Published in final edited form as:

Med Eng Phys. 2014 February ; 36(2): 169–176. doi:10.1016/j.medengphy.2013.06.005.

Validity of Using Tri-Axial Accelerometers to Measure Human Movement - Part I: Posture and Movement Detection

Vipul Lugade, **Emma Fortune**, **Melissa Morrow**, and **Kenton Kaufman***

Motion Analysis Laboratory, Division of Orthopedic Research, Mayo Clinic Rochester, MN 55905 USA

Vipul Lugade: lugade.vipul@mayo.edu; Emma Fortune: fortune.emma@mayo.edu; Melissa Morrow: morrow.melissa@mayo.edu; Kenton Kaufman: kaufman.kenton@mayo.edu

Abstract

A robust method for identifying movement in the free-living environment is needed to objectively measure physical activity. The purpose of this study was to validate the identification of postural orientation and movement from acceleration data against visual inspection from video recordings. Using tri-axial accelerometers placed on the waist and thigh, static orientations of standing, sitting, and lying down, as well as dynamic movements of walking, jogging and transitions between postures were identified. Additionally, subjects walked and jogged at self-selected slow, comfortable, and fast speeds. Identification of tasks was performed using a combination of the signal magnitude area, continuous wavelet transforms and accelerometer orientations. Twelve healthy adults were studied in the laboratory, with two investigators identifying tasks during each second of video observation. The intraclass correlation coefficients for inter-rater reliability were greater than 0.95 for all activities except for transitions. Results demonstrated high validity, with sensitivity and positive predictive values of greater than 85% for sitting and lying, with walking and jogging identified at greater than 90%. The greatest disagreement in identification accuracy between the algorithm and video occurred when subjects were asked to fidget while standing or sitting. During variable speed tasks, gait was correctly identified for speeds between 0.1m/s and 4.8m/s. This study included a range of walking speeds and natural movements such as fidgeting during static postures, demonstrating that accelerometer data can be used to identify orientation and movement among the general population.

Keywords

Acceleration; Accuracy; Gait Velocity; Movement Analysis

*Corresponding Author: Kenton Kaufman PhD, Motion Analysis Laboratory, Department of Orthopedic Surgery, Charlton North L-110L, Mayo Clinic, Rochester, MN 55905, Telephone: 507-284-2262, Fax: 507-266-2227, kaufman.kenton@mayo.edu.

Competing Interests: The authors report no conflict of interest.

Ethical Approval: The study protocol was approved by the Mayo Clinic Institutional Review Board (IRB #12-004133) and written informed consent was obtained from all research participants prior to beginning data collection.

1. Introduction

Identifying human body position and movement in the free-living environment can provide subject-specific data on activity or disability as well as elucidate changes due to intervention or rehabilitation among patients [1]. Accelerometer based activity monitors provide objective measurements of patient function during free-living [2, 3], and have been used in a variety of populations including healthy individuals, patients with Parkinson's disease [4], total hip arthroplasty [5], and osteoarthritis [6]. Central to the clinical and research utility of activity monitors is the validity of analysis methodologies, applied to the raw body accelerations, to decipher static body postures and dynamic movement activities during activities of daily living (ADLs). Further, for clinical efficacy, the validation procedures must go beyond controlled conditions that test human movement which is considered "normal" and typical of healthy individuals. Slow walking is often characteristic of disease and disability, and patients with a decreased walking speed are at high risk for functional decline, morbidity, and mortality [7, 8]. In addition to the inclusion of a wide range dynamic activity in validation procedures, it is important to include walking performed at slow speeds for applicability of the analysis methodology to patient populations.

Commercial devices such as the Intelligent Device for Energy Expenditure and Activity (IDEEA) [9], DynaPort MoveMonitor [10], and the activPAL [11] have demonstrated the ability to discriminate posture, though the description of methodologies are absent or lacking, with detection algorithms based on third party black box classification. Previous validation studies report highly accurate results, though movements were performed in a controlled environment measuring only a limited set of postures, neglecting transitions between postures [9, 12], and collecting over a narrow range of walking speeds. Additionally, sensitivities of other postural algorithms often were reported based on the likelihood of a posture or activity being detected [13–15], rather than second by second analysis of the total collection duration. There have been no previous validation studies that included a wide range of walking speeds, postural transition detection, or detection of fidgeting while sitting and standing.

