

Prediction of sustained harmonic walking in the free-living environment using raw accelerometry data

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NOTE

Prediction of sustained harmonic walking in the free-living environment using raw accelerometry data

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28 February 2018Jacek K Urbanek¹, Vadim Zipunnikov², Tamara Harris³, William Fadel⁴, Nancy Glynn⁵, Annemarie Koster⁶, Paolo Caserotti⁷, Ciprian Crainiceanu² and Jaroslaw Harezlak⁸¹ Division of Geriatric Medicine and Gerontology, Department of Medicine, School of Medicine, Johns Hopkins University, Baltimore, MD, United States of America² Department of Biostatistics, Bloomberg School of Public Health, Johns Hopkins University, Baltimore, MD, United States of America³ Laboratory of Epidemiology, Demography, and Biometry, National Institute on Aging, Bethesda, MD, United States of America⁴ Department of Biostatistics, Indiana University School of Medicine, Indianapolis, IN, United States of America⁵ Center for Aging and Population Health, Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh, Pittsburgh, PA, United States of America⁶ Department of Health, Medicine and Life Sciences, Social Medicine, Maastricht University, Maastricht, Netherlands⁷ Department of Sports Science and Clinical Biomechanics, University of Southern Denmark, Odense, Denmark⁸ Department of Epidemiology and Biostatistics, Indiana University School of Public Health, Bloomington, IN, United States of AmericaE-mail: harezlak@iu.edu**Keywords:** accelerometry, movement recognition, physical activity, walking quantification, wearable computing, free-living data**Abstract**

Objective: Using raw, sub-second-level accelerometry data, we propose and validate a method for identifying and characterizing walking in the free-living environment. We focus on sustained harmonic walking (SHW), which we define as walking for at least 10 s with low variability of step frequency. *Approach:* We utilize the harmonic nature of SHW and quantify the local periodicity of the tri-axial raw accelerometry data. We also estimate the fundamental frequency of the observed signals and link it to the instantaneous walking (step-to-step) frequency (IWF). Next, we report the total time spent in SHW, number and durations of SHW bouts, time of the day when SHW occurred, and IWF for 49 healthy, elderly individuals. *Main results:* The sensitivity of the proposed classification method was found to be 97%, while specificity ranged between 87% and 97% and the prediction accuracy ranged between 94% and 97%. We report the total time in SHW between 140 and 10 min d⁻¹ distributed between 340 and 50 bouts. We estimate the average IWF to be 1.7 steps-per-second. *Significance:* We propose a simple approach for the detection of SHW and estimation of IWF, based on Fourier decomposition.

1. Introduction

Accelerometers are now widely used to monitor physical activity in large observational studies where thousands of subjects are observed for weeks at a time. Walking patterns are very often the main focus of such studies as they have been shown to be associated with major health and aging outcomes, including survival (Studenski *et al* 2011), Parkinson's disease (Din *et al* 2016), obesity (Browning 2006), and overall physical capability (Godfrey *et al* 2015). Here, we propose a method for estimating when and how people walk based on high-frequency data obtained from wearable accelerometers. These data exhibit extraordinary levels of heterogeneity due to the natural within- and between-person variability, as well as due to measuring devices that are prone to batch effects, rotations, and random artifacts. Heterogeneity makes walking prediction in the natural environment much more difficult than for 'in-the-lab' experiments (Grant *et al* 2006a, Ermes *et al* 2008, Francois *et al* 2009). The differences between data collected 'in-the-lab' under strict protocols and data collected in large observational studies is dramatic. Thus, we use the term data collected 'in-the-wild' to emphasize the highly unstructured nature of the data obtained during free-living human activity.

There are a number of accelerometry-based wearable devices designed to recognize and quantify walking 'in-the-wild'. These include ankle-worn step counters (Coleman *et al* 1999) that provide well-validated information on the occurrence and duration of walking as well as the number of steps per minute. Such devices have

been widely used in large epidemiological studies, allowing researchers to study the walking habits of individuals (Orendurff *et al* 2008, Dall *et al* 2015). Another popular device that has been used to detect the walking patterns and posture of individuals is a thigh-worn activPAL monitor (PAL Technologies Ltd, Glasgow, UK). Grant *et al* (2006) discussed the validity of these devices in posture and activity recognition for ‘in-the-lab’ experiments, whereas in Dall *et al* (2015) and Klenk *et al* (2011) the authors use activPAL to collect data on walking patterns in a large group of participants ‘in-the-wild’. While the utility of such devices is undisputable, researchers might often want to address overall physical activity levels rather than the ambulation exclusively (Weuve *et al* 2004). In this paper we propose a method for the detection of walking on data collected by hip-worn, accelerometry-based physical activity monitors.

