	Estimate	p-value	
TAM: (All, $n = 34$)				AIM: (All, $n = 34$)			
Intercept	0.431	0.002	*	Intercept	8.507	0.005	*
Gender	0.036	0.022	*	Gender	0.041	0.905	
SRH	−0.068	< 0.001	*	SRH	−1.239	< 0.001	*
Age	−0.004	0.047	*	Age	−0.080	0.060	.
Separated	0.077	0.360		Separated	0.471	0.684	
Divorced	−0.096	< 0.001	*	Divorced	−1.776	< 0.001	*
Widowed	0.021	0.346		Widowed	−0.173	0.614	
Never married	0.015	0.524		Never married	−0.212	0.575	
TAV: (All, $n = 34$)				AIV: (All, $n = 34$)			
Intercept	0.436	< 0.001	*	Intercept	12.241	< 0.001	*
Gender	0.024	0.028	*	Gender	−1.546	0.015	*
SRH	−0.048	< 0.001	*	SRH	−1.637	< 0.001	*
Age	−0.001	0.293		Age	−0.073	0.107	
Separated	0.049	0.100		Separated	0.523	0.569	
Divorced	−0.064	< 0.001	*	Divorced	−1.982	0.006	*
Widowed	0.012	0.377		Widowed	−0.537	0.188	
Never married	0.008	0.597		Never married	−0.999	0.048	*
TAM: (Female, $n = 25$)				AIM: (Female, $n = 25$)			
Intercept	0.625	0.002	*	Intercept	11.308	0.009	*
SRH	−0.066	0.003	*	SRH	−1.171	< 0.001	*
Age	−0.006	0.025	*	Age	−0.118	0.038	*
Separated	0.049	0.585		Separated	−0.012	0.993	
Divorced	−0.140	< 0.001	*	Divorced	−2.463	0.005	*
Widowed	0.024	0.285		Widowed	−0.112	0.755	
Never married	0.053	0.006	*	Never married	0.489	0.069	.
TAV: (Female, $n = 25$)				AIV: (Female $n = 25$)			
Intercept	0.608	< 0.001	*	Intercept	13.821	0.001	*
SRH	−0.035	0.006	*	SRH	−1.246	< 0.001	*
Age	−0.003	0.015	*	Age	−0.115	0.044	*
Separated	0.021	0.518		Separated	−0.052	0.962	
Divorced	−0.075	< 0.001	*	Divorced	−1.991	0.036	*
Widowed	0.017	0.207		Widowed	−0.383	0.353	
Never married	0.035	0.007	*	Never married	−0.049	0.865	

Table S1. Results for different models. Models are defined by the outcome (labeled “TAM”, “TAV”, “AIM”, “AIV”), number of subjects (labeled as “All, $n = 34$” or “Female, $n = 25$”), and covariates (displayed under the outcome). The baseline for models labeled “All, $n = 34$” is “married subject”and for models labeled “Female, $n = 25$” is “married female”.