For accurate detection of postural transitions, walking, and jogging from body accelerations, wavelet transforms provide a better representation of the signal complexity than Fourier transforms. Building on a previously validated methodology [16], the current study provides algorithms for postural detection while including daily activities such as fidgeting while sitting or standing, transitions, and a range of walking speeds. Using wavelet transforms, it is possible to determine the changing frequency content over time on a non-stationary signal [17]. By representing the signal as a sum of a scaled and time shifted mother wavelet, wavelet transforms have previously demonstrated their utility in obtaining transition and gait pattern information [17, 18]. In this study, we utilize continuous wavelet transforms (CWT) to identify slow walking instants.

A robust method for classifying postural orientation and movement needs to be established that can be applied to healthy and patient populations. Therefore, the purpose of this study was to develop and validate an algorithm for the identification of static postures and dynamic movement from acceleration data against visual inspection from video recordings in the laboratory. Specifically, the utility of tri-axial accelerometers in detecting static orientations of standing, sitting and lying down as well as dynamic movements of walking, jogging and transitions was assessed for validity and reliability. Identification of walking and jogging was further assessed over a range of gait velocities.

2. Materials and Methods

2.1 Experimental Design

This investigation included 12 healthy adults (9 females; median (range) age of 31 (25–55) years; average (SD) body mass index (BMI) of 24.7 (5.5) kg/m^2), who were free of musculoskeletal deficits, neurological impairment or lower extremity surgery. Subjects were asked to perform two experimental protocols. During the first protocol, an approximately 5 minute series of static postures and dynamic movements were conducted, consisting of sitting, standing, lying, walking, jogging and stair climbing in the laboratory (Table 1). Additionally, during a portion of the sitting and standing tasks, subjects were asked to 'shuffle' their body to simulate changing body position or fidgeting during sitting and standing tasks. An investigator provided verbal cues for performing each task.

For the second protocol, in order to test the ability of the algorithm to accurately detect postures and movements at a range of gait speeds, subjects were asked to walk across an 8.5 meter walkway at 7 to 10 self-selected slow, medium and fast speeds. During each trial, photocells placed on either end of the walkway recorded the subject's walking duration, with walking velocity calculated based on the distance traversed and the time duration. Following each trial, subjects were asked to walk at a slower or faster speed, in order to obtain a range of gait speeds.

2.2 Data Collection

Static orientations and dynamic movement was recorded using a hand held video camera and activity monitors. The video camera collected data at 60 Hz, with an investigator ensuring that the subject remained within the capture volume throughout the experiment. Custom built activity monitors, developed at the Mayo Clinic, collected acceleration data at 100 Hz. Each sensor contained a tri-axial MEMS accelerometer (analog, ± 16g, Analog Devices), microcontroller (12 bit ADC, Texas Instruments), power source (Tadiran battery, semiconductor voltage regulator), and onboard data storage (NAND flash memory, 0.5 GB memory chip, Micron). Accuracy of the accelerometers was determined to be within ± 0.56%. Two activity monitors, each weighing 22 grams with dimensions of 4.7cm × 2.8cm × 1.2cm, were donned on subjects on a waist band on the pants between the two ASIS and on the lateral midpoint of the right thigh. Monitors were oriented such that the y-axis pointed vertically. The x- and z- axes were directed in the anterior and lateral directions for the waist; and in the lateral and posterior directions for the thigh. The study protocol was approved by the Mayo Clinic Institutional Review Board and written informed consent was obtained from all research participants prior to beginning data collection. Video data were synchronized to the accelerometer data by asking all subjects to perform three vertical jumps prior to performing the described protocol. The two accelerometers were also synchronized to each other based on the onset of jumping. Prior to data collection, both accelerometers were calibrated to record +1g, 0g and −1g when placed in orthogonal orientations.

