Estimation of free-living walking cadence from wrist-worn sensor accelerometry data and its association with SF-36 quality of life scores

Marta Karas[1], Jacek K. Urbanek[2], Vittorio P. Illiano[3], Guy Bogaarts[3], Ciprian M. Crainiceanu[1], Jonas F. Dorn[3]

[1]Department of Biostatistics, Johns Hopkins University, 615 N Wolfe St, Baltimore, MD 21205, USA, [2]Division of Geriatric Medicine and Gerontology, Department of Medicine, Johns Hopkins University, 2024 E Monument St, Baltimore, MD 21205, USA, [3]Novartis Pharma AG, Fabrikstrasse 2, 4056 Basel, Switzerland

E-mail: mkaras2@jhu.edu

May 2021

Abstract.
Objective: We evaluate the stride segmentation performance of the Adaptive Empirical Pattern Transformation (ADEPT) for subsecond-level accelerometry data collected in the free-living environment using a wrist-worn sensor.
Approach: We substantially expand the scope of the existing ADEPT pattern-matching algorithm. Methods are applied to subsecond-level accelerometry data collected continuously for 4 weeks in 45 participants, including 30 arthritis and 15 control patients. We estimate the daily walking cadence for each participant and quantify its association with SF-36 quality of life (QoL) measures.
Main results: We provide free, open-source software to segment individual walking strides in subsecond-level accelerometry data. Walking cadence is significantly associated with the Role physical score reported via SF-36 after adjusting for age, gender, weight and height.
Significance: Methods provide automatic, precise walking stride segmentation, which allows estimation of walking cadence from free-living wrist-worn accelerometry data. Results provide new evidence of associations between free-living walking parameters and health outcomes.

1. Introduction

1.1. Motivation

Gait characteristics have become increasingly important in epidemiological and clinical studies. Traditional lab-measured walking features that quantify functional exercise capacity (e.g., distance covered and gait speed in the 6-minute walk test) (ATS 2002, Studenski et al. 2011) have been shown to be associated with survival. Walking cadence (steps per minute), stride pattern variability, and gait symmetry have recently been

proposed (Brown et al. 2014, Urbanek et al. 2017, Del Din et al. 2019) as complementary measures of the associations between walking characteristics and health outcomes. Indeed, 3 out of 7 submissions to the FDA for electronic Clinical Outcome Assessment qualifications of digital endpoints are quantifying gait parameters (*COA Qualification Program Submissions* n.d.).

However, recent publications suggest that walking features measured in a laboratory setting may only be weakly associated with the same features derived from data collected in the free-living environment (Van Ancum et al. 2019, Mueller et al. 2019, Del Din et al. 2016). This may be due to the difference between the individual ability to perform specific activities (what people can do) versus activities performed (what people do do).

1.2. Wearable accelerometers in health studies

A growing number of studies have been collecting wearable accelerometers data. Accelerometers are small electromechanical devices that collect acceleration along three orthogonal axes at high frequency (typically 10-100 Hz). These data can provide detailed characteristics of walking in the lab and in the free-living environment. Recent advances in technology (smaller devices, decreasing cost, and increasing ergonomics) make it possible to monitor individuals continuously for weeks without recharging the battery (Karas, Bai, Straczkiewicz, Harezlak, Glynn, Harris, Zipunnikov, Crainiceanu & Urbanek 2019).

Accelerometry monitoring of unsupervised physical activity in the home has been an active area of research, fueled by the developments of home wireless network technologies (Mathie, Coster, Lovell & Celler 2004). Application examples include long-term monitoring of functional status (Mathie, Coster, Lovell, Celler, Lord & Tiedemann 2004, Jehn et al. 2013), detection of events such falls (Lan et al. 2012, Bianchi et al. 2010), and identification of cognitive impairment (Marmeleira et al. 2017, Chen et al. 2019).

In early free-living studies, participants typically wore devices close to their body center of mass (lower back, hip, waist) (Straczkiewicz et al. 2019). However, recent large observational studies (e.g., UK Biobank, U.S. National Health and Nutrition Examination Survey (NHANES)) largely shifted to wrist-worn devices to improve the comfort of participants and adherence (Troiano et al. 2014). Controlled scientific data collection is thus aligning with the consumer market, where affordability of wrist-worn consumer-grade devices has generated a wealth of data that is increasingly being used for health research (Lai et al. 2017). While wrist-worn accelerometry data has become increasingly available, there is a substantial gap in methods dedicated to quantifying gait characteristics in the free-living environment.

1.3. Methodology gaps

A detailed characterization of walking often requires precise identification of the start and duration of a step or stride (two subsequent steps). Proposed methods for strides

segmentation in accelerometry data are typically based on landmark events (e.g., heel-strike, push-off or swing) (Selles et al. 2005, McCamley et al. 2012, Godfrey et al. 2015, Wang et al. 2012, Willemsen et al. 1990). They are designed for a specific body location (e.g., foot) and cannot be easily adapted to data collected at the wrist. Template matching-based methods were proposed for segmenting steps during a standardized test using data collected at the waist (Soaz & Diepold 2016) and shoe (Barth et al. 2015, Ying et al. 2007), respectively. The ADEPT template-matching method (Karas, Straczkiewicz, Fadel, Harezlak, Crainiceanu & Urbanek 2019) for stride segmentation was validated with accelerometry data collected at wrist during an outdoor walk. While most consumer-grade accelerometers collect step counts, their algorithms remain proprietary.

To the best of our knowledge, there are currently no open-source methods and software that can perform walking strides segmentation in actigraphy data collected at wrist in the free-living environment.

1.4. Challenges

Despite its importance, quantifying walking is difficult. Indeed, even proprietary algorithms of consumer-grade wearable devices can be inaccurate when estimating the step counts (Maganja et al. 2020). This is likely due to the larger heterogeneity and lower signal amplitude associated with wrist movement during walking. To better highlight some data traits, Figure 1 displays the raw three-dimensional accelerometry data collected with a wrist-worn sensor at a frequency of 30 Hz. The upper panel shows 60 minutes of data collected from an individual between 10:30 am and 11:30 am, the middle panel shows 10 minutes-long subset of the top panel data, and the bottom panel shows 40 seconds-long subset of the middle panel data. Grey shaded area and black vertical dashed lines indicate the subset of data displayed on the following panel. Data in the lower panel between 10:36:52 and 10:37:15 likely correspond to walking activity. While the pattern can be observed and recognized, designing a method that mimics a human observer is quite difficult. Moreover, there is substantial variation in shape, duration, and amplitude of the accelerometry signal of a walking stride. Another problem is the lack of publicly available datasets collected during free-living that contain detailed activity labels. The lack of a gold standard thus makes it difficult to validate and compare stride segmentation methods.

1.5. This paper's contribution

We propose to narrow the substantial methodological gap outlined above. We substantially expand the scope of the existing ADEPT algorithm to incorporate wrist-accelerometer data collected in the free-living environment. Methods are applied to data collected continuously for 4 weeks for each study participant in a sample of 45 participants, including 30 arthritis patients. Daily walking cadence is estimated for each study participant and the association with measures of quality of life (QoL) is quantified.

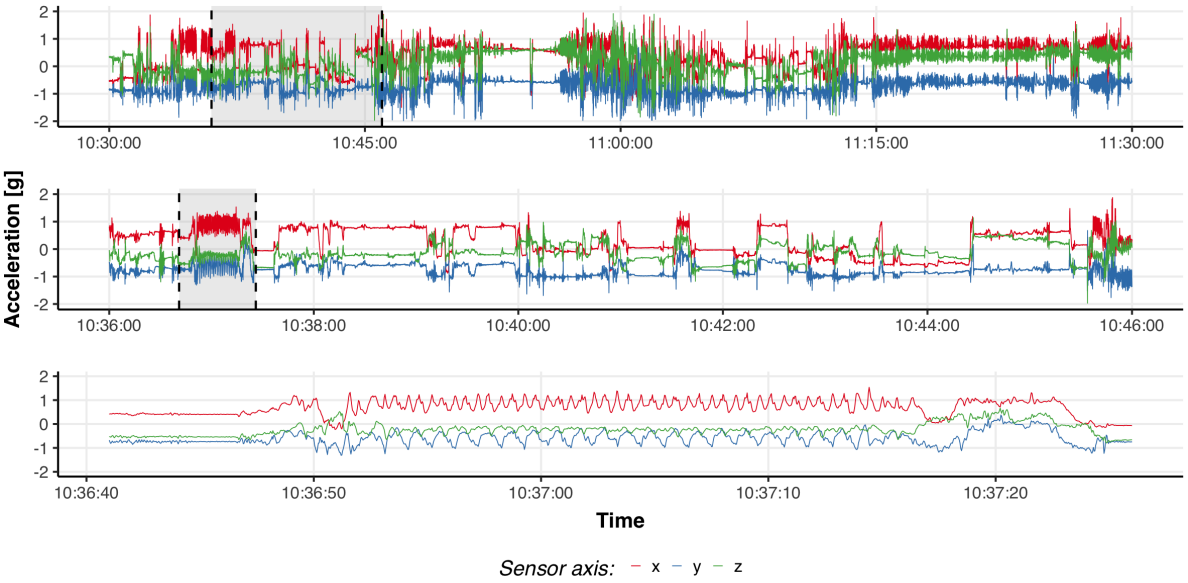

Figure 1. Raw three-dimensional accelerometry data collected with a wrist-worn sensor at frequency 30 Hz. Top panel: 60 minutes of data; middle panel: 10 minutes-long subset of the top panel data; bottom panel: 40 seconds-long subset of the middle panel data. Grey shaded area and black vertical dashed lines indicate the subset of data displayed on the following panel.

We provide open-source software and publish data examples that could be used for a performance comparison of strides segmentation and cadence estimation methods in future studies.

2. Methods

2.1. Study participants and data collection

Data were collected as a part of an observational study on a population with arthritis and healthy individuals, funded by Novartis Pharma AG (Basel, Switzerland). This dataset is described in Perraudin et al. (2018).

2.1.1. Recruitment procedure. A total of 30 arthritis patients (AP) were recruited, among whom 18 patients had rheumatoid arthritis, 2 patients had psoriatic arthritis, and 10 patients had osteoarthritis. In addition, a group of 15 healthy volunteers (HV) was recruited with age and gender distribution matched with that of the arthritis patients. The AP cohort was recruited through Tallaght Hospital via Trinity College Dublin. The HV cohort was recruited through University College Dublin. Informed written consent was obtained prior to inclusion following ethical approval by the institutional ethics committee.

2.1.2. Actigraphy data collection and preprocessing. Participants were equipped with the ActiGraph GT9X Link device (ActiGraph, Pensacola, FL) and instructed to wear it for 4 weeks on the wrist of their choice, without removing it for sleep. The devices were configured to collect raw tri-axial accelerometer measurements at a sampling frequency of 30 Hz. Participants were instructed to charge the device weekly during the study period. The ActiLife software was used to retrieve raw tri-axial and 1-minute epoch data. A modified version of the Choi (Choi et al. 2011) non-wear time detection algorithm was used to estimate non-wear epochs.

2.1.3. Onsite visit. A study staff member visited each participant at home at the beginning of the study to provide written and verbal instructions. Under the supervision of the study staff member, each participant performed a series of short activity tasks, including a short straight walk wearing the ActiGraph device.

2.1.4. SF-36 survey data collection. The 36-Item Short Form Health Survey (SF-36) (Ware & Sherbourne 1992) was administrated to each participant by a study staff member on the first and last day of the study. The SF-36 evaluates eight health-related domains, including physical function (limitations in physical activities because of health problems), physical role (limitations in usual role activities because of physical health problems), body pain, general health (general health perceptions), vitality (energy and fatigue), social function (limitations in social activities because of physical or emotional problems), emotional role (limitations in usual role activities because of emotional problems), and general mental health (psychological distress and well-being). The SF-36 survey also provides two summary scores: physical component summary and mental component summary. The total score for each SF-36 component ranges between 0 and 100, with a higher score corresponding to a better quality of life (QoL).

2.2. Segmentation of individual walking strides in raw accelerometry data

2.2.1. Three-axial accelerometry signal preprocessing. The first step of data processing was to transform the three-dimensional time-series sensor output from Cartesian to spherical coordinates. Denote by (x_t, y_t, z_t) and (az_t, el_t, r_t) the data in the Cartesian and spherical coordinate system, respectively. Here az_t represents the azimuth angle – rotation of the accelerometer in the plane of an activity monitor face, el_t represents the elevation angle – tilt relative to the plane of an activity monitor face, and r_t represents the radius – acceleration vector magnitude. More precisely, for a three dimensional vector (x, y, z) $az = \text{atan2}(y, x)$, $el = \text{atan2}(z, \sqrt{x^2 + y^2})$, $r = \sqrt{x^2 + y^2 + z^2}$, where $\text{atan2}(y, x)$ is the inverse tangent of y and x. The choice of spherical coordinates was motivated by (a) the fact that r_t is the base of the algorithm the current paper expands on (see Sect. 2.2.2), (b) our hypothesis that az_t and el_t of acceleration collected by a wrist-worn sensor are better suited to characterize movements expected during some of the walking, such as arm swing and tilt, and that they allow for a more intuitive

interpretation of the raw acceleration data. Figure 2 displays the same accelerometry data from the lower panel of Figure 1 in spherical coordinates.

