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A pilot study of physical activity and sedentary behavior distribution patterns in older women

Emma Fortune[a], Benjamin Mundell[a], Shreyasee Amin[b], Kenton Kaufman[a,*]

[a] Motion Analysis Laboratory, Division of Orthopedic Research, Mayo Clinic, Rochester, MN 55905, USA
[b] Division of Rheumatology, Mayo Clinic, Rochester, MN 55905, USA

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ABSTRACT

The study aims were to investigate free-living physical activity and sedentary behavior distribution patterns in a group of older women, and assess the cross-sectional associations with body mass index (BMI).

Eleven older women (mean (SD) age: 77 (9) yrs) wore custom-built activity monitors, each containing a tri-axial accelerometer (± 16 g, 100 Hz), on the waist and ankle for lab-based walking trials and 4 days in free-living. Daily active time, step counts, cadence, and sedentary break number were estimated from acceleration data. The sedentary bout length distribution and sedentary time accumulation pattern, using the Gini index, were investigated. Associations of the parameters' total daily values and coefficients of variation (CVs) of their hourly values with BMI were assessed using linear regression.

The algorithm demonstrated median sensitivity, positive predictive value, and agreement values > 98% and < 1% mean error in cadence calculations with video identification during lab trials. Participants' sedentary bouts were found to be power law distributed with 56% of their sedentary time occurring in 20 min bouts or longer. Meaningful associations were detectable in the relationships of total active time, step count, sedentary break number and their CVs with BMI. Active time and step counts had moderate negative associations with BMI while sedentary break number had a strong negative association. Active time, step count and sedentary break number CVs also had strong positive associations with BMI.

The results highlight the importance of measuring sedentary behavior and suggest a more even distribution of physical activity throughout the day is associated with lower BMI.

1. Introduction

Physical inactivity is defined as a lack of regular moderate-to-vigorous physical activity (MVPA), whereas sedentary behavior (SB) is defined as sitting/reclining with low energy expenditure while awake. Physical inactivity and SB are recognized as two distinct and separate risk factors for metabolic syndrome and cardiovascular disease (CVD), in addition to not enough low-intensity physical activity (LPA) and sleep [1]. Understanding the health benefits of replacing sedentary time with LPA or sleep is of substantial public health interest, particularly for older adults as physical inactivity and metabolic syndrome prevalence increase with aging [2].

Current objective SB measures involve the use of accelerometers. However, many accelerometer-based studies use methods of limited accuracy, classifying SB using activity count cut-points without considering posture [3,4]. Furthermore, these cut-points differ between studies. Even most studies that consider posture using ActivPAL only look at a limited number of daily mean SB parameters [5,6]. Using only the daily mean values of SB parameters may mean that we are missing important information about individual's sedentary patterns. Significant sedentary time accumulation pattern differences were reported with no significant total sedentary time differences between active and sedentary young to middle-aged adult participants [7]. Furthermore, reducing SB throughout the day by increasing walking or standing may be more effective at compensating the harmful sedentary time effects on insulin and plasma levels than one hour of daily exercise with equivalent energy expenditure [6]. Therefore, daily sedentary breaks distribution and sedentary time accumulation may be important variables of SB to be examined. The majority of physical activity (PA) and SB research has focused on younger and middle-aged adults, despite older adults being less active and more sedentary [8]. Recent studies have begun to look at PA and SB in older adults [9–12], including PA and SB patterns [8,13–18]. However, these studies also used accelerometer-based tools with cut-points, or for which step

* Corresponding author at: Mayo Clinic, Motion Analysis Laboratory, 200 First Street SW, Rochester, MN 55905, USA.
E-mail addresses: fortune.emma@mayo.edu (E. Fortune), mundell.benjamin@mayo.edu (B. Mundell), amin.shreyasee@mayo.edu (S. Amin), kaufman.kenton@mayo.edu (K. Kaufman).

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detection accuracy has been reported as low for gait velocities < 0.5 m/s [19] which can be typical for lower functioning older adults.

We previously developed an accelerometer-based algorithm to measure active time, steps and cadence for gait velocities as low as 0.1 m/s [20–22]. The study aims were to (1) verify the step detection validity and validate active time and cadence estimations in a new sample of older women, and (2) investigate their PA and SB patterns in their home and community environments. Abdominal obesity, the most prevalent metabolic syndrome factor, is shown by some studies, although not all [13], to be affected by sedentary time [13,23]. This study's third aim was to determine the cross-sectional associations of PA and SB total daily parameters and their distributions with body mass index (BMI), an indicator of abdominal obesity [24].

2. Methods

2.1. Experimental design

The step detection accuracy of the accelerometer-based algorithm has previously been validated for 11 young to middle-aged adults and 19 older adults (including 3 participants in the present study) [22]. To further test algorithm robustness, validity was tested for active time, steps and cadence measurements on the present study's participants using comparison to video recordings during lab-based walking trials. Accelerometer and video data were acquired from 11 ambulatory, community-dwelling older women as they performed 10–14 walking trials at self-selected normal gait velocity over an 8.5 m walkway (with additional acceleration/deceleration room). Participants wore accelerometer-based activity monitors (AMs) on the waist (below the navel) and bilateral ankles. Steps were counted visually by one rater. A total of 119 trials were recorded.