2.3 Movement Detection

Prescribed postures and movements performed by the research participants during the protocol were analyzed and identified (Figure 1). Accelerometer analyses were performed using custom MATLAB programs (MathWorks, Natick, MA). Acceleration signals from the waist accelerometer were used to differentiate dynamic activity from static postures. In order to remove any high-frequency noise spikes, a median filter with a window size of 3 was applied to each of the three orthogonal raw acceleration signals [16]. The resulting filtered signal was separated into its gravitational component by using a third-order zero phase lag elliptical low pass filter, with a cutoff frequency of 0.25 Hz, 0.01 dB passband ripple and

NIH-PA Author Manuscript

NIH-PA Author Manuscript

−100 dB stopband ripple. Subtracting the gravitational component from the original median filtered signal provided the bodily motion component.

The gravitational and bodily motion components of the acceleration signal were used to identify all possible outcome configurations (Figure 2). The bodily motion component was utilized in determining static versus dynamic activity, with signal magnitude area (SMA) values above a threshold of 0.135 *g* identified as movement [19]. The signal magnitude area was computed over each one second window (t) across all three orthogonal axes (a_x, a_y, a_z) (Equation 1).

$$SMA=\frac{1}{t} * (\int a_x(t)dt+\int a_y(t)dt+\int a_z(t)dt) \quad (1)$$

Of those seconds of data identified as non-movement (i.e. or those seconds below 0.135 g), a continuous wavelet transform was utilized [20]. The Daubechies 4 Mother Wavelet was applied in this study on the waist acceleration signal. Data which fell within a range of 0.1–2.0 Hz was further identified as movement, if it exceeded a scaling threshold of 1.5 over each second. The wavelet toolbox in Matlab was used to calculate the wavelet transforms.

2.4 Postural Orientation

The gravitational component of the signal provided the tilt angle over all three orientations (θ, φ, α) for the device [16]. Both the waist and thigh accelerometer orientations were used to identify postures (Equation 2).

$$\theta=\arccos(\frac{a_x}{g}); \phi=\arccos\left(\frac{a_y}{g}\right); \alpha=\arccos(\frac{a_z}{g}) \quad (2)$$

Lying down was determined when the absolute value of the vertical waist angle was between 50 and 130 degrees, with undefined orientations defined for waist angles greater than 130 degrees and upright postures between 0 and 50 degrees. Among upright postures, standing and sitting were differentiated based on the thigh angle, in relation to gravity, of less than 45 degrees or greater than 45 degrees, respectively [21]. To differentiate lying conditions between supine, prone, left and right positions, the waist angles in transverse plane were portioned into four equal 90 degree segments [16].

2.5 Dynamic Classification

Among dynamic portions of data, the orientation of the waist again indicated whether an individual was sitting, lying down or upright on both feet. Rolling over while lying down was classified as a transition, specifically lying to lying. For the remaining transitions of upright to lying, lying to upright, sit to stand or stand to sit, beginning and ending segments of lying and sitting were identified. If a different orientation (lying, sitting, standing) was identified up to 2 seconds prior to and 2 seconds after the beginning and ending points, the appropriate transition was labeled for the active seconds of postural change. Among upright movement, sitting while fidgeting was identified by the thigh angle. Walking and jogging were differentiated among the remaining upright movements based on a threshold of 0.80 *g* for the SMA. The walking category included stair climbing, level walking, and portions of standing while fidgeting.

Thresholds for static and dynamic classification were determined based on observations made on a single random subject prior to complete validation on the remaining participants, with chosen values similar to those previously utilized [16, 21]. Initial thresholds were based on algorithms previously reported [16], with visual optimization performed for modification of the orientation values and SMA thresholds.