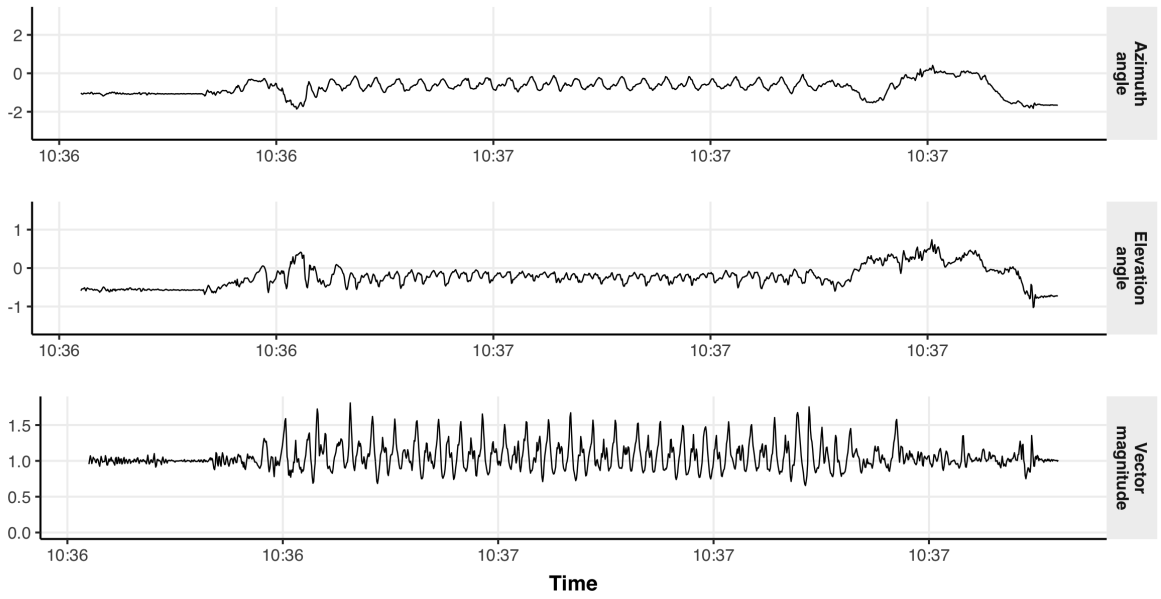

Figure 2. Raw three-dimensional accelerometry data after transformation from Cartesian (x_t, y_t, z_t) to spherical (az_t, el_t, r_t) coordinate system. The displayed (az_t, el_t, r_t) data correspond directly to (x_t, y_t, z_t) data showed on the lower panel in Figure 1.

2.2.2. Walking stride pattern segmentation with the ADEPT method. The second step of data processing was to use the Adaptive Empirical Pattern Transformation (ADEPT) method (Karas, Straczkiewicz, Fadel, Harezlak, Crainiceanu & Urbanek 2019) to segment walking stride patterns in vector magnitude of raw accelerometry data, r_t. ADEPT is a dictionary-based, statistical pattern recognition algorithm optimized for precise (at sub-second resolution) identification of time and duration of walking strides. The method was validated with data collected from wrist-worn sensors during continuous walking. The referenced study did not have a true gold standard of strides segmentation and instead validated the ADEPT against manual strides segmentation; visual inspection of the results and comparison of the results across multiple simultaneous sensor locations were also performed. ADEPT implementation is freely available for download as `adept` R package (Karas, Urbanek, Crainiceanu, Muschelli & Gherman n.d.), accompanied by user tutorials (Karas, Urbanek & Crainiceanu (n.d.*a*), Karas, Urbanek & Crainiceanu (n.d.*b*)). The ADEPT algorithm uses a predefined template and detects its repetitions by maximizing the local correlation between a collection of scale-transformed templates and the observed data signal at every time point. For the correlation maximizing step, the observed data undergoes moving average smoothing with the length of a smoothing window corresponding to

to 0.2 seconds of data collection. The scale-transformation adjusts the duration of the dictionary template, allowing for the detection of patterns that are shorter or longer than the original dictionary template. Multiple distinct baseline templates can be used simultaneously to account for various shapes of stride patterns in the data.

In the ADEPT segmentation, three wrist-specific stride templates publicly available in `adeptdata` R package (Karas, Urbanek, Fadel & Harezlak n.d.) were used. The templates were derived by Karas, Straczkiewicz, Fadel, Harezlak, Crainiceanu & Urbanek (2019) using data collected from 32 healthy participants between 23 and 52 years of age. The ADEPT result describes each segmented stride by its: (a) start time, (b) duration time (seconds), and (c) correlation with the best-fit stride template.

2.2.3. Identification of free-living walking strides from ADEPT-segmented data. The third step of the data processing procedure was to filter ADEPT-derived strides to keep those that: (1) have a correlation with the best-fit template stride of at least 0.85; (2) have duration time between 0.8 and 1.4 seconds; and (3) have $(r_t)_t$ amplitude and mean amplitude deviation within $[0.2, 2.0]g$ and $[0.05, 2.0]g$, respectively. To further increase the specificity of the procedure, strides were identified only if they occurred in a sequence of at least three that have similar duration, median azimuth angle $(az_t)_t$ and median elevation angle $(el_t)_t$. The algorithm is described in detail in Appendix A.1. The algorithm's default parameter values were established based on the exploratory analysis of supervised-walking data and underwent sensitivity analysis (see Section Appendix A.3). The implementation of the algorithm with its default parameters is provided in `segmentWalking()` function in `adept R` package; an example of stride segmentation from independent data not used in the present study is publicly available on GitHub at `https://git.io/J35LV`.

Quality control of free-living walking segmentation is described in Appendix A.2. An extensive sensitivity analysis of was conducted to study the effect of the choice parameter values on the robustness of results; methods are described in Appendix A.3.

2.2.4. Estimation of walking strides during supervised walking. The data window of a participant's short supervised walking (see Section 2.1.3) was determined based on its start and end time annotated by a visiting staff member. The supervised walking strides were identified in these data with the same algorithm as for free-living walking strides, except the last conditions of imposing consecutiveness and similarity of three ADEPT-segmented patterns were omitted. The relaxation of these conditions was meant to increase sensitivity of the identification in a very short walking distance (as constrained by participant's dwelling).

2.3. Estimating the association between cadence and SF-36 survey outcomes

2.3.1. Daily cadence. Segmented strides were used to estimate the walking cadence (expressed as a number of steps per minute) at every time of the day when walking was

identified. Next, the mode of all estimated cadences during the day was computed; we refer to this measurement as participant's *daily cadence*. The mode was used instead of the average because it more closely represents the typical walking cadence and is more robust to artefacts and outliers.

2.3.2. Model for association between cadence and QoL measurements. The association between free-living daily cadence and SF-36 survey scores was estimated using a linear mixed model (LMM) for each SF-36 score. In each LMM model the participant- and day-specific cadence was the outcome, while the SF-36 score average (of the first and last day measurements) and weekend-day indicator were fixed-effect covariates. The model also contained a random intercept and a random slope for the weekend-day indicator. Three scenarios were considered to account for different levels of confounding adjustment:

(i) model (1): no additional adjustment in the LMM formula,

(ii) model (2): adjustment for age, gender, weight, height,

(iii) model (3): adjustment for age, gender, weight, height, and supervised walking cadence.

The main conceptual idea behind model (1) was that the presence of both AP and HV cohorts would yield substantial variability in both QoL scores and free-living walking cadence and hence their association can be captured despite the small size of our sample. Model (2) attempts to account for covariates which we hypothesized could further explain variability in walking cadence values; while some works reported no pair-wise correlation between cadence and age, height and body weight (Samson et al. 2001), the works that model cadence or walking speed (a function of cadence and stride length) with multiple regression tend to account for these and sex covariates (O'Brien et al. 2018, Jerome et al. 2015). Finally, model (3) additionally included supervised walking cadence to observe if it can substantially change the estimated association between cadence and QoL scores.

In this work, further quantification of associations regarding AP versus HV cohorts was not pursued; the differences between individuals from the three suptypes of arthritis condition were not studied either. Indeed, the data set available lacked a detailed information about how arthritis condition was pronounced and affecting each of the AP participants, and the sample size was considered too small to allow meaningful condition-related conclusions given a mixture of the arthritis suptypes present.

The model formulas are specified in Appendix A.4. For each participant, only data from valid days (defined as $\geq$ 80% sensor wear time) were used. Models were fit using the `lme4::lmer` function (Bates et al. 2015) in `R` statistical software. The 95% confidence interval for the SF-36 score coefficient estimate was obtained using the bootstrap percentile method implemented in the `lme4::confint` function in `R`.

2.3.3. Sample size calculation with upstrap method. To supplement the statistical modeling results, the upstrap method (Crainiceanu & Crainiceanu 2018) was used

to estimate the sample size required to identify a statistically significant association between the SF-36 score and outcome at the $\alpha = 0.05$ level with a power of $1 - \beta = 0.8$.

The upstrap was implemented separately for each LMM. The procedure started by setting a grid of sample sizes n_{tmp} ranging from 30 to 300. For each sample size n_{tmp} considered, $B = 1000$ samples were generated by sampling with replacement n_{tmp} study participants. The LMM was fit for every upstrapped data set and a p-value for the association between the SF-36 score and the outcome was obtained using the `lmerTest::summary.lmerModLmerTest` function (Kuznetsova et al. 2017) in `R`. For each n_{tmp} value, the proportion of $B = 1000$ resamples where the association was statistically significant was calculated. The sample size was then estimated as the smallest n_{tmp} where this proportion was at least 0.8. Results are shown for three different strategies for multiplicity adjustment to account for the $k = 10$ SF-36 scores: (a) no p-value correction, (b) Benjamini and Hochberg (Benjamini & Hochberg 1995) correction, (c) Bonferroni correction (Dunn 1961).

3. Results

3.1. Characteristics of study participants

Table 1 summarizes the demographics and SF-36 survey component scores for all study participants and separately for sub-groups of arthritis patients (AP) and healthy volunteers (HV). The study sample had a higher proportion of females (69%) and had an average age of 51.9 (sd=12.5). The average SF-36 survey Summary scores were 44.0 and 51.8 for the Physical Component and Mental Component, respectively. The average for the other SF-36 survey components ranged between 53.0 (Vitality) to 82.0 (Role emotional). One specifics not captured by the Table 1 is that overall, men tended to be older than women (average age was 55.2 (sd=12.5) and 50.4 (sd=12.3), respectively), and had higher BMI than women (average BMI was 27.6 (sd=4.37) and 25.9 (sd=5.21), respectively).

The proportion of females and the age averages were similar in the AP and HV sub-groups. The AP sub-group had a higher average BMI (28.1) compared to AP sub-group (22.9). All SF-36 survey components had a lower average in AP sub-group compared to the HV sub-group; the largest differences between sub-groups (more than 40.0) were observed for the items Physical function and Role physical.

3.2. Estimated walking strides

Figure 3 displays the cadence estimates expressed in steps per minute (y-axis) for each study participant (x-axis). Each coloured dot corresponds to the mode of the cadence on a given day, i.e. *daily cadence* (see Sect. 2.3.1); red dots correspond to the AP sub-group participants and blue dots correspond to the HV sub-group participants. Each black dot corresponds a person-specific mode of daily cadence across all days, i.e. *typical daily cadence*. Typical daily cadence varied between 99.6 and 130.8 steps per minute

Table 1. Summary of demographic information (rows 1-6) and SF-36 survey component scores (rows 7-16) for all study participants ($n = 45$), and for sub-groups of arthritis patients ($n = 30$) and healthy volunteers ($n = 15$). The values shown are mean (sd), except for gender where count (percentage) is showed.