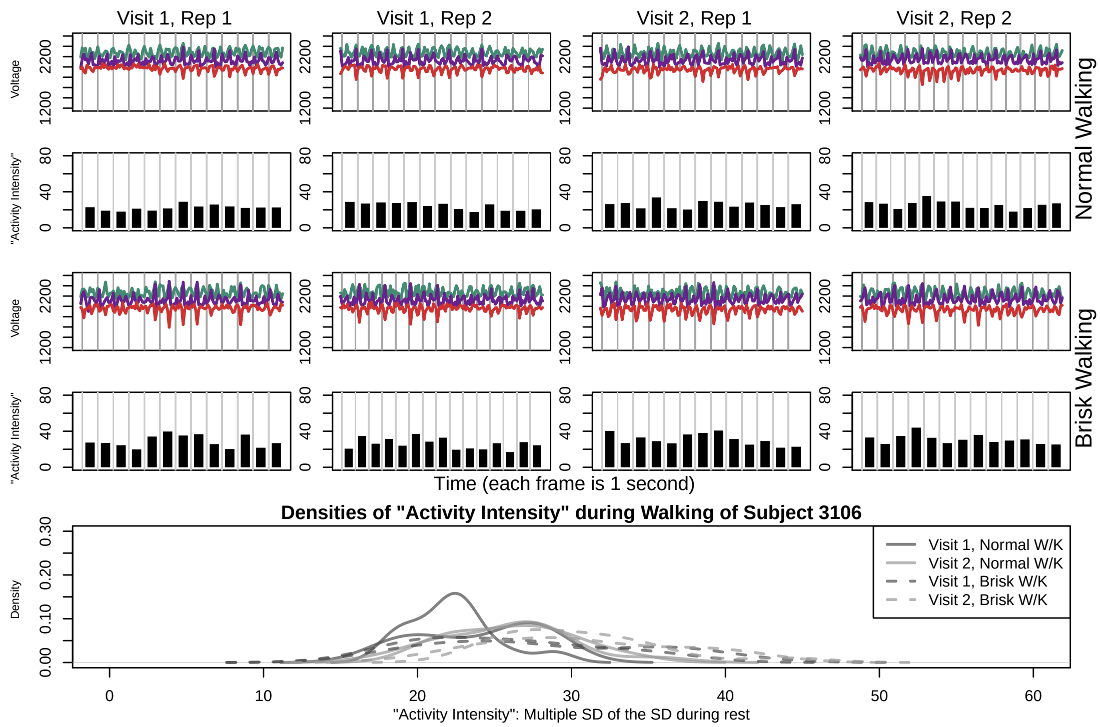

Fig. S2. AI for subject 3106 for normal walking (raw data and AI shown in top panels) and brisk walking (raw data and AI shown in the middle panels). Histograms of AI for four repetitions of normal walking (histograms shown as solid lines) and brisk walking (histograms shown as dashed lines.)

normal walking. Interestingly, the AI distributions corresponding to brisk walking have a larger standard deviation. This could be due to a number of reasons including decreased motion control or the persistent need for low acceleration associated with re-balancing or intrinsic between-stride human walk kinematics.

For each subject we also computed the median and standard deviation of AI for brisk and normal walking, respectively. Figure S4(a) displays the median AI for the 10 subjects during normal walking (cross-hairs on the left) and brisk walking (cross-hairs on the right). The medians for the two types of walking for the same subject are connected by straight lines. Obviously, AI for