2.6 Reliability

Video data were imported into Windows Movie Maker (Microsoft, Seattle, WA). Two raters, each with greater than one year of gait analysis experience, determined the starting and ending times for each static orientation and movement. The video data were considered the gold standard for all validation analysis. Classified data were organized into one second windows for the video data. Reliability of inter-rater video observations were determined using intraclass correlations across all subjects for the total time spent in each posture or movement (ICC) (A,1) [22]. Fidgeting while sitting and standing was categorized as activity by video observers, with fewer than 4 continuous steps taken identified as fidgeting [23].

2.7 Validity

Validity of the accelerometer algorithm to properly identify different postures and movement was assessed with sensitivity and positive predictive value. Similar to the video classification, accelerometer data were organized into one second windows. Sensitivity described the percentage of an observation category which was correctly detected by the accelerometers, or the ratio of true positives to the sum of true positives and false negatives. Positive predictive value (PPV) provided the percentage of true positives that was identified when compared to the total number of true positives and false positives determined by the accelerometers. The sensitivity and PPV were considered substantial when greater than 60% and almost perfect when greater than 80% [24]. In a recent study, a sensitivity of 71.7% and specificity of 67.8% were classified to be acceptable for detecting sitting postures in healthy children [25]. The Bland-Altman method was utilized to compare the total time spent in each posture or movement type as determined by both the accelerometers and video observation [26].

3. Results

All twelve participants completed the protocol as prescribed, with complete acceleration traces acquired for eleven subjects (Figure 2). For one individual, the waist accelerometer came loose during the laying down transitions, and therefore all subsequent analyses during the first protocol for this subject were not utilized.

3.1 Reliability

The total time to complete the first protocol averaged 359 ± 42 seconds, with further discrimination of movement demonstrating only slight differences between the two observers for most postures (Table 2). Reliability of video observation was high, with ICC values greater than 0.95 for all postures and activity, except for transitions. Video identification of transition had ICC values of 0.47, indicating differences between the two raters in identifying lying to lying, upright to lying, lying to upright, sit-to-stand, and stand-to-sit transitions. All further analyses were performed comparing accelerometer identification to a single observer.

3.2 Validity

Only the waist accelerometer was required to accurately detect onset of movement. The addition of the thigh monitor allowed for identification of sitting postures. The current algorithm did not provide a means for discriminating stair climbing from level walking. The results of a second-by-second comparison of accelerometer data to rater identification of different tasks demonstrated median sensitivities above 98% for static orientations of sitting and lying down (Figure 3A). A greater number of false positives were detected for standing, as accelerometers categorized fidgeting while standing as movement, with the identification of standing having sensitivity values of 86%. Among dynamic orientations, walking and jogging were accurately identified, with median sensitivities of greater than 96%. Second-by-second transition identification demonstrated a median sensitivity of 87%. Average positive predictive values were greater than 80% for all static and dynamic orientations, except for standing and transitions (Figure 3B). Transitions demonstrated the lowest positive predictive values, with an median value of 71%. When fidgeting tasks were excluded, the positive predictive values of static standing and transitions increased to 85%.

The false positive lying orientations that were incorrectly identified by the accelerometer occurred during the fidgeting while sitting task, as individuals would orient themselves such that the waist accelerometer assumed a supine lying stature. False negatives occurred at the beginning or end of the lying tasks, with the accelerometer identifying these seconds as transitional. Among the lying positions, supine, prone, left or right lying orientations were correctly identified at greater than 98% sensitivity and 94% PPV across all subjects.

The amount of time spent in each static or dynamic task demonstrated substantial agreement, when utilizing the Bland-Altman method to compare the accelerometer to video observation (Figure 4). Larger differences were demonstrated for standing, once again reflective of interpretation in the fidgeting tasks. Transition times were often identified as different static or dynamic task at the start or end of some tasks resulting in greater discrepancy during these seconds of transition. Additionally, waist accelerations did not reach the predetermined threshold for jogging in one individual. By jogging and walking at similar speeds, incorrect identification of the jogging task led to a single subject falling outside the 1.96 SD range for both movements. Among transitional standing tasks, individuals often took small steps, turns or other slight movements as they awaited instruction. While video observation listed these fidgeting seconds as static standing, the accelerometer would identify these times as activity if the SMA reached the predetermined threshold.