		All participants $n = 45$	Sub-group: arthritis patients $n = 30$	Sub-group: healthy volunteers $n = 15$
1	Gender: female	31 (68.9%)	21 (70.0%)	10 (66.7%)
2	Gender: male	14 (31.1%)	9 (30.0%)	5 (33.3%)
3	Age	51.9 (12.5)	53.9 (11.3)	47.9 (14.1)
4	Height [cm]	166.9 (7.7)	165.1 (7.6)	170.5 (6.7)
5	Weight [kg]	73.4 (13.8)	76.6 (13.4)	67.1 (12.7)
6	BMI	26.4 (5.0)	28.1 (4.9)	22.9 (3.0)
7	Physical function	64.8 (30.2)	49.2 (24.8)	96.0 (5.2)
8	Role physical	67.4 (29.4)	53.9 (26.1)	94.6 (10.5)
9	Bodily pain	61.5 (26.7)	48.3 (21.5)	87.8 (13.1)
10	General health	60.9 (24.8)	49.6 (21.6)	83.5 (11.8)
11	Vitality	53.0 (21.6)	44.7 (21.0)	69.6 (10.4)
12	Social functioning	78.1 (22.4)	69.8 (22.4)	94.6 (9.7)
13	Role emotional	82.0 (19.0)	76.2 (19.6)	93.6 (11.0)
14	General mental health	77.1 (13.3)	74.2 (14.7)	82.8 (7.4)
15	Physical Component Summary	44.0 (12.3)	37.5 (9.7)	57.1 (2.6)
16	Mental Component Summary	51.8 (7.1)	50.8 (7.9)	53.9 (4.7)

(mean (sd) 113.4 (7.5)), and was on average slightly higher in the HV sub-group (mean (sd) 114.8 (7.3)) than in the AP sub-group (mean (sd) 112.7 (7.6)). Participant IDs are ordered from the smallest (ID 22) to the largest (ID 40) typical daily cadence and the observed trend is a consequence of this ordering. The size of the dots corresponds to the number of strides summarized by it. Black "x" signs are the cadence estimated from supervised walking. Table B1 in Appendix B.1 summarizes the data from Figure 3.

Both the number of strides and free-living daily cadence varied considerably between and within participants. For example, participants with ID 1, 30, 33, and 38 had a standard deviation of daily cadence of 3, whereas participant with ID 27 had a standard deviation of daily cadence of 11.4. The correlation between the supervised cadence and free-living typical daily cadence was 0.21. Moreover, the estimated cadence in the supervised context tends to be lower than in the free-living environment (note the "x" signs that are predominantly below the black dots). This low correlation and bias may be, at least in part, due to: (1) very short supervised walking bout duration; (2) differences between the ability (can-do) and the need and will to engage in walking (do-do); and (3) the environment where walking is performed.

Figure 4 displays 200 estimated strides for each of three study participants with different typical daily cadence: 105.6 (participant ID: 38), 112.8 (ID: 11), and 120 (ID:

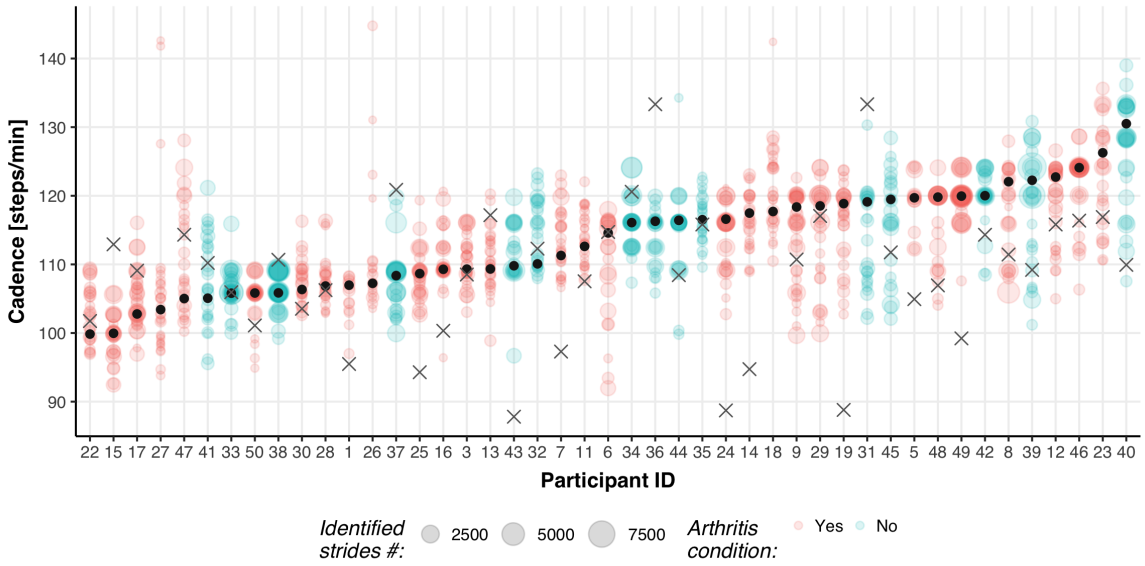

Figure 3. Red (AP sub-group participants) and blue (HV sub-group participants) points: daily cadence estimates (y-axis) for each valid day by study participant ID (x-axis). The size of a point represents the number of strides identified for a participant on a particular day. Black solid points: person-specific mode of daily cadence across all days. Black "x" signs are the cadence estimated from supervised walking. Individuals are ordered according to typical daily cadence.

5) steps per minute, respectively. For each of the three study participants data were chosen from a randomly selected valid day. Plots in the first row display the vector magnitude (y-axis) as a function of clock time (x-axis). Plots in the second row display the same vector magnitudes as a function of the time standardized to the $[0, 1]$ interval. The red line is the point-wise mean of the standardized vector magnitude signals.

Each plot in Figure 4 exhibits a characteristic "W"-shaped pattern of a walking stride, similar to shapes reported previously from a wrist-worn sensor data (Karas, Straczkiewicz, Fadel, Harezlak, Crainiceanu & Urbanek 2019). However, vector magnitude signals vary both between and within participants. For example, strides for study participant 5 (top right panel) tend to be more consistent in terms of duration, timing (similar peak and through locations), and amplitude (similar peak and through sizes). In contrast, data for the participants 38 and 11 exhibits substantially more variability in all these directions.

3.3. Quality control of segmentation results

Manual quality control of segmentation results is described in Appendix B.2. In short, we concluded ADEPT with default parameters is highly specific.

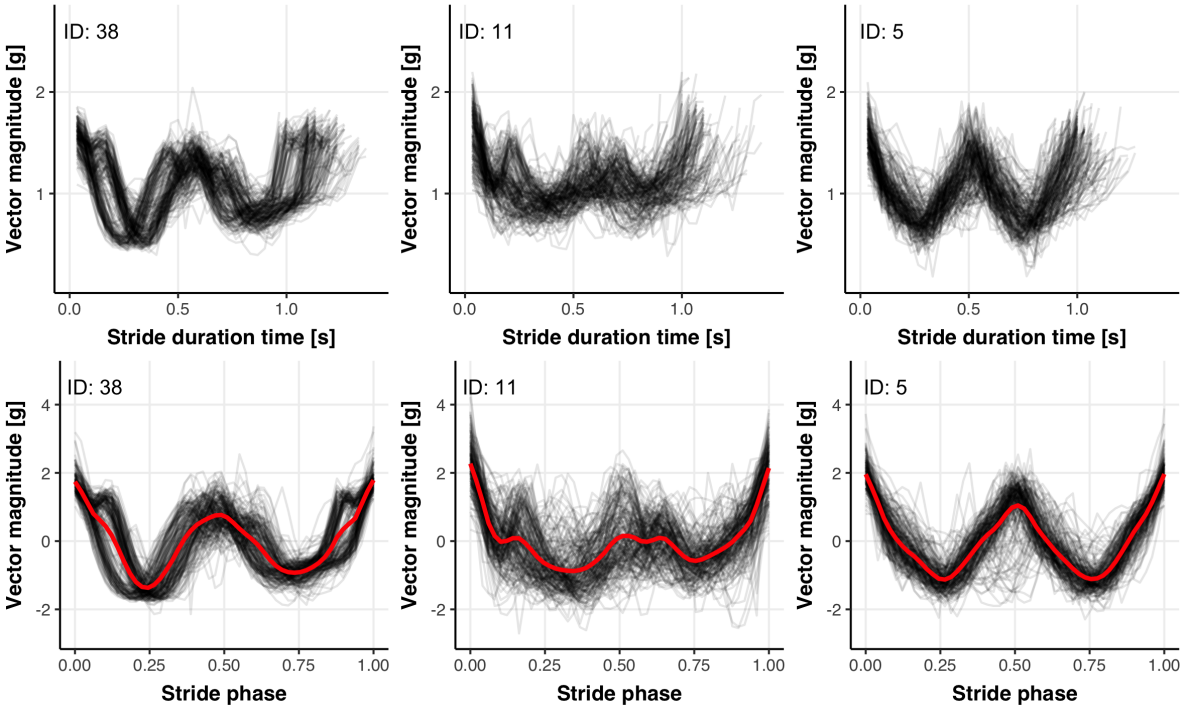

Figure 4. Visualization of 200 estimated strides for each of three study participants with different typical daily cadence: 105.6 (participant ID: 38), 112.8 (ID: 11), and 120 (ID: 5) steps per minute, respectively. Plots in the first row display the vector magnitude (y-axis) as a function of clock time (x-axis). Plots in the second row display the same vector magnitude as a function of the time standardized to the $[0, 1]$ interval. The red line is the point-wise mean of the standardized vector magnitude signals.

3.4. ADEPT sensitivity analysis to choice of parameters

Figures B2 and B3 in Appendix B.3 provide results of an extensive sensitivity analysis of the effect of algorithm parameters' values on strides segmentation. Overall, stride numbers and cadence estimates were stable around the values selected for the present analyses (default values of the algorithm implementation).

3.5. Association between free-living walking cadence and SF-36 survey outcomes

Figure 5 provides the point estimates and 95% confidence intervals for the fixed effect of SF-36 score on free-living cadence in the three models: model (1) without covariate adjustment, model (2) with adjustment for age, gender, weight, height, model (3) with adjustment for age, gender, weight, height, and supervised walking cadence. A separate LMM was fit for each SF-36 score (see Section 2.3.2). The values of estimators $\hat{\beta}$ and corresponding 95% confidence intervals for all fixed effects considered, across all the models in which a particular fixed effect was included, are reported in Tables B2-B8 in Appendix B.

For model (1), the SF-36 score coefficient estimates were positive for all but one fit

(Vitality); their estimated effect ranged from -0.062 to 0.759 steps per minute change in free-living cadence per 10 points increase in the SF-36 score, and was not statistically significant for any score. The fixed effect of a weekend day was statistically significant in each SF-36 score's fit, estimated -1.6 steps per minute of daily free-living cadence on a weekend day compared to a week day (the reference level).

For model (2), the SF-36 score coefficient effect was statistically significant ($\alpha = 0.05$) for Role physical score, suggesting that 10 points increase of Role physical score was associated with 0.53 (95% CI: $[0.002, 1.075]$) steps per minute increase of daily cadence while adjusting for age, gender, weight, height, and weekend versus weekday indicator. Equivalently, 40.7 points increase of Role physical score (difference in averages between HV and AP sub-groups) was associated with 2.24 steps per minute increase of daily cadence while adjusting for age, gender, weight, height, and weekend versus weekday indicator. Overall, for all model (2) LMM fits, the SF-36 score point estimates were positive. For most of the scores, the 95% confidence intervals corresponded to results being close to statistical significance (see Figure 5).

For model (2), the fixed effect of a weekend day compared to a week day had its estimates essentially unchanged compared with model (1), and remained statistically significant across all SF-36 score fits. Overall, the fixed effects of age were estimated negative for all but one SF-36 score fit (Physical Component Summary), with increase in age by 1 year associated with between -0.052 to 0.001 of change in steps per minute of daily free-living cadence (while keeping other covariates fixed); they were all not statistically significant, and – differently to SF-36 score effect coefficients – their confidence intervals were all centered roughly at 0.0. The fixed effects of weight (kg) were estimated all negative, with increase in weight by 1 kg associated with between -0.05 to -0.003 of change in steps per minute (while keeping other covariates fixed); they were all not statistically significant. The fixed effects of height (cm) were estimated all negative, with increase in height by 10 cm associated with between -2.06 to -1.34 of change in steps per minute (while keeping other covariates fixed) across the SF-36 score fits; while they were all not statistically significant, the confidence intervals were largely shifted to negative values (see Table B7 in Appendix B.). Finally, a relatively large magnitude of male versus female gender effect has been observed, with male indicator coefficient ranging from -5.05 to -4.25 across SF-36 score fits; while they were all not statistically significant, the confidence intervals were very largely shifted to negative values, yielding the effect being close to statistical significance (see Table B5 in Appendix B.) We hypothesize that the differences in age distibution between males and females in this sample (see Sect. 3.1) might have contributed to relatively large magnitude of estimated gender effect.

For model (3) with covariate adjustment increased by including supervised cadence estimate, the interpretation of results does not change substantially compared to model (2). The supervised cadence effect was not statistically significant in any of the SF-36 score fits, and the coefficient confidence intervals were all centered roughly at 0.0. This aligns with our earlier observations of low correlation between free-living and supervised

cadence estimates in this study.