Our work is preceded by a number of approaches. For example, Dijkstra *et al* (2008) and Weiss *et al* (2013) both proposed walking-recognition procedures for tri-axial, hip-worn accelerometers. These methods used a pre-defined threshold of recorded signals to classify walking activities. Lugade *et al* (2014) introduced an algorithm for the classification of postural orientation and movement using data collected by four custom-build activity monitors, while in their follow-up work Fortune *et al* (2014) discussed the problem of gait features extraction. Maurer *et al* (2006) presented a range of classifiers, for different body location of the sensor, including hip-worn devices. Most recently, Hickey *et al* (2017) introduced a prediction algorithm dedicated for data collected in the free-living environment and validated it against video recordings of daily activities.

The definition of walking based on accelerometry measurements is quite ambiguous. For example, the accelerometry signal might have a fundamentally different structure for a 6 min relaxed walk versus multiple bouts of a few seconds of walking interspersed with other activities. Moreover, laboratory studies typically collect labeled data that is consistent with 6 min of walking (e.g. a 400 m walk (Chang *et al* 2004) or simply, a 6 min walking task (Enright 2003)). Thus, in practice it is often difficult to validate walking periods that are not consistent with the laboratory-standardized definition without proper gold-standard labels (e.g. video recordings). For these reasons we focus here on sustained harmonic walking (SHW), defined as walking for at least 10 s with low variability of step frequency. Based on our observation, we assume that such type of walking is similar in nature to well-controlled walking, and therefore can be identified with methods trained on data collected ‘in-the-lab’ and applied in ‘in-the-wild’ settings.

2. Methods

2.1. Data collection

The data were collected in the Developmental Epidemiologic Cohort Study (DECOS), a study of healthy older individuals. The participants wore tri-axial ActiGraph GT3X+ devices that collected the raw accelerometry signal with a sampling frequency of 80 Hz. The devices were placed on the left hip via an elastic strap. The weight of the devices was 18 g and the dimensions were $4.6 \times 3.3 \times 1.5$ cm.

We concentrate on the data from $N = 49$ individuals (24 females and 25 males) who have both ‘in-the-lab’ and ‘in-the-wild’ accelerometry measurements together with associated demographic and clinical covariates. The median age of the participants was equal to 78.0 years ($Q1 = 74.0$, $Q3 = 82.25$).

During the ‘in-the-lab’ phase of the experiment all participants were asked to perform a series of physical tasks including 400 m of fast walking, simulated dressing, simulated shopping, and chair stands. During the 400 m of fast walking the participants were instructed to walk 10 laps, of 40 m each, at a fast pace. For a simulated dressing activity, the participants were instructed to unfold a lab jacket, put the jacket on (no zipping or buttoning), then remove it, place it on a hanger, and put the hanger on a nearby hook. For simulated shopping participants were instructed to walk a few steps along the wall, stop by target items, remove them from the upper shelf, and place them on the lower shelf. When completed, the participants walked back in the opposite direction, moving the target items back to the top shelf.

Median time to finish a 400 m walk was 5 min 49 s ($Q1 = 4$ min 40 s, $Q3 = 6$ min). The dressing activity was set up to last exactly 3 min, the median time to finish the shopping activity was 2 min 38 s ($Q1 = 1$ min 56 s, $Q3 = 3$ min), and the median time of standing up from the chair task was 19 s ($Q1 = 13$ s, $Q3 = 24$ s).

‘In-the-wild’ accelerometry data activities were collected over a 1-week period in the natural living environment with no activity labels.

2.2. Modeling approach

2.2.1. Definitions and notation

We define SHW as steady-pace walking performed for at least 10 s with a roughly constant step-to-step frequency. Here we propose a method for automatic recognition of SHW intervals in raw accelerometry data together with estimation of instantaneous walking (step-to-step) frequency. The reported frequency of human steps ‘in-the-wild’ ranges between 1.4–2.5 Hz (Pachi and Ji 2005). However, we will conservatively focus on the range of 1.2–4.0 Hz to include slow walking of older individuals and running.

