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Validity of using tri-axial accelerometers to measure human movement – Part II: Step counts at a wide range of gait velocities

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ABSTRACT

A subject-specific step counting method with a high accuracy level at all walking speeds is needed to assess the functional level of impaired patients. The study aim was to validate step counts and cadence calculations from acceleration data by comparison to video data during dynamic activity. Custom-built activity monitors, each containing one tri-axial accelerometer, were placed on the ankles, thigh, and waist of 11 healthy adults. ICC values were greater than 0.98 for video inter-rater reliability of all step counts. The activity monitoring system (AMS) algorithm demonstrated a median (interquartile range; IQR) agreement of 92% (8%) with visual observations during walking/jogging trials at gait velocities ranging from 0.1 to 4.8 m/s, while FitBits (ankle and waist), and a Nike Fuelband (wrist) demonstrated agreements of 92% (36%), 93% (22%), and 33% (35%), respectively. The algorithm results demonstrated high median (IQR) step detection sensitivity (95% (2%)), positive predictive value (PPV) (99% (1%)), and agreement (97% (3%)) during a laboratory-based simulated free-living protocol. The algorithm also showed high median (IQR) sensitivity, PPV, and agreement identifying walking steps (91% (5%), 98% (4%), and 96% (5%)), jogging steps (97% (6%), 100% (1%), and 95% (6%)), and less than 3% mean error in cadence calculations.

1. Introduction

Physical inactivity is an independent risk factor for chronic disease and disability and is estimated to result in 3.2 million deaths world-wide each year [1]. Regular physical activity has been associated with health improvements in many populations [2]. Many commonly used mobility assessment methods have limitations such as subjectivity [3] or involve clinical-based evaluations that fail to mimic real-world functional requirements, such as the 10 m walk test which underestimates gait velocity predictions in a community setting [4]. It is important to quantitatively assess mobility in the free-living environment as health and wellness measure. This can be accomplished with accurate measurement of step counts and cadence in the home and community.

Step counting is one of the most commonly used measures of physical activity [5]. Sensors can provide objective information on movement while their small size and light weight allow for home deployment. One of the main issues associated with step counts as a physical activity measure is that high accuracy is needed. Many previous studies have assessed the step count and gait event accuracy of pedometers, accelerometers, and gyroscopes [6–11]. However, limited information on the algorithms and the data analysis methods are provided and the protocols performed are overly simplified, often consisting of long periods of continuous walking which are inconsistent with most daily living activities. The step detection accuracy of many sensors has also been shown to decrease for shorter activity duration and at slower walking speeds [8,12–14], particularly in older patients. The need for accurate step counts at slow walking speeds is of critical importance as slow walking speeds can be indicative of movement disorders [15], mobility disability [16], and have been linked to high risk for reduced function, morbidity, and mortality [17]. Increases in walking speed and the ability to vary cadence demonstrate increased function level [18], reduced risk, and higher predictions of survival [17,19]. While a small number of studies have shown that results from the methods they used are not affected by different walking speeds, accuracy during shuffling, stair climbing, and jogging have yet to be investigated and only limited gait velocity ranges are examined [14,20,21]. Furthermore, the use of step counts as a measure of physical activity is limited as the characteristics of the steps are unknown. An activity monitoring system (AMS) capable of identifying walking step counts, jogging step counts, and the ability to vary cadence while walking and jogging can be beneficial as it gives information on an individual's functional level. Furthermore, an objective

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portable method for the functional assessment of patients, particularly those with slow walking speeds, could serve as a beneficial motivational rehabilitation tool and an effective clinical outcomes measure in the free-living environment.

The aim of this study was to determine the validity and reliability of a custom-designed AMS as an objective adaptive step counter. The algorithm's accuracy was validated with visual step counts and was compared to two commercial step counters (Fitbit Tracker (Fitbit, San Francisco, CA) and Nike+ Fuelband (Nike, Beaverton, OR)) during walking and jogging trials at a range of gait velocities. The validity and reliability of the AMS algorithm were also evaluated for walking and jogging segments in healthy adults during a protocol of simulated free-living dynamic activities in the laboratory by comparison to video recordings.