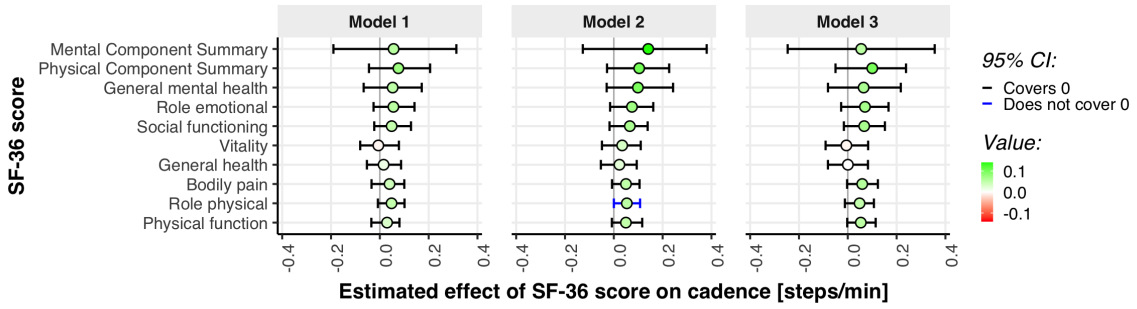

Figure 5. Linear mixed model estimates (x-axis) and corresponding 95% confidence intervals for the association between SF-36 scores and free-living cadence (steps per minute). The point color corresponds to the value of a model coefficient point estimate (green: positive, white: close to zero, red: negative). The confidence interval color is blue if the confidence interval does not cover 0, and is black otherwise.

3.5.1. Upstrap results. Figure 6 provides the upstrap-estimated sample sizes required for a 80% power to detect the association between SF-36 scores and cadence (see Section 2.3.3). The estimated sample size is below 300 participants for all but three (Mental Component Summary, Vitality, General health) SF-36 scores. This holds even for the most conservative p-value adjustment scenario (Bonferroni correction for $k = 10$ multiple comparisons reflecting $k = 10$ SF-36 scores being tested). These upstrap analysis results could be used to better inform sample size needed in a future similar study.

4. Discussion

4.1. Contributions

We introduce the first open-source method for identifying walking strides with high specificity from subsecond-level accelerometry data collected in the free-living environment with a wrist-worn sensor. The approach is different from other approaches that require the sensor to be worn at the ankle, thigh, or lower back, or are designed for standardized settings, such as continuous walking on a treadmill. This method allows the estimation of various walking characteristics, including walking cadence.

Methods were applied to data collected continuously for ~ 4 weeks for each study participant in a sample of 45 individuals, including 30 arthritis patients. Segmented strides were used to estimate the daily walking cadence for each study participant. Typical daily cadence varied between 99.6 and 130.8 steps per minute (mean (sd) 113.4

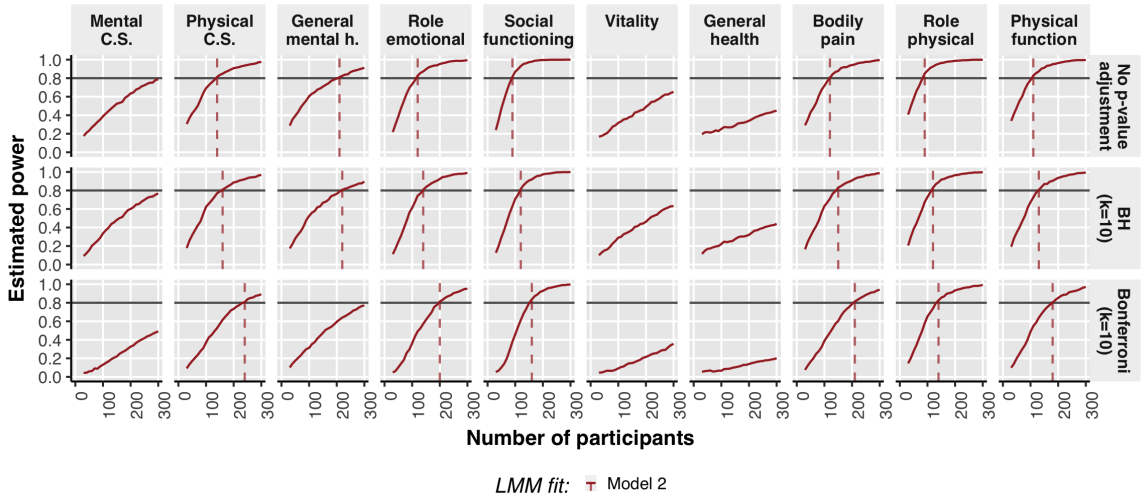

Figure 6. Upstrap-estimated power (y-axis) for identifying the effect of SF-36 score on estimated free-living cadence depending on the number of participants (x-axis) for the linear mixed model (2). The horizontal dashed line corresponds to 0.8 power threshold (y-axis). Panel columns: different SF-36 scores. Panel rows: no adjustment, Benjamini and Hochberg correction, and Bonferroni corrections. Corrections were done assuming multiple comparisons for $k = 10$ SF-36 scores.

(7.5)), and was on average slightly higher in the HV sub-group (mean (sd) 114.8 (7.3)) than in the AP sub-group (mean (sd) 112.7 (7.6)). These results are consistent with the weighted mean of 115.2 steps per minute from eight studies observing pedestrian cadence (Tudor-Locke & Rowe 2012). It is also consistent with the mean cadence of 1.98 steps per second (corresponding to 118.8 steps per minute) reported in (Karas, Straczkiewicz, Fadel, Harezlak, Crainiceanu & Urbanek 2019) using wrist-worn sensor data collected during a continuous outdoor walk in a sample of $n = 32$ healthy participants.

Results indicated that daily walking cadence is significantly positively associated with Role physical scores reported via SF-36 after adjusting for age, gender, weight, and height. This result is aligned with some previous works, e.g. showing association of daily walking cadence and physical function in symptomatic patients with peripheral artery disease (Gardner et al. 2018), and itself provides new evidence of associations between free-living walking parameters and self-reported health outcomes. While the estimated fixed effects for age, male gender (relative to female), weight, height and a weekend day (compared to a weekday) indicator were negatively associated with free-living cadence across almost all of the model fits considered, only the weekend day indicator effect was statistically significant.

4.2. Limitations

There are several limitations to our work. First, as the data was initially collected for a different purpose, no labels were available to evaluate the quality of the segmented walking strides. To address this, quality control was performed without gold standards and complemented by sensitivity analyses. Future studies could employ wireless sensorized shoe insoles (Crea et al. 2014) to provide a gold standard of walking segmentation; alternatively, a weaker standard could be provided by e.g. adapting Follick et al. (1984) diary component and asking participants to mark (any subset of) minutes spent walking during a day.

Second, our algorithm is designed to identify walking strides occurring as a sequence of at least three, corresponding to at least 6 steps. However, many in-home tasks require 5 or fewer steps, which are not captured by our method. While our algorithm can estimate walking cadence for bouts of 6 and more steps, it is less suited to estimating total step count. In particular, this could result in an unexpectedly low number of identified strides (and potentially higher daily cadence variability between the days) for individuals who perform a majority of their walking activity in very short bouts.

Third, contextual information about walking was not available. For example, brisk walking and light jogging may have been incorporated among segmented walking periods. However, these estimators are not likely to affect the mode of the cadence, which is a robust statistics to both outliers and heavy tail distributions.

Fourth, the cadence estimate obtained during the supervised component is based only on a very short distance limited by the availability of a straight line in the participants' homes. Future studies could employ a more extensive supervised walking component to allow more in-depth insight into associations between free-living cadence, supervised cadence, and SF-36 quality of life scores. We also hypothesize that with an interventional instead of observational study, we would be likely to identify stronger associations because the range of measurements would be wider.

4.3. Outlook

The proposed method provides an valuable resource for the growing number of studies that are focused on the association between health outcomes and objectively derived walking parameters obtained in the free-living environment. It could enrich measurements derived in future studies collecting subsecond-level accelerometry data from wrist-worn sensors as well as discover new associations in existing studies.

5. Conclusion

We introduced the first open-source method for precise walking strides identification in subsecond-level accelerometry data collected in free-living with a wrist-worn sensor. Methods were applied to 4-week observation data from 30 people with and 15 people

without arthritis. The association between the individual estimated walking cadence and self-reported health status quantified via SF-36 survey was studied.

6. Acknowledgments

J.K.U. and C.M.C. have nothing to declare. The data collection study was funded by Novartis Pharma AG, Basel, Switzerland. The major part of the methodology (ADEPT extension) was developed when M.K. worked as a summer intern with Novartis Pharma AG, Basel, Switzerland in 2019. V.P.I., G.B., and J.F.D. were employees of Novartis Pharma AG, Basel, Switzerland during summer 2019.

7. Ethical statement

The study protocol has been approved by the research institute's committee on human research. The participants of this study gave their written informed consent prior to participation. Ethical approval was obtained for this study for all participants – for the patients through Trinity College Dublin/Tallaght Hospital and for the healthy volunteers through University College Dublin. The informed consent allows Novartis Pharma AG to share the data from this study with direct collaborators only.

Appendix A. Methods

Appendix A.1. Walking segmentation algorithm

Algorithm 1 Walking strides segmentation from $(r_t)_t$ vector magnitude of subsecond-level accelerometry data collected at wrist

INPUT:

`template` – A list of numeric vectors, or a numeric vector. Distinct pattern template(s) of walking stride.
`xyz` – A numeric matrix of $n \times 3$ dimension. Three-dimensional raw accelerometry data time-series.
`fs` – A numeric scalar. Frequency at which a time-series `xyz` is collected, expressed in a number of observations per second.
`sim_MIN` – A numeric scalar. Minimum value of correlation between pattern template(s) and $(r_t)_t$ vector magnitude of accelerometry data. Default used is `0.85`.
`sim_MAX` – A numeric scalar. Maximum value of correlation between pattern template(s) and $(r_t)_t$ vector magnitude of accelerometry data. Default used is `1`.
`dur_MIN` – A numeric scalar. Minimum value of a stride duration allowed to be identified. Expressed in seconds. Default used is `0.8`.
`dur_MAX` – A numeric scalar. Maximum value of a stride duration allowed to be identified. Expressed in seconds. Default used is `1.4`.
`ptp_r_MIN` – A numeric scalar. Minimum value of "peak to peak" difference in $(r_t)_t$ data of a stride. Default used is `0.2`.
`ptp_r_MAX` – A numeric scalar. Maximum value of "peak to peak" difference in $(r_t)_t$ data of a stride. Default used is `2.0`.
`vmc_r_MIN` – A numeric scalar. Minimum value of VMC in $(r_t)_t$ data of a stride. Default used is `0.05`.
`vmc_r_MAX` – A numeric scalar. Maximum value of VMC in $(r_t)_t$ data of a stride. Default used is `0.5`.
`mean_abs_diff_med_p_MAX` – A numeric scalar. Maximum value of MAD* of Azimuth median for 3 subsequent valid strides. Here, MAD stands for mean of 2 absolute differences between 3 subsequent values. Default used is `0.5`.
`mean_abs_diff_med_t_MAX` – A numeric scalar. Maximum value of MAD* of Elevation median for 3 subsequent valid strides. Here, MAD stands for mean of 2 absolute differences between 3 subsequent values. Default used is `0.2`.
`mean_abs_diff_dur_MAX` – A numeric scalar. Maximum value of MAD* of duration time for 3 subsequent valid strides. Here, MAD stands for mean of 2 absolute differences between 3 subsequent values. Default used is `0.2`.

PROCEDURE:

(i) Compute `ptr` – three-dimensional time-series of `xyz` after transformation from Cartesian to spherical coordinates.
(ii) Compute `out` – three-columns data frame. Result of applying `segmentPattern(x = ptr[, 3], x.fs = fs, template = template, pattern.dur.seq = seq(0.5, 4, length.out = 30), similarity.measure = ''cor'', similarity.measure.thresh = -1, x.adept.ma.W = 0.2, finetune = ''maxima'', finetune.maxima.ma.W = NULL, finetune.maxima.nbh.W = 0.6, x.cut = TRUE, x.cut.vl = 6000)`, where `segmentPattern()` is ADEPT algorithm implementation in `adept` `R` package. In `out` data frame, each row describes one identified pattern occurrence:
- column 1 – `tau_i` - index of data vector `ptr[, 3]` where pattern starts
- column 2 – `T_i` - pattern duration, expressed in vector length.
- column 3 – `sim_i` - similarity between a pattern template and and data vector `ptr[, 3]`.