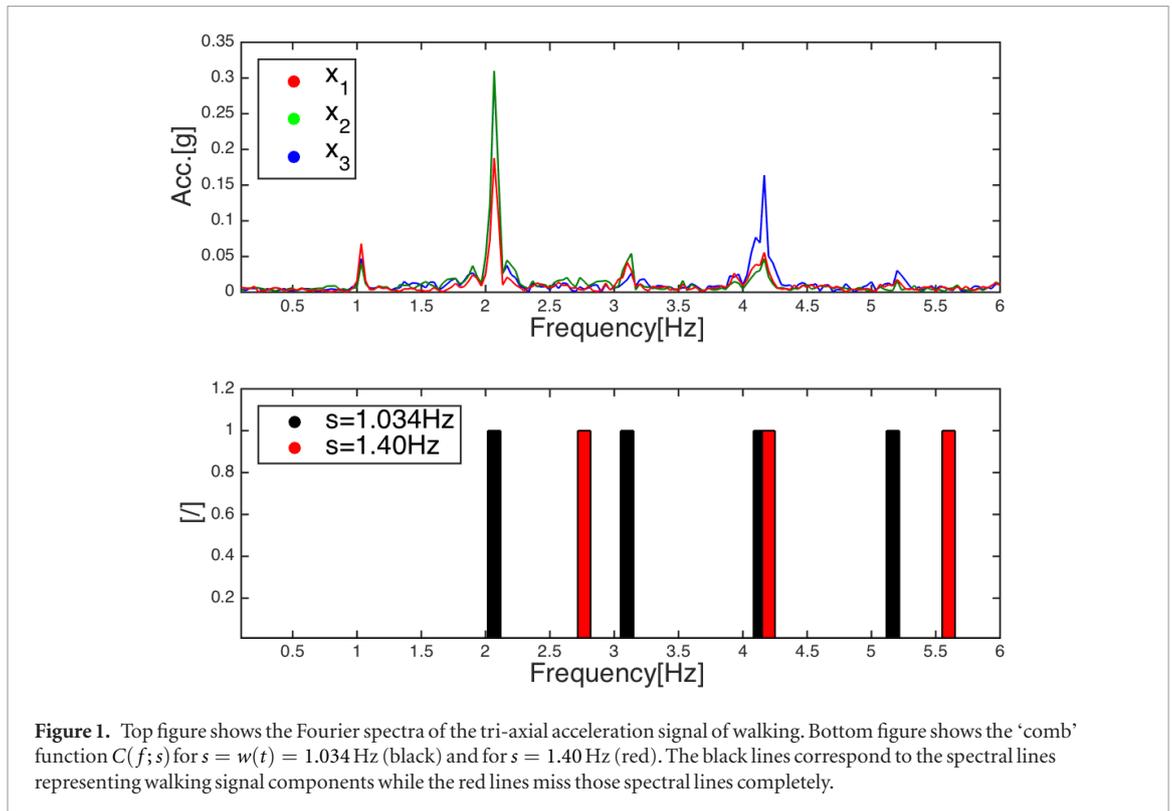


Figure 1. Top figure shows the Fourier spectra of the tri-axial acceleration signal of walking. Bottom figure shows the ‘comb’ function $C(f; s)$ for $s = w(t) = 1.034$ Hz (black) and for $s = 1.40$ Hz (red). The black lines correspond to the spectral lines representing walking signal components while the red lines miss those spectral lines completely.

Let $\mathbf{x}(t) = \{x_1(t), x_2(t), x_3(t)\}$ denote the measured signal, where $x_k(t)$ (expressed in g-units) is the measurement at time index $t = 1, \dots, T$ along the axis $k = 1, 2, 3$. For notational simplicity we drop the subject index. We denote the sampling frequency of the data expressed as the number of observations per second by f_0 .

Our goal is to estimate the walking indicator $y(t)$, where $y(t) = 1$ corresponds to SHW and $y(t) = 0$ corresponds to non-SHW. This is achieved by employing a short-time Fourier transform (STFT) for each axis separately. The discrete Fourier transform (DFT) for axis k is $X_k(f) = \sum_{t=0}^{T-1} x_k(t) e^{-i2\pi f \frac{t}{T}}$, where f is the frequency index, t is the time index, and T is the total number of observations. We define the STFT at time t for axis k of the acceleration signal $\mathbf{x}(t)$ as

$$X_k(t, f; \tau) = \sum_{u=[t-\tau/2]}^{[t+\tau/2]} x_k(u) h(u) e^{-i2\pi f \frac{u}{T}}, \quad (1)$$

where τ is the parameter specifying the number of observations in the interval centered at t . We use the Hann window defined as $h(u; \tau) = 0.5[1 - \cos\{2\pi u/(\tau - 1)\}]$. The spectrum is defined as $S_k(t, f; \tau) = |X_k(t, f; \tau)|$, where $|\cdot|$ denotes the absolute value of a complex number. Next, we introduce the comb function, a function that ‘combs’ the spectrum for those frequencies that are likely to be related to walking (see figure 1). A comb function is defined by the fundamental frequency s , and the thickness of the comb ‘teeth’ with the same width for all frequencies and the total number of teeth is equal to n_m . For any frequency s , we define a neighborhood, $N_s = \{s - \frac{1}{U}, s, s + \frac{1}{U}\}$, where the local FFT is applied, where U is the duration of the window expressed in seconds. Thus, N_s is the shortest frequency interval centered at s and consists of three subsequent frequency components. The comb family of functions, $C(f; s)$, indexed by s , is defined as

$$C(f; s) = \begin{cases} 1 & \text{for } f \in \cup_{l=2}^{n_m} N_{ls} \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