Utilizing a combination of SMA and wavelet transform thresholds, walking was accurately detected at speeds ranging from 0.1 and 4.8 m/s (Figure 5). Most discrepancies occurred at the endpoint seconds of activity segments, thereby reducing the sensitivity of faster walking segments which were completed in a short duration. During the outlier trials, subjects additionally performed stutter steps at the beginning of the trial, with investigators not identifying these seconds as movement.

4. Discussion

The purpose of this study was to develop and validate an algorithm using accelerometers to classify static postures and dynamic movement. Additionally, accuracy of these devices to recognize movement was quantified over a range of tasks, gait velocities, and realistic daily activity such as fidgeting while sitting and standing. Utilizing two accelerometers allowed for accurate assessment of static and dynamic orientations. Tri-axial accelerometers attached to the waist and thigh can therefore be utilized to accurately track individuals in the free-living environment. The ability to identify movement at slow velocities below 1.0 m/s can allow for accurate detection among adults and patients with slow walking velocities [7].

While previous studies have utilized one accelerometer to detect posture and movement [10, 27], the use of a second monitor attached to the thigh can provide greater accuracy in discriminating weight bearing and non-weight bearing activities [28, 29]. Additionally, the use of a 16g accelerometer can allow for proper assessment of an extensive range of daily physical activity, including possible fall event detection [29, 30].

Inter-rater reliability was almost perfect, with ICC values greater than 0.92, when comparing all video observations except for poor reliability during transitions between postures or activities. ICC values for standing, sitting and walking are comparable to previous results, in which walking, sitting, standing, and lying ICCs were found to be 0.95, 0.78, 0.99 and 0.98, respectively [10, 31]. Inter-rater reliability of transitions has not been previously reported. Discrepancies between observers occurred due to differences in the frame selection at the beginning or end of postures. Rater selection of transition times was therefore variable. Since the variance and length of time spent in transition was small, the ICC values also became smaller with any differences observed [32]. Variable observer identification can therefore affect accuracy values for posture and movement.

While incorrect identification of movement and posture could lead to under- or overestimation of intervention efficacy among clinical populations, the current algorithm demonstrated a valid detection of movement and posture. Among the subjects tested, median sensitivity and positive predictive values of static posture, walking, and jogging classification was greater than 85%.

These results are superior to or similar to those previously reported for other accelerometer based activity monitors [16, 21, 33], where walking, standing, sitting and lying demonstrating agreement ranging from 65.1–98.9% during a fixed protocol and 68.3–85.9% in the home environment [10]. While average sensitivities across subjects were adequate, some subjects demonstrated reduced sensitivity during the standing posture. For these subjects, fidgeting during stance and imprecise monitor placement due to body habitus resulted in decreased accuracy of the accelerometer identification. Subjects were asked to don the waist monitor below the navel, and discrepancies in the vertical orientation of the monitor produced tilt angles of greater than 0 degrees when standing upright due to excessive adipose tissue. When standing, lying or sitting, these angles often became exaggerated, with incorrect identification of the static orientation occurring across several seconds.

The use of SMA to distinguish walking from other activity has demonstrated good sensitivity and specificity [20]. While such analysis has previously been utilized to detect movement during self-selected walking speeds of healthy adults, it cannot accurately recognize movement among slower walking adults. By using wavelet transforms, the ability to identify slow walking is additionally accomplished in this study, with high accuracy down to 0.1m/s. By detecting slow gait velocities, it becomes possible to accurately quantify walking in older adults and patients. No studies to our knowledge have investigated walking detection at slow gait velocities, though high accuracy of step counting has been reported for speeds between 0.90m/s and 1.84m/s when walking over ground and on a treadmill [34]. Investigating slow walking speed is of clinical importance, as of those older adults who walk at less than 0.25 m/s, only 36% are independent in all ADL functions [7]. Increasing gait velocity beyond 0.55 m/s increases ADL functionality, with adults walking faster than 1.0 m/s demonstrating good functional status and better survival rates [7, 8, 35].