(iii) For each ADEPT-derived data segment, compute its data statistics:
- `ptp_r` – "peak to peak" difference of $(r_t)_t$ data (`ptr[, 3]`),
- `vmc_r` – VMC of $(r_t)_t$ data (`ptr[, 3]`),
- `med_p` – median of azimuth data (`ptr[, 1]`),
- `med_t` – median of elevation data (`ptr[, 2]`).
- `dur_i` – pattern duration, expressed in seconds (based on `T_i`).

(iv) Filter ADEPT-derived data segments to keep only those individual segments which pass all the following conditions:
- `sim_i >= sim_MIN`
- `sim_i <= sim_MAX`
- `dur_i >= dur_MIN`
- `dur_i <= dur_MAX`
- `ptp_r >= ptp_r_MIN`
- `ptp_r <= ptp_r_MAX`
- `vmc_r >= vmc_r_MIN`
- `vmc_r <= vmc_r_MAX`

PROCEDURE (cont.):

(v) Further filter ADEPT-derived data segments to keep only those individual segments which pass all the following conditions:

- Segment is a part of at least 3 consecutive ADEPT-derived data segments which passed the (iv) filtering
- Segment is a part of at least 3 consecutive ADEPT-derived data segments for which mean of 2 absolute differences between 3 subsequent values of `med_p` is `<= mean_abs_diff_med_p_MAX`
- Segment is a part of at least 3 consecutive ADEPT-derived data segments for which mean of 2 absolute differences between 3 subsequent values of `med_t` is `<= mean_abs_diff_med_t_MAX`
- Segment is a part of at least 3 consecutive ADEPT-derived data segments for which mean of 2 absolute differences between 3 subsequent values of `dur_i` is `<= mean_abs_diff_dur_MAX`

OUTPUT:

out_final - data frame; **out** data frame subset to only those ADEPT-derived data segments which passed the filtering step; these are determined by algorithm to correspond to walking strides only.

Appendix A.2. Quality control of segmentation results

Due to a lack of gold-standard walking data labels, we cannot validate the accuracy of our walking segmentation approach directly. Instead, we propose to conduct quality control of the segmentation results using several weaker standards and prior expertise.

First, we performed a systematic visual inspection of segmentation results using an internally developed visualization tool (see the tool screenshot in Figure A1 below). The tool consisted of two main plot panels, both focusing on data of one individual at a time. The upper panel showed a heatmap of the proportion of time identified as walking across 3 minutes-long windows of a day (x-axis), across all study days (y-axis). The bottom panel showed $(r_t)_t$ accelerometry data corresponding to the 3 minutes-long window, as selected in the upper plot by a mouse click. Start and end time point of any identified walking stride were annotated. In the quality control procedure, for each participant, five windows were randomly selected in the upper plot panel; then, any strides identified in corresponding $(r_t)_t$ data were screened for quality by visual inspection.

Second, we hypothesized that if walking strides were identified correctly, we would observe a positive association between cadence and intensity of movement on participant's level. For each identified stride data segment, we computed vector magnitude count (VMC). VMC, also known as mean absolute deviation of vector magnitude $(r_t)_t$, was shown to perform well in classifying the intensity of physical activity in adults (Aittasalo et al. 2015). We estimated the association with the linear mixed model (LMM) using measurements derived from individual walking strides. In the LMM formula, we defined VMC as an outcome, defined cadence as a covariate, and specified participant-specific intercept and cadence slope. In the LMM fit, we only used data from participant's strides whose duration fell into participant-specific $[0.25, 0.75]$ quantiles range.

Appendix A.3. Sensitivity analysis of algorithm parameters

To evaluate the robustness of the segmentation results, we performed an extensive sensitivity analysis of the effect of input parameter values. For each algorithm parameter, we defined a wide grid of values. We then reran the walking stride segmentation for all participants for each of the grid values separately, while keeping the other parameters fixed at their values used in the final segmentation. We summarized the parameter value-specific results by computing: (a) number of identified strides, (b) walking cadence aggregate (an empirical mode) per each study participant.

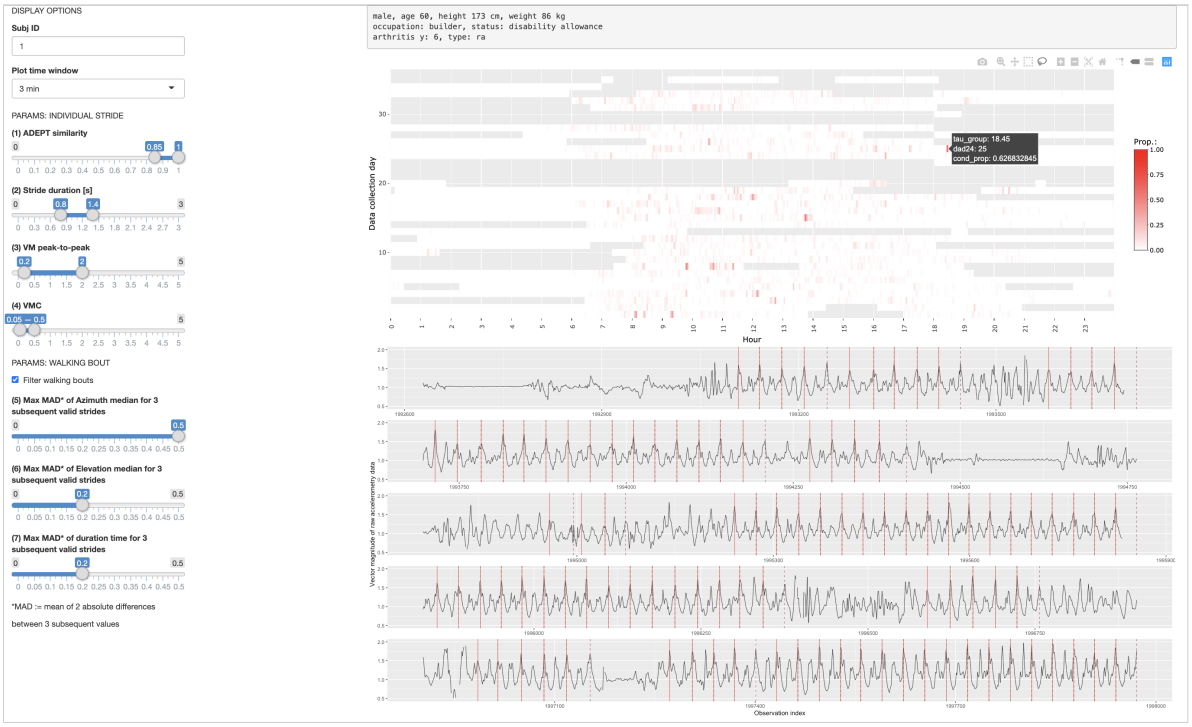

Figure A1. A screenshot of a full window of the visualization tool used for quality control of the walking strides segmentation results. The two main components of the tool were the upper and bottom plot panels. For a selected participant ID, the upper plot panel showed a heatmap with the proportion of data segments identified as walking strides in 3 minutes-long time windows across all days of data collection. The bottom panel showed vector magnitude of raw accelerometry data, $(r_t)_t$, corresponding to the three minutes-long time window (as selected in the upper plot by a mouse click) together with an annotation for start and end points of any identified walking stride (solid and dashed red vertical lines, respectively). In many cases showed, the end point of the n-th identified stride overlaps perfectly with a start point of the $(n+1)$-th identified stride.

Appendix A.4. Model for association between cadence and QoL measurements

Denote $i = 1, \ldots, 45$ – index of a study participant, n_i – number of valid days for i-th participant, $j = 1, \ldots, n_i$ – index of a participant-specific valid day of data collection. Denote y_{ij} to be participant- and day-specific cadence, $SF36_i^{(k)}$, $k = 1 \ldots, 10$ – k-th SF-36 survey score average (of the first and last day measurements) of i-th study participant, A_i – age of i-th study participant, A_i – age of i-th study participant, G_i – gender of i-th study participant, W_i – weight of i-th study participant, H_i – height of i-th study participant, $\mathbb{I}(\text{is weekend})_{ij}$ – whether or not j-th day of i-th study participant is a weekend day, SC_i – estimated supervised walking cadence for i-th study participant.

We defined the following statistical models to estimate association between cadence and QoL measurement, separately for each of the $k = 1 \ldots, 10$ SF-36 survey score:

$$y_{ij} \overset{\text{model (1)}}{=} (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})\, \mathbb{I}(\text{is weekend})_{ij} + \beta_2 SF36_i^{(k)} + \epsilon_{ij}, \tag{A.1}$$

$$\begin{aligned} y_{ij} \overset{\text{model (2)}}{=} & (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})\, \mathbb{I}(\text{is weekend})_{ij} + \beta_2 SF36_i^{(k)} \\ & + \beta_3 A_i + \beta_4 G_i + \beta_5 W_i + \beta_6 H_i + \epsilon_{ij}, \end{aligned} \tag{A.2}$$

$$\begin{aligned} y_{ij} \overset{\text{model (3)}}{=} & (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})\, \mathbb{I}(\text{is weekend})_{ij} + \beta_2 SF36_i^{(k)} \\ & + \beta_3 A_i + \beta_4 G_i + \beta_5 W_i + \beta_6 H_i + \beta_7 SC_i + \epsilon_{ij}, \end{aligned} \tag{A.3}$$

where $b_{0i} \sim N(0, \sigma_{b0}^2)$, $b_{1i} \sim N(0, \sigma_{b1}^2)$, $\epsilon_{ij} \sim N(0, \sigma^2)$, and all b_{0i}, b_{1i} and ϵ_{ij} are mutually independent random variables.

Appendix B. Results

Appendix B.1. Strides segmentation results

Table B1. Summary of strides segmentation results. In 3rd column, *# all days* denotes the number of all days of actigraphy data collection period, *# valid days* – subset of all days with sensor wear time ≥80%. In 4th column, *# strides* denotes participant- and day-specific number of walking strides identified in free-living; the values in the column are participant-specific aggregates of *# strides* across valid days. In columns 5-7, *daily cadence* denotes participant- and day-specific daily cadence in the free-living environment (steps per minute); the values in the columns 5-7 are participant-specific aggregates of *daily cadence* across valid days. In 8th column, *S. cadence* denotes supervised walking cadence estimate (steps per minute).