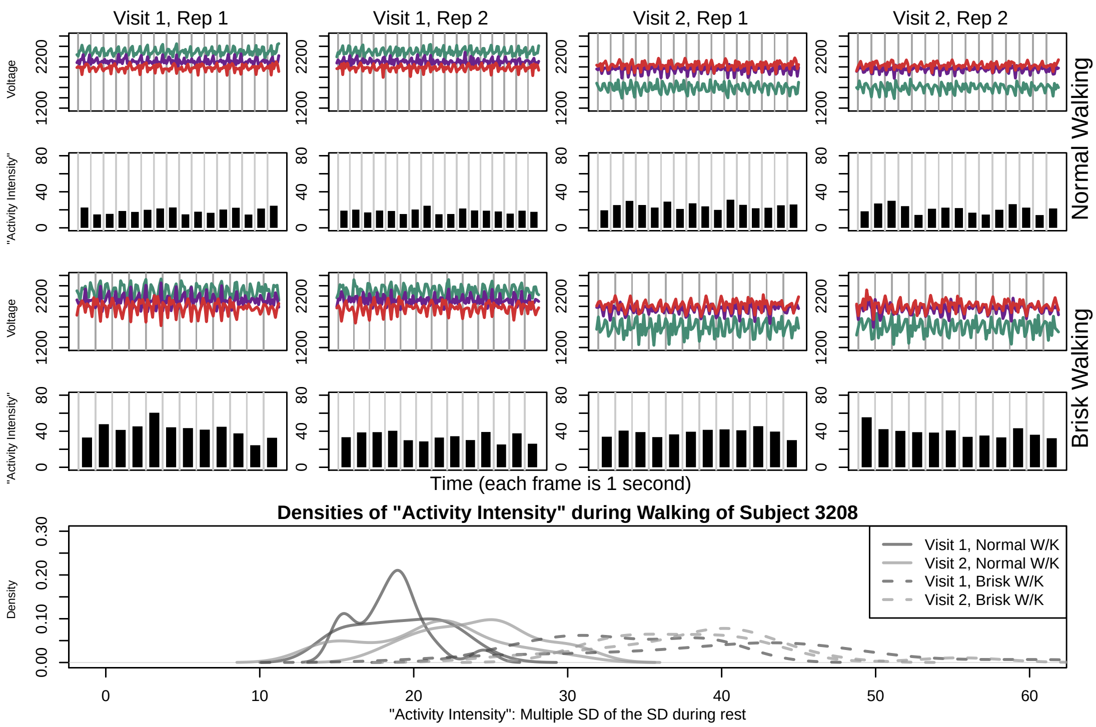

Fig. S3. AI for subject 3208 for normal walking (raw data and AI shown in top panels) and brisk walking (raw data and AI shown in the middle panels). Histograms of AI for four repetitions of normal walking (histograms shown as solid lines) and brisk walking (histograms shown as dashed lines.)

brisk walking has larger median than normal walking for all 10 subjects. Figure S4(b) illustrates the similar comparison of standard deviation of AI. Again, brisk walking corresponds to a larger SD of AI for all subjects. However, the magnitude of the difference varies from person to person. In particular, Subject 3106 has the smallest slope in Figure S4(a). The corresponding density plot in Figure S2 indicates that separation between the density curves of AI for normal and brisk walking for this subject is not obvious. This is consistent with a careful inspection of the raw acceleration time series, which are very hard to differentiate. This indicates that some subjects, even when told to walk briskly cannot really do so. This suggests new ways of measuring ability

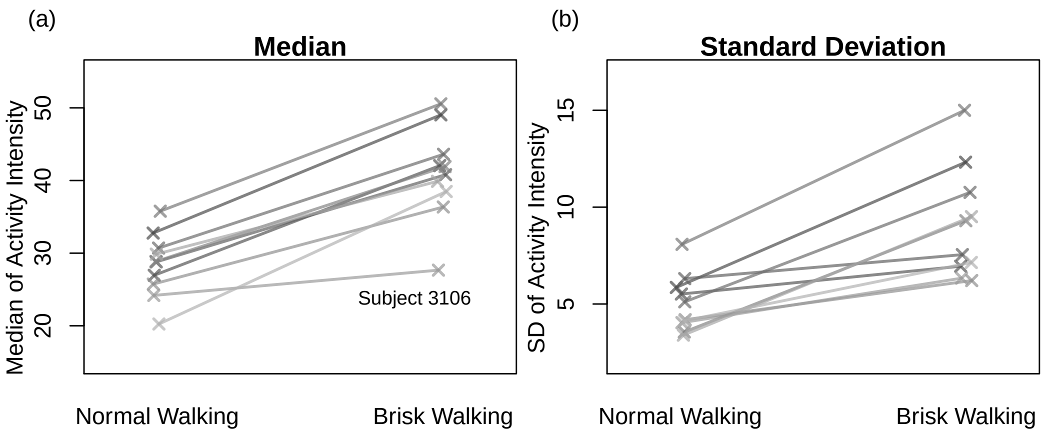

Fig. S4. Left panel: median AI for 10 subjects during normal and brisk walking. Right panel: standard deviation of AI for for 10 subjects during normal and brisk walking.

to walk and move.