Accelerometer data were also acquired as participants wore the AMs for 4 days in their free-living environments in the week succeeding the lab-based testing. Participants were instructed to wear the AMs at all times except during sleeping, bathing, or swimming. A valid AM hour was defined as ≤30 min of consecutive zero values and a valid day as ≥10 wear hours per day. Participants' median (min–max) age and mean (SD) BMI were 76 (65–91) years, and 26.1 (4.9) kg m^{-2}, respectively. As participants were recruited from a larger study on fall risk and fracture in older women, exclusion criteria included being on the osteoporosis drugs teriparatide or denosumab, unable to walk for > 1 block without a walking aid, bilateral hip replacements or surgery history, or lower extremity joint replacement within the prior year. The Institutional Review Board approved the protocol and participants provided written informed consent before participating.

2.2. Data collection

The custom-built AMs were secured with straps on the ankles and a clip on the waist. Each AM incorporated a tri-axial MEMS accelerometer (analog, ± 16 g, Analog Devices) with a sampling frequency of 100 Hz, and onboard data storage of up to 0.5 GB [20]. Video data were simultaneously acquired at 60 Hz using a handheld camera during the lab-based data collection. Video and accelerometer data were synchronized by an investigator shaking the AMs three times in view of the handheld camera prior to participant wear.

2.3. Signal processing

All accelerometer data post-processing and analysis were performed offline using MATLAB (Version 7.11.0, Mathworks, MA). The acceleration data were filtered to extract the gravitational component [22]. Subtracting the gravitational component from the original median filtered signal provided the bodily motion component.

2.4. Activity detection

Dynamic activity and steps were detected using algorithms previously developed and validated for 11 younger to middle-aged participants with gait velocities ranging from 0.1–4.8 m/s [20,21] and 19 older adult participants with gait velocities ranging from 0.5 to 2.0 m/s [22]. Upright dynamic activity was identified for 1 s epochs when the angle estimation calculated from the waist acceleration gravitational motion component was < 50°, and the waist acceleration bodily motion component's signal magnitude area exceeded 0.135 g or the acceleration data within a range of 0.1–2.0 Hz exceeded a scaling threshold of 1.5 when a continuous wavelet transform was applied. In this study, each period of continuous 1 s epochs of detected activity is referred to as an activity segment. Step numbers and heel-strike timings were determined by applying a peak detection algorithm with adaptive acceleration and timing thresholds to the ankle acceleration data for all upright dynamic activity periods detected using the waist AM. Algorithm details can be found in previous studies [20–22].

2.5. Validity

Activity detection, step detection, and cadence calculations were validated against video data. For active time, accelerometer and video data were compared as 1 s windows. For step counts, each step event was compared between accelerometer and video data. Agreement, sensitivity, and positive predictive value (PPV) were used to assess the algorithm's ability to accurately detect active seconds and steps. Agreement is the percentage of total active time seconds/step number detected using the algorithms compared with those from video data. Sensitivity is the ratio of true positives (steps or active seconds which were detected by the algorithm and from video data) to the sum of true positives and false negatives (steps or active seconds which were not detected by the algorithm but were from video data). PPV is the ratio of true positives to the sum of true positives and false positives (steps or active seconds which were detected by the algorithm but not from video data). Cadence as determined by the algorithm was compared to cadence as determined by video observation by plotting the difference between the two methods, as a percentage of the video-based estimation, against the video-based estimations. Heel-strike times were visually identified to calculate cadence from video data.

2.6. Parameters to evaluate physical and sedentary behavior in the free-living environment

The PA parameters of interest were: (1) active time, (2) step counts, and (3) cadence. Activity segments were classified as LPA, moderate physical activity (MPA), or vigorous physical activity (VPA) using previously defined cadence cut-points [13]: LPA < 93 steps min^{-1}, MPA ≥ 93 steps min^{-1} and ≤124 steps min^{-1}, and VPA > 124 steps min^{-1}.

SB parameters of interest were: (1) daily number of breaks in sedentary time, (2) sedentary breaks distribution, (3) sedentary bout length distribution, and (4) sedentary time accumulation pattern. Some accelerometry-based studies define sedentary time as all minutes for which the activity count per minute is less than a defined cut-point and a sedentary break as any sedentary time interruption for which the activity count per minute is equal to or exceeds the defined cut-point [3,4]. However, in addition to no cut-point value agreement, cut-point methodology introduces issues such as the inability to differentiate between sitting and standing, or to accurately and repeatedly separate out low versus no acceleration activities both within and between participants. In this study, acceleration data were classified as either active or sedentary time on a second by second basis and a sedentary break was identified when an activity segment of ≥30 s (at least 1 min of activity when rounding to the nearest minute) was detected using our activity detection algorithm [20–22] with at least one second of