Spectra shown in the top panel of figure 1 correspond to a sample walking interval. The bottom panel displays the comb function corresponding to the fundamental frequency of the walking acceleration signal $s = 1.034$ Hz. The tooth centered at $2s = 2.067$ Hz also contains the frequencies between 1.967 and 2.167 Hz. There are additional ‘comb teeth’ centered at $3s = 3.102$ Hz and so on. Figure 1 also displays an example of another comb shown in red corresponding to $s = 1.40$ Hz, a frequency unrelated to a walking acceleration signal. Note that integrating the spectrum in areas corresponding to the ‘black’ comb will result in a higher value than for the spectrum integrating the areas corresponding to the ‘red’ comb, which does not match the spectral peaks. The comb function idea was inspired by the widely used comb filter of harmonic components (Chu *et al* 1984). However, in contrast to a filter that uses the entire range of spectral components, our comb uses only frequencies

between $2s$ and $n_m s$ to limit the number of high and low frequency components and reduce both high-frequency random noise and low-frequency oscillation resulting from other non-harmonic body movements.

2.2.2. Prediction of walking periods and its characteristics

We now provide the technical description of the SHW prediction approach. Specifically, for each axis k , we define the area under the full spectrum, $S_k(\cdot)$, as $IS_k(t) = \int_{f=0}^{f_0/2} S_k(f, t; \tau) df$ and the area under the spectrum corresponding to the comb function $C(f, s)$ as $IS_k(t, s) = \int_{f=0}^{f_s/2} (f, t; \tau) C(f; s) df$. All the functions under the integral are positive and $IS_k(t) > IS_k(t, s)$ for every s and t . Next, we define

$$Y_k(t, s) = \frac{IS_k(t, s)}{IS_k(t) - IS_k(t, s)}, \quad (3)$$

which is a measure of the size of the periodic content of the component of the accelerometry signal corresponding to the fundamental frequency s , along axis k .

We use $Y(t, s) = \max_k \{Y_k(t, s)\}$, which is the maximum of the fraction of the signal explained by the frequency s along the three axes $k = 1, 2, 3$ to estimate the SHW periods. For a threshold δ of $Y(t, s)$, we estimate that a person performs SHW by

$$\hat{y}_\delta(u) = \begin{cases} \text{if } \max_{s \in D_f} Y(t, s) > \delta, \\ 0, \end{cases} \quad (4)$$

for every $u \in [t - \tau/2, t + \tau/2]$, where δ is a threshold δ of $Y(t, s)$, and D_f is the family of frequencies corresponding to walking (here, $D_f = 1.2, \dots, 4$ Hz). Therefore, if walking was detected for only one window, it was classified as a bout lasting for 10 s.

For the SHW periods, we estimate IWF, denoted as $\hat{w}(t)$, as the double of frequency s , that maximizes $Y(t, s)$. More precisely,

$$\hat{w}(t) = \begin{cases} 2 \operatorname{argmax}_{s \in D_f} \{Y(t, s)\} \text{ for } \hat{y}_\delta(t) = 1, \\ \text{Nan.} \end{cases} \quad (5)$$

A complete description of the approach is summarized in Algorithm 1.

Algorithm 1

Input: $\mathbf{x}(t)$ —accelerometry signal, f_s —sampling frequency, T —observation time, τ —time window, δ —threshold, $s_{\min} = 0.6$ Hz, $s_{\max} = 2.0$ Hz.

Output: $\mathcal{Y}(t)$ —walking indicator, $v(t)$ —vector magnitude, $w(t)$ —IWF.

Step 1. Compute the value of the ‘comb’ function $C(f; s)$ for each value of $s \in D_f$.

Step 2. Compute the spectrum, $S_k(t, f, \tau)$, for each axis $k = 1, 2, 3$ and the area under the spectrum $IS_k(t)$ for each t .

Step 3. Compute the partial area under the spectrum $IS_k(t, s)$ for each s and each k .

Step 4. Calculate the periodic content of the signal $Y_k(t, s) = \frac{IS_k(t, s)}{IS_k(t) - IS_k(t, s)}$ for each k .

Step 5. Estimate $y_\delta(t)$ with $\max_{s \in D_f} Y_k(t, s)$.

Step 6. For the times t with $\hat{y}_\delta(t) = 1$ estimate $w(t)$ by finding the s that maximizes $Y(t, s)$.

Step 7. Identify walking if any of the estimators $\hat{y}_\delta(t)$ is 1.