Participant ID	Has arthritis	# days valid (all)	# strides median [min,max]	Daily cadence median [min,max]	Daily cadence mean (sd)	Daily cadence mode	S. cadence
1	Yes	13 (36)	443 [242, 648]	106.2 [97.2, 108.0]	105.0 (3.0)	106.8	95.4
3	Yes	28 (33)	570 [220, 2123]	110.4 [103.2, 116.4]	110.4 (3.6)	109.2	108.6
5	Yes	12 (29)	1016 [325, 2002]	120.0 [112.2, 124.2]	119.4 (4.2)	120.0	105.0
6	Yes	21 (33)	1322 [167, 2278]	112.8 [91.8, 118.2]	109.2 (8.4)	114.6	114.6
7	Yes	28 (29)	302 [113, 1977]	112.8 [106.8, 123.0]	113.4 (4.8)	111.0	97.2
8	Yes	23 (30)	925 [70, 4656]	120.0 [106.2, 127.8]	117.6 (6.6)	121.8	111.6
9	Yes	33 (35)	823 [142, 2594]	115.8 [99.6, 122.4]	113.4 (6.6)	118.2	111.0
11	Yes	28 (30)	225 [65, 515]	113.4 [108.0, 121.8]	114.0 (3.6)	112.8	107.4
12	Yes	26 (31)	1017 [239, 1759]	120.6 [105.0, 126.6]	118.2 (6.0)	123.0	115.8
13	Yes	30 (33)	286 [88, 527]	109.8 [99.0, 120.0]	110.4 (4.2)	109.2	117.0
14	Yes	27 (33)	381 [84, 1044]	116.4 [109.2, 123.0]	116.4 (4.2)	117.6	94.8
15	Yes	25 (32)	1160 [118, 2743]	99.6 [92.4, 105.6]	99.0 (3.6)	100.2	112.8
16	Yes	25 (34)	838 [67, 1667]	109.2 [96.6, 120.6]	111.0 (4.8)	109.2	100.2
17	Yes	31 (33)	1015 [81, 2423]	104.4 [97.2, 115.8]	105.0 (4.2)	102.6	109.2
18	Yes	28 (28)	294 [30, 992]	120.0 [110.4, 142.2]	121.2 (6.6)	117.6	NA(1)
19	Yes	28 (30)	540 [229, 1753]	117.6 [102.6, 123.6]	115.8 (6.0)	118.8	88.8
22	Yes	26 (29)	498 [205, 1251]	102.6 [97.2, 109.2]	102.6 (4.2)	99.6	102.0
23	Yes	24 (33)	688 [97, 2209]	124.2 [110.4, 135.6]	123.0 (7.8)	126.0	117.0
24	Yes	29 (29)	897 [0, 3080]	115.8 [102.6, 121.2]	114.0 (4.8)	116.4	88.8
25	Yes	28 (28)	807 [222, 2587]	108.6 [102.6, 119.4]	108.6 (3.6)	108.6	94.2
26	Yes	19 (32)	228 [53, 790]	108.6 [103.8, 144.6]	112.2 (10.8)	107.4	NA(1)
27	Yes	32 (33)	146 [62, 581]	103.2 [93.6, 142.8]	105.6 (11.4)	103.2	NA(1)
28	Yes	26 (29)	327 [68, 1167]	106.8 [102.6, 116.4]	108.0 (3.6)	106.8	106.2
29	Yes	26 (42)	742 [151, 4667]	116.4 [100.2, 124.2]	114.0 (7.2)	118.8	117.0
30	Yes	26 (35)	506 [146, 1043]	107.4 [102.6, 116.4]	107.4 (3.0)	106.2	103.8
31	No	26 (36)	526 [193, 1488]	115.2 [102.0, 130.2]	114.0 (7.2)	119.4	133.2
32	No	28 (35)	590 [314, 1466]	115.2 [108.0, 123.0]	114.6 (4.8)	109.8	112.2
33	No	31 (31)	993 [353, 5806]	106.2 [100.2, 115.8]	106.2 (3.0)	105.6	106.2
34	No	27 (39)	1714 [375, 3859]	116.4 [107.4, 124.2]	115.8 (3.6)	115.8	120.6
35	No	26 (36)	264 [58, 761]	116.4 [109.8, 123.0]	117.0 (3.6)	116.4	115.8
36	No	25 (31)	752 [130, 2834]	115.8 [105.6, 120.0]	114.0 (3.6)	116.4	133.2
37	No	26 (33)	2328 [494, 3898]	107.4 [100.2, 120.0]	107.4 (4.8)	108.6	120.6
38	No	31 (33)	2681 [637, 5494]	105.6 [99.0, 109.2]	106.2 (3.0)	105.6	110.4
39	No	26 (38)	849 [230, 9045]	120.0 [101.4, 130.8]	117.6 (8.4)	122.4	109.2
40	No	28 (34)	1716 [530, 3413]	128.4 [107.4, 139.2]	126.6 (8.4)	130.8	109.8
41	No	28 (29)	584 [178, 1427]	107.4 [95.4, 121.2]	108.0 (6.6)	105.0	110.4
42	No	23 (34)	1154 [169, 3157]	120.0 [108.6, 124.2]	120.0 (4.2)	120.0	114.6
43	No	22 (30)	1334 [313, 4534]	111.0 [96.6, 120.0]	111.6 (4.8)	109.8	87.6
44	No	21 (30)	1602 [134, 2968]	115.8 [99.6, 134.4]	114.6 (7.2)	116.4	108.6
45	No	23 (28)	946 [396, 2311]	116.4 [102.0, 128.4]	115.8 (7.8)	119.4	111.6
46	Yes	27 (29)	1474 [114, 3925]	124.2 [106.2, 128.4]	121.2 (5.4)	124.2	116.4
47	Yes	27 (31)	396 [138, 2177]	108.0 [100.2, 127.8]	111.0 (7.8)	105.0	114.6
48	Yes	20 (22)	1464 [327, 3334]	118.2 [103.8, 124.2]	115.2 (6.0)	120.0	106.8
49	Yes	28 (34)	2904 [285, 4986]	120.0 [107.4, 124.2]	119.4 (3.6)	120.0	99.0
50	Yes	26 (28)	768 [111, 2294]	105.6 [94.8, 109.2]	105.0 (3.6)	105.6	101.4

(1): Unable to segment any walking stride from data corresponding to supervised walking.

Table B2. Summary of point estimates $\hat{\beta}_2$ and 95% confidence intervals for fixed effect of SF-36 score ($[0, 100]$) on free-living cadence (number of steps per minute) in the three models: (1) without further covariates adjustment, (2) with adjustment for age, gender, weight, height, (3) with adjustment for age, gender, weight, height, supervised cadence.

SF-36 score name	$\hat{\beta}_2$ [95% CI]		
	Model 1	Model 2	Model 3
	$\frac{1}{10}\times$	$\frac{1}{10}\times$	$\frac{1}{10}\times$
Mental Component Summary	0.563 [-1.902, 3.135]	1.410 [-1.270, 3.805]	0.549 [-2.464, 3.561]
Physical Component Summary	0.759 [-0.445, 2.059]	1.039 [-0.278, 2.268]	1.002 [-0.503, 2.385]
General mental health	0.525 [-0.663, 1.716]	0.987 [-0.293, 2.427]	0.649 [-0.811, 2.171]
Role emotional	0.555 [-0.258, 1.419]	0.744 [-0.152, 1.616]	0.703 [-0.272, 1.669]
Social functioning	0.484 [-0.229, 1.276]	0.656 [-0.176, 1.385]	0.672 [-0.160, 1.520]
Vitality	-0.062 [-0.805, 0.781]	0.342 [-0.486, 1.102]	-0.059 [-0.910, 0.834]
General health	0.154 [-0.530, 0.870]	0.229 [-0.530, 0.938]	0.003 [-0.813, 0.826]
Bodily pain	0.399 [-0.341, 1.002]	0.498 [-0.074, 1.054]	0.592 [-0.028, 1.232]
Role physical	0.479 [-0.080, 1.010]	0.533 [0.002, 1.075]	0.484 [-0.118, 1.070]
Physical function	0.295 [-0.348, 0.804]	0.495 [-0.080, 1.164]	0.533 [-0.023, 1.142]

Table B3. Summary of point estimates $\hat{\beta}_1$ and 95% confidence intervals for fixed effect of a weekend day (as compared to a week day – the reference level) on free-living cadence (number of steps per minute) in the three models. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_1$ [95% CI]		
	Model 1	Model 2	Model 3
Mental Component Summary	-1.642 [-2.824, -0.470]	-1.641 [-2.781, -0.509]	-1.943 [-2.952, -0.870]
Physical Component Summary	-1.642 [-2.734, -0.412]	-1.648 [-2.759, -0.576]	-1.945 [-3.122, -0.760]
General mental health	-1.642 [-2.743, -0.552]	-1.642 [-2.709, -0.393]	-1.944 [-3.148, -0.832]
Role emotional	-1.641 [-2.769, -0.453]	-1.642 [-2.845, -0.534]	-1.941 [-3.188, -0.921]
Social functioning	-1.642 [-2.765, -0.338]	-1.644 [-2.768, -0.486]	-1.941 [-3.097, -0.745]
Vitality	-1.641 [-2.782, -0.576]	-1.643 [-2.697, -0.663]	-1.944 [-3.230, -0.855]
General health	-1.642 [-2.756, -0.654]	-1.644 [-2.798, -0.352]	-1.944 [-3.123, -0.866]
Bodily pain	-1.643 [-2.817, -0.510]	-1.649 [-2.758, -0.472]	-1.947 [-2.983, -0.748]
Role physical	-1.645 [-2.683, -0.614]	-1.651 [-2.788, -0.392]	-1.947 [-3.099, -0.682]
Physical function	-1.641 [-2.894, -0.562]	-1.645 [-2.754, -0.521]	-1.943 [-3.110, -0.798]

Table B4. Summary of point estimates $\hat{\beta}_3$ and 95% confidence intervals for fixed effect of age on free-living cadence (number of steps per minute) in model 2 and model 3. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_3$ [95% CI]	
	Model 2	Model 3
	$\frac{1}{10}\times$	$\frac{1}{10}\times$
Mental Component Summary	-0.517 [-1.965, 1.092]	-0.111 [-1.784, 1.372]
Physical Component Summary	0.012 [-1.140, 1.375]	0.145 [-1.076, 1.419]
General mental health	-0.584 [-2.053, 0.863]	-0.285 [-1.663, 1.173]
Role emotional	-0.459 [-1.731, 0.938]	-0.311 [-1.612, 0.943]
Social functioning	-0.285 [-1.474, 1.009]	-0.161 [-1.371, 1.148]
Vitality	-0.208 [-1.516, 1.106]	0.102 [-1.196, 1.406]
General health	-0.164 [-1.439, 1.149]	0.073 [-1.296, 1.531]
Bodily pain	-0.017 [-1.390, 1.382]	0.128 [-1.035, 1.438]
Role physical	-0.049 [-1.381, 1.173]	0.078 [-1.074, 1.346]
Physical function	-0.032 [-1.444, 1.202]	0.110 [-1.156, 1.371]

Table B5. Summary of point estimates $\hat{\beta}_4$ and 95% confidence intervals for fixed effect of gender: male (as compared gender: female – the reference level) on free-living cadence (number of steps per minute) in model 2 and model 3. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_4$ [95% CI]	
	Model 2	Model 3
Mental Component Summary	-4.809 [-9.138, -0.609]	-4.258 [-8.176, -0.252]
Physical Component Summary	-4.699 [-8.527, -0.667]	-4.256 [-8.584, -0.563]
General mental health	-4.556 [-8.844, -0.669]	-4.102 [-8.590, 0.060]
Role emotional	-4.249 [-8.328, -0.170]	-3.895 [-7.985, 0.168]
Social functioning	-5.002 [-8.924, -1.379]	-4.626 [-8.814, -0.402]
Vitality	-5.045 [-8.783, -1.285]	-4.107 [-9.060, -0.133]
General health	-4.863 [-8.890, -0.845]	-4.185 [-8.560, 0.114]
Bodily pain	-4.646 [-8.431, -0.705]	-4.331 [-8.386, -0.553]
Role physical	-4.325 [-8.154, -0.581]	-4.012 [-7.994, -0.155]
Physical function	-4.577 [-8.825, -0.591]	-4.042 [-8.010, -0.270]

Table B6. Summary of point estimates $\hat{\beta}_5$ and 95% confidence intervals for fixed effect of weight (kg) on free-living cadence (number of steps per minute) in model 2 and model 3. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_5$ [95% CI]	
	Model 2	Model 3
	$\frac{1}{10}\times$	$\frac{1}{10}\times$
Mental Component Summary	-0.033 [-0.158, 0.105]	-0.106 [-0.258, 0.055]
Mental Component Summary	-0.325 [-1.582, 1.052]	-1.065 [-2.579, 0.547]
Physical Component Summary	-0.366 [-1.648, 0.881]	-0.928 [-2.161, 0.391]
General mental health	-0.212 [-1.489, 1.382]	-0.911 [-2.235, 0.519]
Role emotional	-0.225 [-1.600, 1.154]	-0.790 [-2.131, 0.616]
Social functioning	-0.139 [-1.496, 1.126]	-0.705 [-1.992, 0.621]
Vitality	-0.500 [-1.784, 0.647]	-1.252 [-2.623, 0.283]
General health	-0.454 [-1.888, 0.908]	-1.209 [-2.617, 0.214]
Bodily pain	-0.335 [-1.709, 0.837]	-0.861 [-2.119, 0.462]
Role physical	-0.394 [-1.692, 0.716]	-0.947 [-2.027, 0.407]
Physical function	-0.299 [-1.644, 1.039]	-0.862 [-2.132, 0.480]

Table B7. Summary of point estimates $\hat{\beta}_6$ and 95% confidence intervals for fixed effect of height (cm) on free-living cadence (number of steps per minute) in model 2 and model 3. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_6$ [95% CI]	
	Model 2	Model 3
	$\frac{1}{10}\times$	$\frac{1}{10}\times$
Mental Component Summary	-1.597 [-4.048, 0.929]	-1.024 [-3.817, 1.836]
Physical Component Summary	-1.716 [-4.044, 0.931]	-1.529 [-4.161, 1.094]
General mental health	-1.928 [-4.852, 0.524]	-1.331 [-4.066, 1.037]
Role emotional	-2.064 [-4.567, 0.470]	-1.676 [-4.327, 0.886]
Social functioning	-1.716 [-4.345, 0.691]	-1.446 [-4.065, 1.080]
Vitality	-1.394 [-3.841, 1.257]	-0.815 [-3.596, 1.716]
General health	-1.335 [-3.878, 1.395]	-0.873 [-3.761, 1.691]
Bodily pain	-1.740 [-4.037, 0.734]	-1.510 [-4.023, 1.101]
Role physical	-1.838 [-4.240, 0.759]	-1.588 [-4.134, 1.100]
Physical function	-2.028 [-5.082, 0.434]	-1.986 [-4.428, 0.678]

Table B8. Summary of point estimates $\hat{\beta}_7$ and 95% confidence intervals for fixed effect of supervised cadence (number of steps per minute) on free-living cadence (number of steps per minute) in model 3. First column (*SF-36 score name*) specifies SF-36 score considered as a fixed effect in a particular model fit.