Distinguishing higher physical activity such as jogging was further enabled in this study using the SMA threshold of 0.80 g. This threshold allowed for accurate detection and discrimination between walking and jogging. A previous study that utilized the ratio of the unfiltered to filtered acceleration as well as the filtered vertical to filtered horizontal accelerations at the waist demonstrated the ability to discriminate locomotive tasks from household tasks [27], but identification of walking, jogging, and stair climbing activities was not demonstrated.

Any inaccuracy in classification of standing, sitting, and walking was due to fidgeting tasks, window size resolution, and task duration. All subjects were asked to perform sitting and standing tasks for approximately 15 seconds while fidgeting to recreate motions produced by individuals when fidgeting at the desk or while standing. Such high frequency, short-duration walking behavior was previously demonstrated by nondisabled adults over the course of a 2-week period [36]. While some subjects in our study voluntarily moved only slightly, greater motions resulted in reduced sensitivities for some subjects. When assessing non-fidgeting sitting and standing tasks, classification accuracy increased beyond 85%. Not including fidgeting tasks, classification errors occurred only at the beginning or end of each activity. These differences can be attributed to segmentation of both the accelerometer and video data to one second windows.

Greater resolution in window size would presumably provide even greater accuracy. Mathie and colleagues suggested window width around one second, consistent with the timescale of human movement, though a smaller window size might provide added optimization [19]. In our study, certain transitions and standing activities were observed to take under 1 second during video analysis. Such quick activity might have added to the errors seen in the transitional periods.

The duration of the tasks in this study was limited to between 15–30 seconds per segment. With longer duration tasks, greater accuracy can be achieved, as misclassification commonly occurs during the one second at the beginning or end of a task. Greater accuracy is expected for long duration postures using the current algorithm, with studies demonstrating an accuracy of 80% for longer duration tasks in both the laboratory and home environment setting [10, 33]. In a previous study investigating posture in elderly adults over the course of 4 days, accuracy of sitting, standing and lying was found to be 92%, 98%, and 95%, respectively, using 1 minute windows [33]. The use of fidgeting, slower walking speeds in this study, and the ability to accurately identify movement in all subjects allows for a robust algorithm. As 40% of walking bouts last 12 steps or fewer [36], fidgeting and short duration tasks were of importance in this study. While longer duration tasks allow for greater accuracy, short duration tasks typically seen in the free-living environment could lead to reduced accuracy. While other authors have further discounted movement that lasted less than 5 seconds [12], all transitions and short duration movements were included in the current analysis.

A limitation of this study is the current inability to differentiate stair climbing from level walking. While further analysis will investigate the differences in these two tasks, it is noted that subjects in the current study were ambulating at similar speeds when walking and stair climbing, with upright locomotion activity properly identified. A second limitation is the lower accuracy in detecting transitions. While identification was poorer for this activity, sensitivity and PPV results still exceed 70%. Utilizing video observation as a gold standard can also be subjective and error prone, as demonstrated by discrepancies in identifying transitions between raters.

While accelerometer based identification utilizes objective measures, raters often identify end points of posture and motion inconsistently, resulting in many of the inaccurate findings throughout the study. While validation was performed in a laboratory setting, the algorithm will be further tested for real-time processing in a free-living environment. The strength of this study is in the inclusion of a range of body types (BMI range of 19.9 to 40.1 kg/m^2) with a less constrained testing procedure that includes more natural movements, such as fidgeting during static postures, and a range of gait speeds.

5. Conclusion

Results of this study suggest that the use of accelerometers can accurately detect static postures and dynamic movement among the general population. The ability to identify static and dynamic tasks as well as at a range of gait velocities can allow for accurate classification of all adults in the home living environment.

Acknowledgments

The body-worn motion detection and recording units were provided by Dr. Barry K. Gilbert, James E. Bublitz, Kevin J. Buchs, Charles A. Burfield, Christopher L. Felton, Dr. Clifton R. Haider, Michael J. Lorsung, Shaun M. Schreiber, Steven J. Schuster, and Daniel J. Schwab from the Special Purpose Processor Development Group at Mayo Clinic. The information or content and conclusions do not necessarily represent the official position of, nor should any official endorsement be inferred by the National Institutes of Health, the United States Navy, the Department of Defense, or the U.S. Government.