2.3. Validation using the ‘in-the-lab’ data

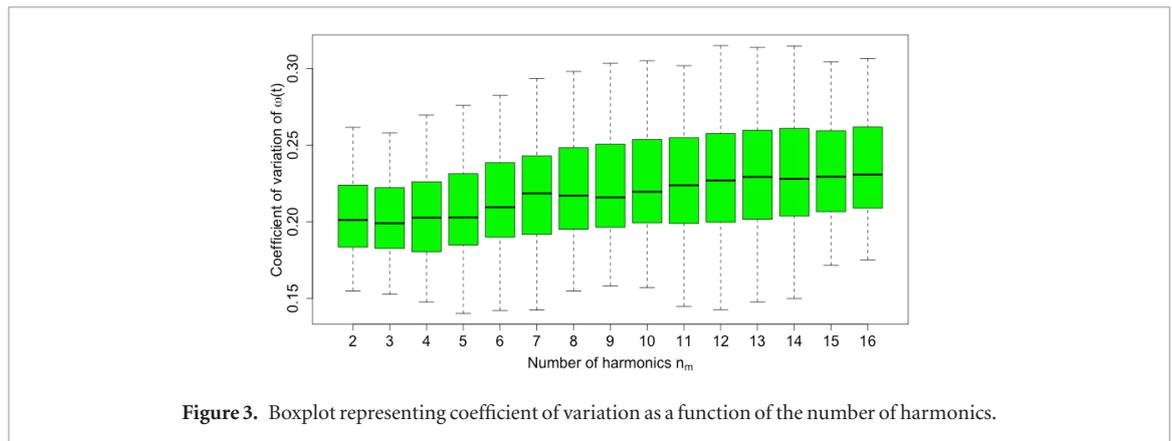
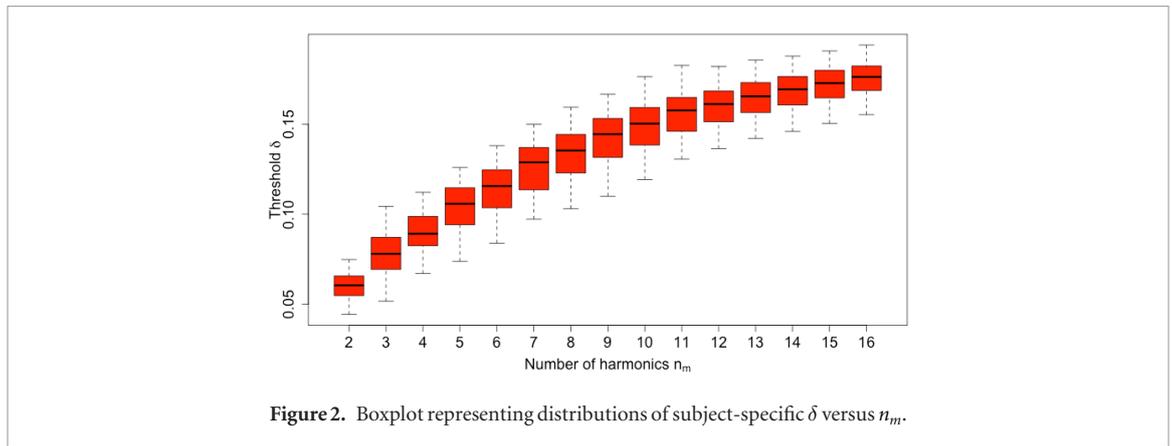
To validate the method, we used data collected during the ‘in-the-lab’ phase of the DECOS study.

2.3.1. Selection of the tuning parameters

In this section, we discuss the tuning parameter choices: the window length τ , the threshold δ of $Y(t, s)$, and the number of harmonics (comb teeth) n_m .

There are trade-offs in choosing τ as (1) longer windows result in more precise spectrum estimation, while (2) shorter time windows are less likely to capture changes in walking frequency or changes in activity type. Based on the empirical evaluation of the ‘in-the-lab’ data, we found that a $\tau = 10$ s interval is long enough for people to maintain their IWF yet short enough to not be sensitive to smooth changes in IWF, resulting in clean spectral signatures.

SHW is estimated in time increments equal to 1 s, so consecutive windows overlap by 90% and a 1 s interval is declared to be SHW if any of the intervals containing it is estimated to be a SHW. The duration of each walking bout is equal to the number of consecutive time windows where walking was estimated to have occurred plus the window duration multiplied by the overlap. For example, if walking was detected in 8 consecutive windows, the



walking bout was determined to have lasted $8 + 0.9 \times 10 = 17$ s. It is important to note that we cannot estimate a length of a walking bout that is shorter than the length of the window τ . Therefore, if walking was detected for only one window, it was classified as a bout lasting for 10 s.