SF-36 score name	$\hat{\beta}_6$ [95% CI]
	Model 3
	$\frac{1}{10}\times$
Mental Component Summary	0.089 [-1.413, 1.657]
Physical Component Summary	-0.298 [-1.967, 1.441]
General mental health	0.005 [-1.507, 1.371]
Role emotional	-0.157 [-1.768, 1.303]
Social functioning	-0.399 [-1.932, 1.220]
Vitality	0.200 [-1.608, 1.785]
General health	0.156 [-1.381, 1.770]
Bodily pain	-0.436 [-1.991, 1.273]
Role physical	-0.387 [-2.022, 1.171]
Physical function	-0.406 [-1.950, 1.082]

Appendix B.2. Quality control of segmentation results

Accelerometry $(r_t)_t$ data and, specifically, their segments identified as walking strides were systematically screened for quality with the visualization tool (see Figure A1 in Appendix A.2). We did not identify any case where the algorithm-identified stride data clearly seemed to be a false-positive; on the contrary, we observed $(r_t)_t$ data not identified as a stride of which we either believed it could be a false negative, or we were unable to determine based on visual inspection. While we lack means of quantifying the false positive and false negative cases, we qualitatively conclude that the algorithm with its default parameters appears to be characterized by high specificity.

As an additional measure of plausibility of the segmented strides, the relationship between vector magnitude count (VMC) and cadence was evaluated using a linear mixed model with random slope and intercept (Figure B1). We hypothesized that faster stride should overall be associated with more intense motion. Indeed, for all but two participants (ID 26 and 27), we observe positive slope of the fitted relationship, ranging from -0.00143 to 0.0059 (mean (sd) 0.00288 (0.00161)). The result supports the hypothesized positive association between data-estimated participant-specific cadence and intensity of the movement.

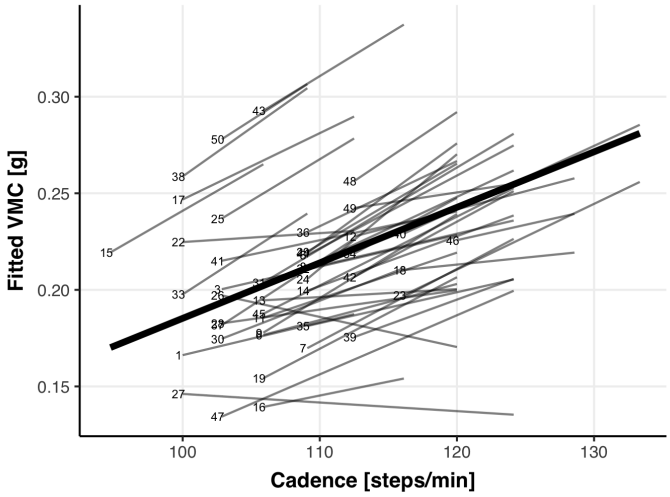

Figure B1. Thin black lines represent fitted values of walking stride vector magnitude count (VMC; y-axis) for various values of walking cadence (x-axis; steps per minute) for each study participant; the number label denotes participant ID. The thick black line represents average fitted values for the study population.

Appendix B.3. Sensitivity analysis of algorithm parameters

Figures B2 and B3 below show results of extensive sensitivity analysis of the effect of algorithm parameters' values on strides segmentation. Overall, stride numbers and cadence estimates were stable around the values selected for the present analyses.

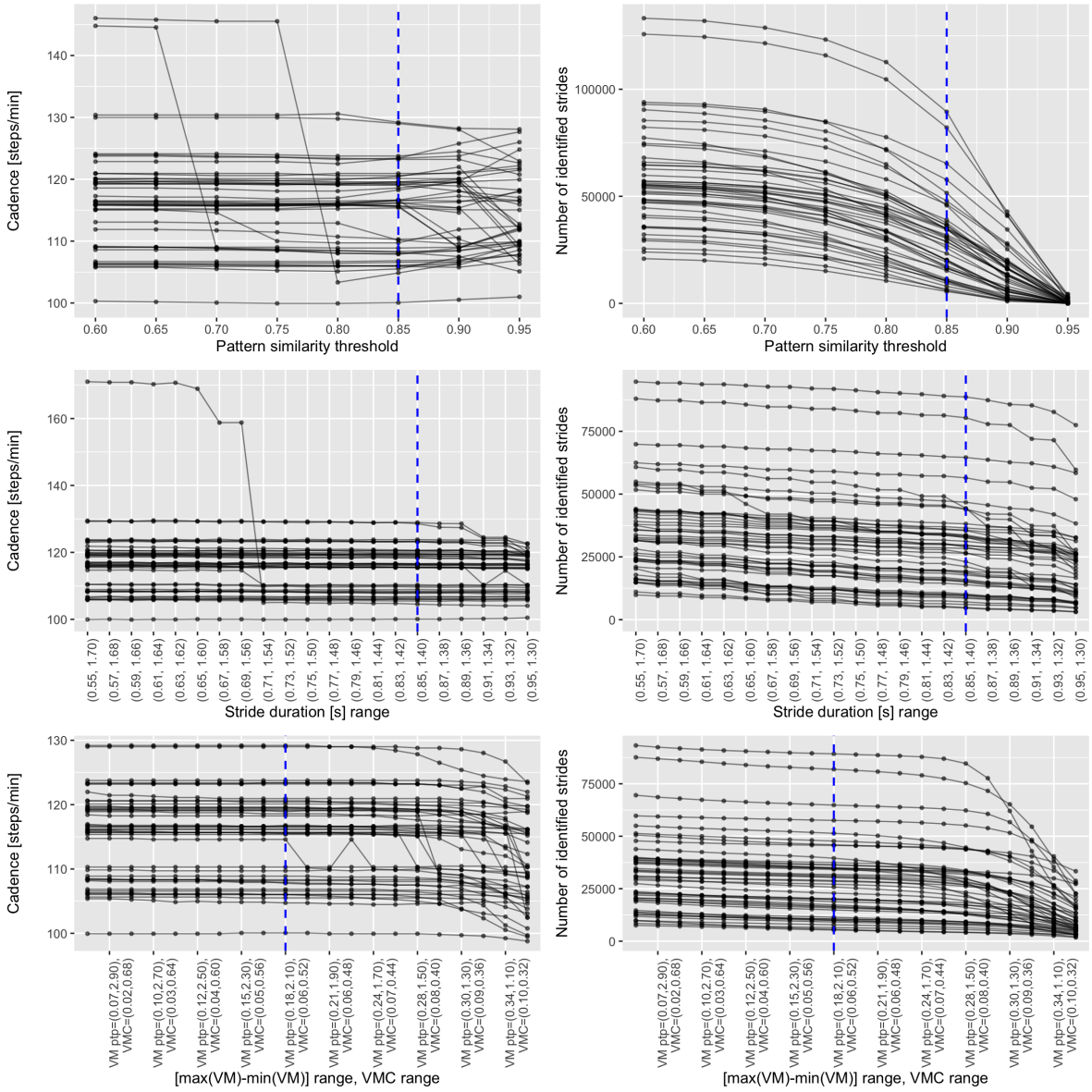

Figure B2. Results of sensitivity analysis of segmentation algorithm parameters: minimum similarity between walking stride template and observed data (1st row data panel), stride duration range [s] (2nd row data panel), range of difference between vector magnitude maximum and minimum, range of VMC (3rd row data panel). Each trajectory denotes the most typical participant's cadence expressed in steps per minute (an empirical mode; left column data panel) and number of identified walking strides (right column data panel) obtained for the specific parameter value considered while keeping the other parameters fixed at their respective final values. The blue vertical dashed line denotes the parameter's final value.

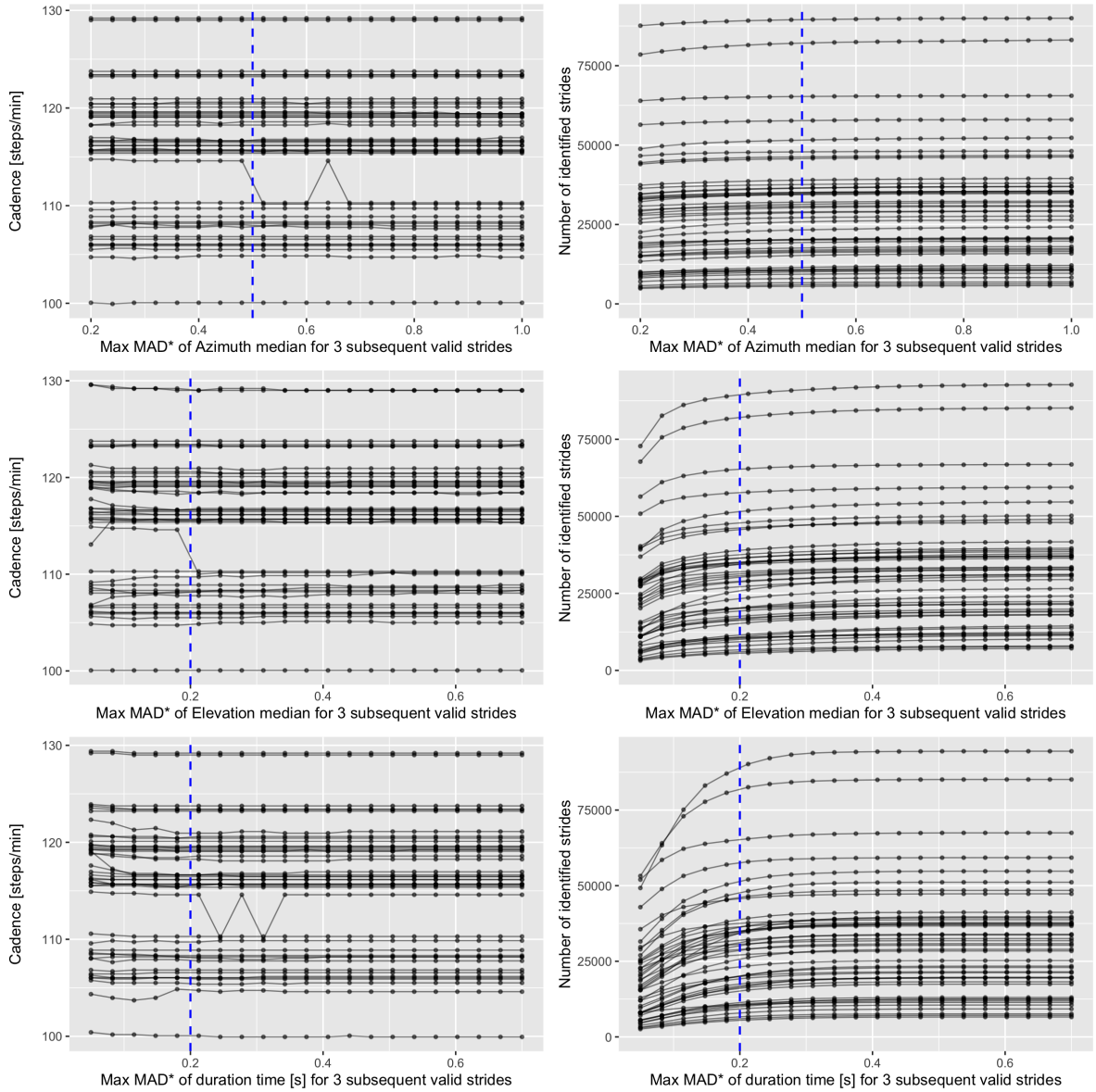

Figure B3. Results of sensitivity analysis of segmentation algorithm parameters: maximum MAD* of Azimuth median for 3 subsequent valid strides (1st row data panel), maximum MAD* of Elevation median for 3 subsequent valid strides (2nd row data panel), maximum MAD* of duration time [s] for 3 subsequent valid strides (3rd row data panel). Here, "MAD" stands for mean of 2 absolute differences between 3 subsequent values. Each trajectory denotes the most typical participant's participant's cadence expressed in steps per minute (an empirical mode; left column data panel) and number of identified walking strides (right column data panel) obtained for the specific parameter value considered while keeping the other parameters fixed at their respective final values. The blue vertical dashed line denotes the parameter's final value.

References

Aittasalo, M., Vähä-Ypyä, H., Vasankari, T., Husu, P., Jussila, A.-M. & Sievänen, H. (2015), 'Mean amplitude deviation calculated from raw acceleration data: a novel method for classifying the intensity of adolescents'physical activity irrespective of accelerometer brand', *BMC Sports Science, Medicine and Rehabilitation* **7**(18).

ATS (2002), 'ATS Statement', *American Journal of Respiratory and Critical Care Medicine* **166**(1), 111–117.
URL: *https://doi.org/10.1164/ajrccm.166.1.at1102*

Barth, J., Oberndorfer, C., Pasluosta, C., Schülein, S., Gassner, H., Reinfelder, S., Kugler, P., Schuldhaus, D., Winkler, J., Klucken, J. & Eskofier, B. M. (2015), 'Stride segmentation during free walk movements using multi-dimensional subsequence dynamic time warping on inertial sensor data', *Sensors* **15**, 6419–6440.