Funding: Funding for this study was provided by NIH T32 HD07447, NIH K12 HD065987, and DOD DM090896.

References

1. Oliver M, Schofield GM, Badland HM, Shepherd J. Utility of accelerometer thresholds for classifying sitting in office workers. Prev Med. 2010; 51:357–60. [PubMed: 20816693]
2. Kang DW, Choi JS, Lee JW, Chung SC, Park SJ, Tack GR. Real-time elderly activity monitoring system based on a tri-axial accelerometer. Disabil Rehabil. 2010; 5:247–53.
3. Yang CC, Hsu YL. Development of a wearable motion detector for telemonitoring and real-time identification of physical activity. Telemed J E-Health. 2009; 15:62–72. [PubMed: 19199849]
4. Salarian A, Russmann H, Vingerhoets FJG, Burkhard PR, Aminian K. Ambulatory monitoring of physical activities in patients with Parkinson's disease. IEEE T Bio-Med Eng. 2007; 54:2296–9.
5. Morlock M, Schneider E, Bluhm A, Vollmer M, Bergmann G, Müller V, et al. Duration and frequency of every day activities in total hip patients. J Biomech. 2001; 34:873–81. [PubMed: 11410171]
6. Farr JN, Going SB, Lohman TG, Rankin L, Kasle S, Cornett M, et al. Physical activity levels in patients with early knee osteoarthritis measured by accelerometry. Arthrit Care Res. 2008; 59:1229–36.
7. Hardy SE, Perera S, Roumani YF, Chandler JM, Studenski SA. Improvement in usual gait speed predicts better survival in older adults. J Am Geriatr Soc. 2007; 55:1727–34. [PubMed: 17916121]
8. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, et al. Gait speed and survival in older adults. JAMA-J Am Med Assoc. 2011; 305:50–8.
9. Zhang K, Werner P, Sun M, Pi-Sunyer FX, Boozer CN. Measurement of human daily physical activity. Obesity. 2003; 11:33–40.
10. Dijkstra B, Kamsma Y, Zijlstra W. Detection of gait and postures using a miniaturised triaxial accelerometer-based system: Accuracy in community-dwelling older adults. Age Ageing. 2010; 39:259–62. [PubMed: 20083616]
11. Godfrey A, Culhane K, Lyons G. Comparison of the performance of the activPAL™ Professional physical activity logger to a discrete accelerometer-based activity monitor. Med Eng Phys. 2007; 29:930–4. [PubMed: 17134934]
12. Bussmann JB, Martens WL, Tulen JH, Schasfoort FC, van den Berg-Emons HJ, Stam HJ. Measuring daily behavior using ambulatory accelerometry: the Activity Monitor. Behav Res Methods. 2001; 33:349–56.
13. Allen FR, Ambikairajah E, Lovell NH, Celler BG. Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models. Physiol Meas. 2006; 27:935. [PubMed: 16951454]
14. Godfrey A, Bourke A, Ólaighin G, van de Ven P, Nelson J. Activity classification using a single chest mounted tri-axial accelerometer. Med Eng Phys. 2011; 33:1127–35. [PubMed: 21636308]