The choice of the threshold δ and the number of harmonics n_m are inter-related. The proportion of the variability ($\max_{s \in D_f} Y(t, s)$) explained is an increasing function of the number of harmonics n_m . We studied δ as a function of n_m , for $n_m = 2, \dots, 17$, where the upper limit of 17 is determined by the sampling frequency of the raw accelerometry data. We estimate the density function of $\max_{s \in D_f} Y(t, s)$ for all SHW and non-SHW periods for all subjects. The parameter δ was then estimated for each subject separately as the intersection between the subject-specific SHW and non-SHW density functions. Figure 2 displays a boxplot of the estimated δ values across subjects as a function of the number of harmonics, n_m . While some between-subject variability exists in the estimation of δ at every value of n_m , having a population level value simplifies the procedure considerably. For example, when $n_m = 6$ harmonics are used as an estimated median value of δ if the population level is equal to 0.115.

The selection of the number of harmonics, n_m , is important for the estimation of IWF, $w(t)$ (equation (5)). In principle, we would like to utilize as many frequencies as possible without degrading the IWF estimation. To study the choice of n_m , we calculated the IWF, $w(t)$, for every subject at each time point during their 400 m walk. For every subject, we then calculated the coefficient of variation of the IWF during this period. Given that this is a well-controlled experiment, the coefficient of variation of the IWF is expected to be small. Figure 3 displays the coefficient of variation as a function of the number of harmonics for every subject. The average coefficient of variation is relatively stable for $n_m = 2, \dots, 6$ and it starts to increase for larger values of n_m . Thus, to use as much information as possible and still keep the coefficient of variation small, we selected $n_m = 6$.

2.3.2. Performance of the algorithm

For further processing we used $\tau = 10$ and $\delta = 0.115$ and a range of possible IWFs between 1.2 and 4.0 steps s^{-1} . The upper boundary for possible IWFs was purposefully set to be relatively high to account for running for active individuals.

Next, we calculated the specificity, sensitivity, and prediction accuracy of the algorithm in three separate classification tasks. Namely, shopping versus walking, chair stands versus walking, and dressing versus walking. Shopping, chair stands, and dressing were defined as non-walking activities, whereas a 400 m walk was defined as a walking activity. For shopping and chair standing activities specificity was equal to 95% and 97%, respectively.

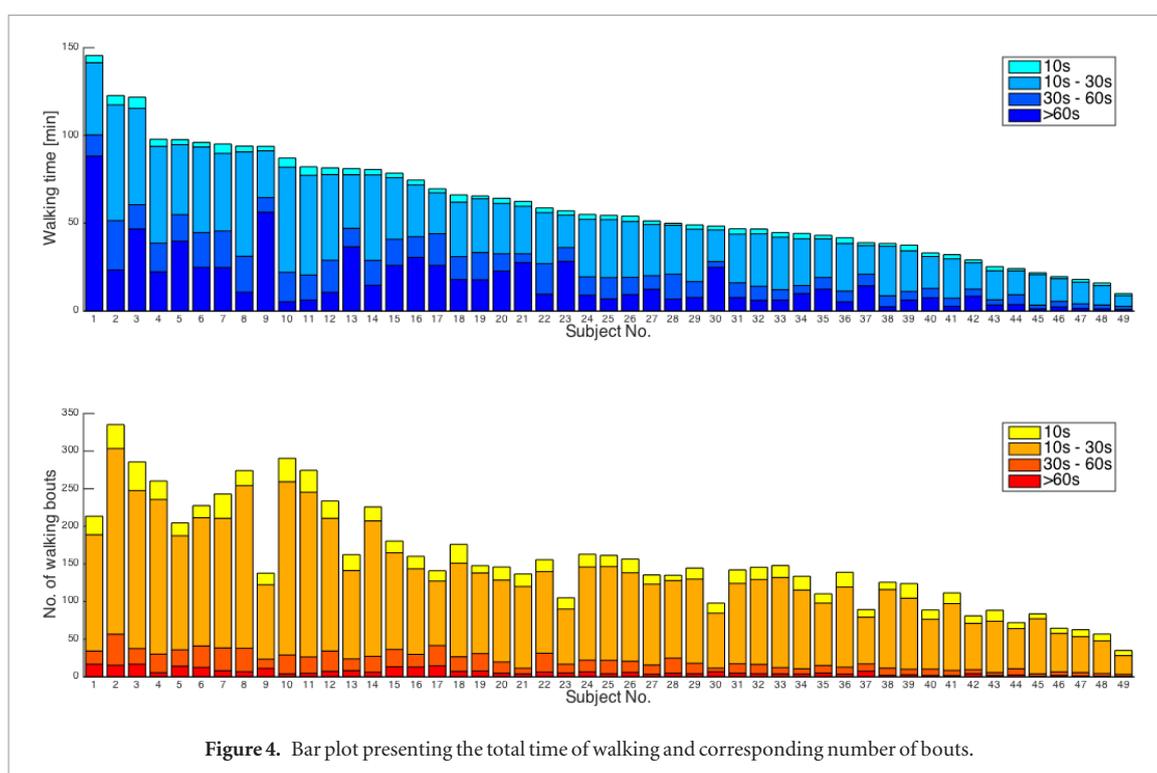


Figure 4. Bar plot presenting the total time of walking and corresponding number of bouts.