Bates, D., Mächler, M., Bolker, B. & Walker, S. (2015), 'Fitting linear mixed-effects models using lme4', *Journal of Statistical Software* **67**(1), 1–48.

Benjamini, Y. & Hochberg, Y. (1995), 'Controlling the false discovery rate: A practical and powerful approach to multiple testing', *Journal of the Royal Statistical Society. Series B (Methodological)* **57**(1), 289–300.

Bianchi, F., Redmond, S. J., Narayanan, M. R., Cerutti, S. & Lovell, N. H. (2010), 'Barometric pressure and triaxial accelerometry-based falls event detection', *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **18**(6), 619–627.

Brown, J. C., Harhay, M. O. & Harhay, M. N. (2014), 'Walking cadence and mortality among community-dwelling older adults', *Journal of General Internal Medicine* **29**(9), 1263–1269.

Chen, R., Jankovic, F., Marinsek, N., Foschini, L., Kourtis, L., Signorini, A., Pugh, M., Shen, J., Yaari, R., Maljkovic, V., Sunga, M., Song, H. H., Jung, H. J., Tseng, B. & Trister, A. (2019), Developing measures of cognitive impairment in the real world from consumer-grade multimodal sensor streams, *in* 'Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery amp; Data Mining', KDD '19, Association for Computing Machinery, New York, NY, USA, p. 2145–2155.
URL: *https://doi.org/10.1145/3292500.3330690*

Choi, L., Liu, Z., Matthews, C. E. & Buchowski, M. S. (2011), 'Validation of accelerometer wear and nonwear time classification algorithm', *Medicine & Science in Sports & Exercise* **43**(2), 357–364.

COA Qualification Program Submissions (n.d.), `https://www.fda.gov/drugs/clinical-outcome-assessment-coa-qualification-program/clinical-outcome-assessments-coa-qualification-program-submissions`. Accessed: 2020-10-15.

Crainiceanu, C. M. & Crainiceanu, A. (2018), 'The upstrap', *Biostatistics* **21**(2), e164–e166.

Crea, S., Donati, M., De Rossi, S. M., Oddo, C. M. & Vitiello, N. (2014), 'A wireless flexible sensorized insole for gait analysis", journal="sensors (basel)', **14**(1), 1073–1093.

Del Din, S., Elshehabi, M., Galna, B., Hobert, M. A., Warmerdam, E., Suenkel, U., Brockmann, K., Metzger, F., Hansen, C., Berg, D., Rochester, L. & Maetzler, W. (2019), 'Gait analysis with wearables predicts conversion to Parkinson disease', *Annals of Neurology* **86**(3), 357–367.

Del Din, S., Godfrey, A., Galna, B., Lord, S. & Rochester, L. (2016), 'Free-living gait characteristics in ageing and Parkinson's disease: Impact of environment and ambulatory bout length', *Journal of NeuroEngineering and Rehabilitation* **13**(46).

Dunn, O. J. (1961), 'Multiple comparisons among means', *Journal of the American Statistical Association* **56**(293), 52–64.

Follick, M. J., Ahern, D. K. & Laser-Wolston, N. (1984), 'Evaluation of a daily activity diary for chronic pain patients', *Pain* **19**(4), 373–382.

Gardner, A. W., Montgomery, P. S., Wang, M. & Xu, C. (2018), 'Predictors of health-related quality of life in patients with symptomatic peripheral artery disease', *Journal of Vascular Surgery* **68**(4), 1126–1134.
URL: *https://www.sciencedirect.com/science/article/pii/S074152141830274X*

Godfrey, A., Din, S., Barry, G., Mathers, J. & Rochester, L. (2015), 'Instrumenting gait with an accelerometer: A system and algorithm examination', *Medical Engineering and Physics* **37**(4), 400–407.

Jehn, M., Prescher, S., Koehler, K., von Haehling, S., Winkler, S., Deckwart, O., Honold, M., Sechtem, U., Baumann, G., Halle, M., Anker, S. D. & Koehler, F. (2013), 'Tele-accelerometry as a novel technique for assessing functional status in patients with heart failure: Feasibility, reliability and patient safety', *International Journal of Cardiology* **168**(5), 4723–4728.
URL: *https://www.sciencedirect.com/science/article/pii/S016752731301396X*

Jerome, G. J., Ko, S. U., Kauffman, D., Studenski, S. A., Ferrucci, L. & Simonsick, E. M. (2015), 'Gait characteristics associated with walking speed decline in older adults: results from the Baltimore Longitudinal Study of Aging', *Arch Gerontol Geriatr* **60**(2), 239–243.

Karas, M., Bai, J., Straczkiewicz, M., Harezlak, J., Glynn, N. W., Harris, T., Zipunnikov, V., Crainiceanu, C. & Urbanek, J. K. (2019), 'Accelerometry Data in Health Research: Challenges and Opportunities', *Statistics in Biosciences* **11**(2), 210–237.

Karas, M., Straczkiewicz, M., Fadel, W., Harezlak, J., Crainiceanu, C. M. & Urbanek, J. K. (2019), 'Adaptive empirical pattern transformation (ADEPT) with application to walking stride segmentation', *Biostatistics* **22**(2), 331–347.
URL: *https://doi.org/10.1093/biostatistics/kxz033*

Karas, M., Urbanek, J. & Crainiceanu, C. (n.d.*a*), *Introduction to adept package*. Vignette to adept R package.
URL: *https://cran.r-project.org/web/packages/adept/vignettes/adept-intro.html*

Karas, M., Urbanek, J. & Crainiceanu, C. (n.d.*b*), *Walking strides segmentation with adept*. Vignette to adept R package.
URL: *https://cran.r-project.org/web/packages/adept/vignettes/adept-strides-segmentation.html*

Karas, M., Urbanek, J., Crainiceanu, C., Muschelli, J. & Gherman, A. (n.d.), *adept: Adaptive Empirical Pattern Transformation*. R package version 1.1.2.
URL: *https://cran.r-project.org/web/packages/adept/index.html*

Karas, M., Urbanek, J., Fadel, W. & Harezlak, J. (n.d.), *adeptdata: Accelerometry Data Sets*. R package version 1.0.1.
URL: *https://cran.r-project.org/web/packages/adeptdata/index.html*

Kuznetsova, A., Brockhoff, P. B. & Christensen, R. H. B. (2017), 'lmerTest package: Tests in linear mixed effects models', *Journal of Statistical Software* **82**(13), 1–26.

Lai, A. M., Hsueh, P. S., Choi, Y. K. & Austin, R. R. (2017), 'Present and Future Trends in Consumer Health Informatics and Patient-Generated Health Data', *Yearb Med Inform* **26**(1), 152–159.

Lan, C.-C., Hsueh, Y.-H. & Hu, R.-Y. (2012), Real-time fall detecting system using a tri-axial accelerometer for home care, *in* '2012 International Conference on Biomedical Engineering and Biotechnology', pp. 1077–1080.

Maganja, S. A., Clarke, D. C., Lear, S. A. & Mackey, D. C. (2020), 'Formative Evaluation of Consumer-Grade Activity Monitors Worn by Older Adults: Test-Retest Reliability and Criterion Validity of Step Counts', *JMIR Form Res* **4**(8), e16537.

Marmeleira, J., Ferreira, S. & Raimundo, A. (2017), 'Physical activity and physical fitness of nursing home residents with cognitive impairment: A pilot study', *Experimental Gerontology* **100**, 63–69.
URL: *https://www.sciencedirect.com/science/article/pii/S0531556517300992*

Mathie, M. J., Coster, A. C. F., Lovell, N. H. & Celler, B. G. (2004), 'Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement', *Physiological measurement* **25**(2), R1—20.
URL: *https://doi.org/10.1088/0967-3334/25/2/r01*

Mathie, M. J., Coster, A. C. F., Lovell, N. H., Celler, B. G., Lord, S. R. & Tiedemann, A. (2004), 'A pilot study of long-term monitoring of human movements in the home using accelerometry', *Journal of Telemedicine and Telecare* **10**(3), 144–151.

McCamley, J., Donati, M., Grimpampi, E. & Mazzà, C. (2012), 'An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data', *Gait and Posture* **36**(2), 316–318.

Mueller, A., Hoefling, H. A., Muaremi, A., Praestgaard, J., Walsh, L. C., Bunte, O., Huber, R. M., Fürmetz, J., Keppler, A. M., Schieker, M., Böcker, W., Roubenoff, R.,

Brachat, S., Rooks, D. S. & Clay, I. (2019), 'Continuous digital monitoring of walking speed in frail elderly patients: Noninterventional validation study and longitudinal clinical trial', *JMIR Mhealth Uhealth* **7**(11), e15191.

O'Brien, M. W., Kivell, M. J., Wojcik, W. R., d'Entremont, G., Kimmerly, D. S. & Fowles, J. R. (2018), 'Step Rate Thresholds Associated with Moderate and Vigorous Physical Activity in Adults', *Int J Environ Res Public Health* **15**(11).

Perraudin, C. G. M., Illiano, V. P., Calvo, F., O'Hare, E., Donnelly, S. C., Mullan, R. H., Sander, O., Caulfield, B. & Dorn, J. F. (2018), 'Observational study of a wearable sensor and smartphone application supporting unsupervised exercises to assess pain and stiffness', *Digital Biomarkers* **2**(3), 106–125.

Samson, M. M., Crowe, A., de Vreede, P. L., Dessens, J. A. G., Duursma, S. A. & Verhaar, H. J. J. (2001), 'Differences in gait parameters at a preferred walking speed in healthy subjects due to age, height and body weigh', *Aging Clinical and Experimental Research* (13), 16–21.

Selles, R., Formanoy, M., Bussmann, J., Janssens, P. & Stam, H. (2005), 'Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls', *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **13**, 81–88.

Soaz, C. & Diepold, K. (2016), 'Step Detection and Parameterization for Gait Assessment Using a Single Waist-Worn Accelerometer', *IEEE Transactions on Biomedical Engineering* **63**(5), 933–942.

Straczkiewicz, M., Glynn, N. W. & Harezlak, J. (2019), 'On Placement, Location and Orientation of Wrist-Worn Tri-Axial Accelerometers during Free-Living Measurements', *Sensors (Basel)* **19**(9).

Studenski, S., Perera, S., Patel, K., Rosano, C., Faulkner, K., Inzitari, M., Brach, J., Chandler, J., Cawthon, P., Connor, E. B., Nevitt, M., Visser, M., Kritchevsky, S., Badinelli, S., Harris, T., Newman, A. B., Cauley, J., Ferrucci, L. & Guralnik, J. (2011), 'Gait speed and survival in older adults', *JAMA* **305**(1), 50–58.

Troiano, R. P., McClain, J. J., Brychta, R. J. & Chen, K. Y. (2014), 'Evolution of accelerometer methods for physical activity research', *Br J Sports Med* **48**(13), 1019–1023.

Tudor-Locke, C. & Rowe, D. A. (2012), 'Using cadence to study free-living ambulatory behaviour', *Sports Med* **42**(5), 381–398.

Urbanek, J. K., Harezlak, J., Glynn, N. W., Harris, T., Crainiceanu, C. & Zipunnikov, V. (2017), 'Stride variability measures derived from wrist- and hip-worn accelerometers', *Gait and Posture* **52**, 217–223.

Van Ancum, J. M., van Schooten, K. S., Jonkman, N. H., Huijben, B., van Lummel, R. C., Meskers, C. G., Maier, A. B. & Pijnappels, M. (2019), 'Gait speed assessed by a 4-m walk test is not representative of daily-life gait speed in community-dwelling adults', *Maturitas* **121**, 28–34.

Wang, J., Lin, C., Jeen-Shing Wang, Che-Wei Lin, Yang, Y.-T. C. & Yu-Jen Ho (2012), 'Walking Pattern Classification and Walking Distance Estimation Algorithms Using Gait Phase Information', *EEE Transactions on Biomedical Engineering* **59**, 2884–2892.

Ware, J. & Sherbourne, C. (1992), 'The mos 36-ltem short-form health survey (sf-36): I. conceptual framework and item selection', *Medical Care* **30**, 473–483.

Willemsen, A. T. M., Bloemhof, F. & Boom, H. B. (1990), 'Automatic Stance-Swing Phase Detection from Accelerometer Data for Peroneal Nerve Stimulation', *IEEE Transactions on Biomedical Engineering* **37**(12), 1201–1208.

Ying, H., Silex, C., Schnitzer, A., Leonhardt, S. & Schiek, M. (2007), 'Automatic Step Detection in the Accelerometer Signal', *4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)* **13**, 80–85.