2. Materials and methods

2.1. Experimental design

Accelerometer and video data were acquired from 12 (3 M, 9 F) healthy adults as they performed 7–10 walking/jogging trials in a straight line over an 8.5 m walkway (with additional room to accelerate and decelerate). Subjects wore two different commercial devices (Fitbit monitors on the right lateral ankle and the waist and a Nike Fuelband on the right wrist) in addition to the AMS which consisted of accelerometers below the navel on the waist, on the right thigh lateral midpoint, and bilateral ankles. Gait velocities were calculated based on the distance travelled and the time duration recorded by photocells placed at either end of the walkway. For the initial trial, subjects were asked to walk at a self-selected normal gait velocity. Following each trial, subjects were given instructions to walk/jog at a slower/faster speed, until a suitable range of gait velocities was obtained. The steps were counted visually by two raters. A total of 105 trials were recorded in total. Accelerometer and video data were also recorded as subjects performed an approximately 5 min protocol of static and dynamic activities involving standing, sitting, lying, postural transitions, walking, stair climbing, and jogging in the laboratory [22]. Verbal cues were provided by an investigator for each task. Additionally, subjects were asked to fidget to simulate activity during selected sitting and standing tasks. All activities were performed at self-selected speeds. At the time of evaluation, the subjects' median (range) age and average (SD) body mass index (BMI) were 31 (25–55) years, and 24.7 (5.5) kg m^{-2}, respectively. Exclusion criteria were a history of musculoskeletal deficits, neurological impairment, or lower extremity surgery. The study protocol was approved by the Mayo Clinic Institutional Review Board and each subject provided written informed consent before participating.

2.2. Data collection

The AMS consisted of four Mayo Clinic custom-built activity monitors which were secured with straps. Each activity monitor incorporated a tri-axial MEMS accelerometer (analog, ±16 g, Analog Devices), and onboard data storage of up to 0.5 GB [22]. Monitors were programmed to sample each axis at 100 Hz. Video data were simultaneously acquired at 60 Hz using a handheld camera. Video data were synchronized to accelerometer data by three vertical jumps performed by subjects prior to and following the described protocol. The four accelerometers were also synchronized to each other after the final jump.

2.3. Signal processing

Step numbers and heel-strike timings for AMS step detection were determined from the bilateral ankle activity monitors (Fig. 1). All accelerometer data post-processing and analysis were performed offline using MATLAB (Version 7.11.0, Mathworks, Natick, MA). A median filter, with a window size of 3, was applied to the orthogonal raw acceleration signals to remove any high-frequency noise spikes. The resulting filtered signal was separated into its gravitational component using a third-order zero phase lag elliptical low pass filter, with a cut-off frequency of 0.25 Hz, 0.01 dB passband ripple and −100 dB stopband ripple. Subtracting the gravitational component from the original median filtered signal provided the bodily motion component [23].

2.4. Activity detection

In a parallel study by the authors [22], dynamic activity was detected by calculating when the signal magnitude area (SMA) of the bodily motion component of the waist accelerometer data exceeded a threshold of 0.135 g [24] for epochs of 1 s. Of those seconds of data (which were below 0.135 g) identified as non-activity, a continuous wavelet transform using a Daubechies 4 Mother Wavelet was applied to the waist acceleration signal. Data which fell within a range of 0.1–2.0 Hz was further identified as activity, if it exceeded a scaling threshold of 1.5 over each second [22]. Upright activity was identified using the angles estimated from the waist and thigh accelerometers. Activity was characterized as jogging when the SMA exceeded 0.8 g and as walking (including stair climbing and fidgeting of the feet while standing) when the SMA was between 0.135 and 0.8 g. The threshold of 0.8 g was determined from this dataset [22], based on comparisons of SMA to video data for a single subject and validated across all subjects.

2.5. Step detection

During identified walking and jogging segments, the antero-posterior accelerations (a_{AP}) of the ankles were filtered using a low-pass butterworth filter with a cut-off frequency of 6 Hz and analyzed using a peak detection method [9] with adaptive a_{AP} thresholds similar to those previously formulated for angular velocity [20] and an adaptive timing threshold to calculate the number of steps taken (Fig. 1).

Gait events, gait velocity, and cadence are useful when describing normal and pathological gait [25]. Step counting methods are often based on toe-off, heel-strike, and/or midswing identification with defined absolute thresholds determining the acceleration values these gait events must reach and how much time must lapse between consecutive gait events to identify valid steps [9]. As gait velocity, cadence, and swing phase usually decrease with increasing disability, the gait event accelerations also decrease and the time between gait events increases [25]. These parameter changes can cause accuracy issues when using absolute thresholds to assess subjects with slower/pathological gait velocities. Even within-subject gait velocity changes can reduce accuracy, i.e. walking slowly while performing household chores, may result in activity underestimation [26]. To overcome these issues, our algorithm incorporates adaptive thresholds for acceleration and time between gait events.

2.5.1. Calculate initial adaptive thresholds (Fig. 1b)

The adaptive peak detection thresholds allow for greater step detection accuracy at different walking speeds. For each continuous data segment classified as walking or jogging, adaptive a_{AP} thresholds to detect heel-strike points were calculated,

$$th_1 = 0.8 \times (1/N) \times \sum_{i=1}^{N} a_{AP_i} < \bar{a}_{AP} \tag{1}$$