Specificity was the lowest for the dressing activity and was equal to 87%. The sensitivity of the classifier was equal to 97%. The prediction accuracy was equal to 97% for shopping versus walking and chair stands versus walking and 94% for dressing versus walking.

3. Analysis of ‘in-the-wild’ data

We applied the approach described in section 2.3 to data collected during the ‘in-the-wild’ portion of the experiment, to estimate when SHW occurs together with the corresponding IWF. We used the same tuning parameters as in section 2.3.2 ($\tau = 10$ and $\delta = 0.115$ and a range of possible IWFs between 1.2 and 4.0 steps s^{-1} , with a 90% time-window overlap).

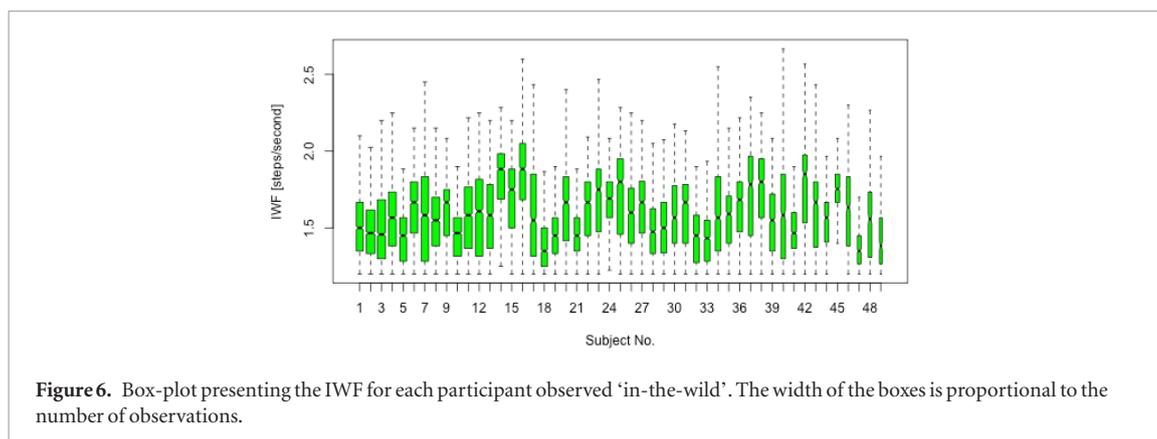
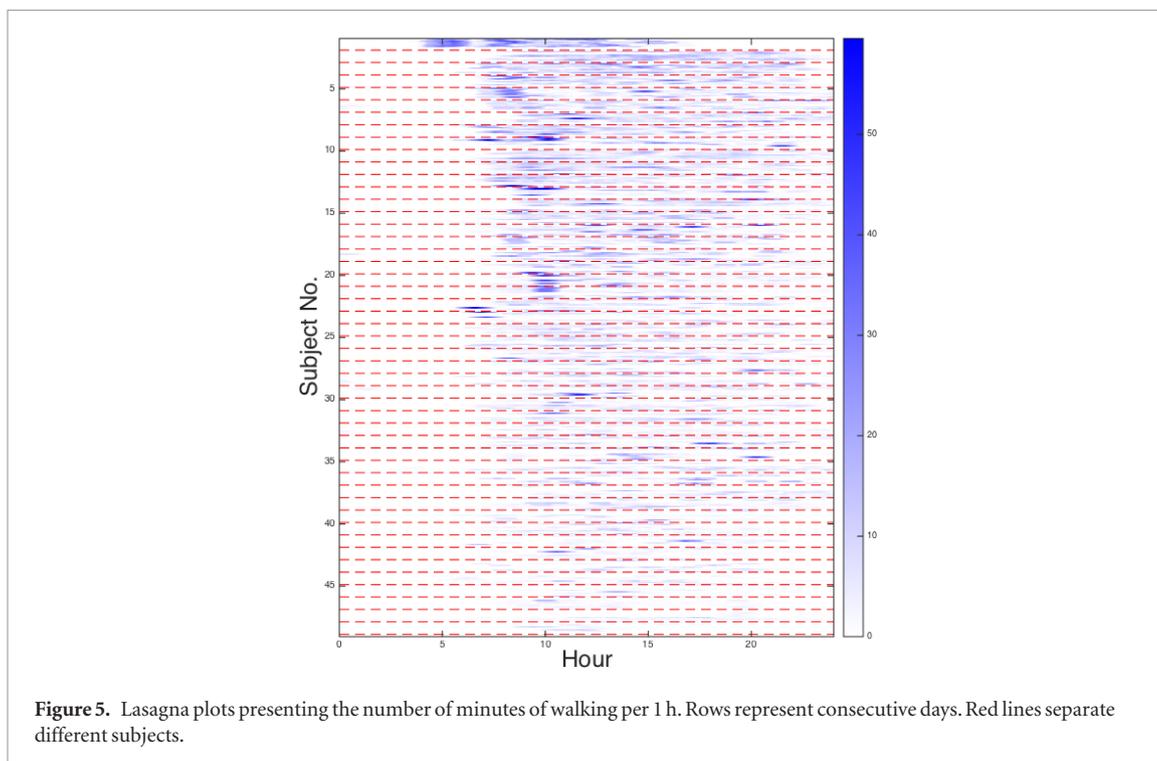
Figure 4 displays the total SHW time (top panel) for each of the 49 participants together with the corresponding total number of walking bouts (bottom panel) as per-day averages from the 7 d of activity. The results are sorted in decreasing order according to the estimated average total walking time. Color shading corresponds to different lengths of walking bouts. For example, the width of the lightest blue bars in the top panel of figure 4 corresponds to the total walking time from walking bouts equal to 10 s. The yellow bars in the bottom panel of figure 4 display the total number of bouts equal to 10 s. The results indicate that a long SHW time does not necessarily indicate a large number of SHW bouts. For example, subject 1 had the longest SHW time per day (140 min), spread over 210 SHW bouts, which is in about the third quartile of the number of SHW bouts for this group. The results indicate that the majority of daily walking bouts for all subjects are between 10 and 30 s.

Figure 5 provides a lasagna plot (Swihart *et al* 2010) for daily walking patterns for all subjects. The shades of blue correspond to the number of minutes of walking within a 1 h window. Each row corresponds to 1 d and the dashed red lines separate the data for individual subjects. The results were sorted using the same ordering as in figure 4, with the subjects with the highest average daily walking time shown at the top.

Figure 6 displays the boxplots of the IWF for each subject sorted according to total walking time. The width of the boxes is proportional to the number of walking bouts.

4. Summary and discussion

We have introduced the definition of SHW together with the classification algorithm based on the quantification of the ‘local degree of periodicity’ of all tri-axial time series. The performance of our method depends strongly on the assumption that SHW is a repetitive and sustained process in a particular time window. For example, it is possible for a window of 10 s to contain 3 to 4 s of walking which are not recognized as walking. Thus, our method will tend to work well at recognizing sustained walking for 10 and more seconds. This can be seen in the results obtained ‘in-the-lab’ where specificity for shopping versus walking was 95% even though the shopping task consisted of some non-sustained walking. The performance of the proposed method is comparable to previously



published results. For example, Dijkstra *et al* (2008) reported a sensitivity of 89.5%, whereas Lugade *et al* (2014) obtained a median sensitivity ranging between 84% and 95% depending on the gait velocity. Also, Maurer *et al* (2006) reported a prediction accuracy equal to 87% for hip worn accelerometers. That compares favorably to our approach with a prediction accuracy between 94% and 97%.

Based on our interpretation of the data we assumed that SHW is similar in both 'in-the-lab' and 'in-the-wild' settings and that methods developed using 'in-the-lab' data can be scaled-up to the free-living experiment. In reality, however, it is difficult to talk about classifiers performance 'in-the-wild' without proper gold standard labels. We believe that our method performs well based on a comparison of the obtained results to previously published studies that used accelerometry. For example, Klenk *et al* (2011) reported a similar daily walking duration in an elderly population, equal to 104.4 ± 50.7 min and 102.9 ± 47.8 min for males and females, respectively. In Orendurff *et al* (2008), the authors presented a comparable distribution of durations of walking bouts, where 60% of all walking bouts lasted 30 s or less, with 20.1% of walking bouts lasting for 10 s or less. This suggests a significant number of walking bouts that do not fall under the definition of SHW. Dall *et al* (2015) reported an average value of step frequency of around 2.0 steps s^{-1} , therefore slightly higher than indicated by our results. A possible explanation for this discrepancy is that the studied population was much younger (mean age 46 years), and therefore characterized by a higher gait speed (Studenski *et al* 2011) and consequently higher step frequency. Although the arguments given above cannot replace proper validation of our algorithm's performance, they suggest that our method is promising for analyzing high-density accelerometry data collected 'in-the-wild'.

In future studies, we will explore alternative validation methods for movement recognition ‘in-the-wild’ using multiple wearable sensors as well as investigating the associations between the SHW features and health outcomes.

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