15. Najafi B, Aminian K, Paraschiv-Ionescu A, Loew F, Bula CJ, Robert P. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. IEEE T Bio-Med Eng. 2003; 50:711–23.
16. Karantonis DM, Narayanan MR, Mathie M, Lovell NH, Celler BG. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE T Inf Technol B. 2006; 10:156–67.
17. Bidargaddi, N.; Sarela, A.; Boyle, J.; Cheung, V.; Karunanithi, M.; Klingbei, L., et al. Wavelet based approach for posture transition estimation using a waist worn accelerometer. Engineering in Medicine and Biology Society 2007; EMBS 2007 29th Annual International Conference of the IEEE: IEEE; 2007. p. 1884-7.
18. Nyan M, Tay F, Seah K, Sitoh Y. Classification of gait patterns in the time–frequency domain. Journal of biomechanics. 2006; 39:2647–56. [PubMed: 16212968]
19. Mathie MJ, Coster AC, Lovell NH, Celler BG. Detection of daily physical activities using a triaxial accelerometer. Med Biol Eng Comput. 2003; 41:296–301. [PubMed: 12803294]
20. Bidargaddi, N.; Sarela, A.; Klingbeil, L.; Karunanithi, M. Detecting walking activity in cardiac rehabilitation by using accelerometer. 3rd International Conference on Intelligent Sensors, Sensor Networks and Information Processing; Melbourne (Australia): IEEE; 2007. p. 555-60.
21. Lyons GM, Culhane KM, Hilton D, Grace PA, Lyons D. A description of an accelerometer-based mobility monitoring technique. Med Eng Phys. 2005; 27:497–504. [PubMed: 15990066]
22. McGraw KO, Wong S. Forming inferences about some intraclass correlation coefficients. Psychol Methods. 1996; 1:30–46.
23. Fortune E, Lugade V, Morrow M, Kaufman K. Validity of Human Movement Using TriAxial Accelerometers - Part II: Step Counts at Wide Range of Gait Velocities. Med Eng Phys. In Submission.
24. Landis JR, Koch GG. The measurement of observer agreement for categorical data. Biometrics. 1977:159–74. [PubMed: 843571]
25. Ridgers ND, Salmon J, Ridley K, O'Connell E, Arundell L, Timperio A. Agreement between activPAL and ActiGraph for assessing children's sedentary time. Int J Behav Nutr Phys Act. 2012; 9:15. [PubMed: 22340137]
26. Bland JM, Altman DG. Measuring agreement in method comparison studies. Stat Methods Med Res. 1999; 8:135–60. [PubMed: 10501650]
27. Oshima Y, Kawaguchi K, Tanaka S, Ohkawara K, Hikihara Y, Ishikawa-Takata K, et al. Classifying household and locomotive activities using a triaxial accelerometer. Gait Posture. 2010; 31:370–4. [PubMed: 20138524]
28. Godfrey A, Conway R, Meagher D, ÓLaighin G. Direct measurement of human movement by accelerometry. Med Eng Phys. 2008; 30:1364–86. [PubMed: 18996729]
29. Mathie MJ, Coster ACF, Lovell NH, Celler BG. Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. Physiol Meas. 2004; 25:R1–R20. [PubMed: 15132305]
30. Bouten CVC, Koekkoek KTM, Verduin M, Kodde R, Janssen JD. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE T Bio-Med Eng. 1997; 44:136–47.
31. Grant PM, Ryan CG, Tigbe WW, Granat MH. The validation of a novel activity monitor in the measurement of posture and motion during everyday activities. Brit J Sport Med. 2006; 40:992–7.
32. Rankin G, Stokes M. Reliability of assessment tools in rehabilitation: an illustration of appropriate statistical analyses. Clin Rehabil. 1998; 12:187–99. [PubMed: 9688034]
33. Culhane K, Lyons G, Hilton D, Grace P, Lyons D. Long-term mobility monitoring of older adults using accelerometers in a clinical environment. Clin Rehabil. 2004; 18:335–43. [PubMed: 15137565]
34. Ryan CG, Grant PM, Tigbe WW, Granat MH. The validity and reliability of a novel activity monitor as a measure of walking. Brit J Sport Med. 2006; 40:779–84.
35. Potter JM, Evans AL, Duncan G. Gait speed and activities of daily living function in geriatric patients. Arch Phys Med Rehab. 1995; 76:997–9.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

36. Orendurff MS, Schoen JA, Bernatz GC, Segal AD, Klute GK. How humans walk: bout duration, steps per bout, and rest duration. J Rehabil Res Dev. 2008; 45:1077–89. [PubMed: 19165696]

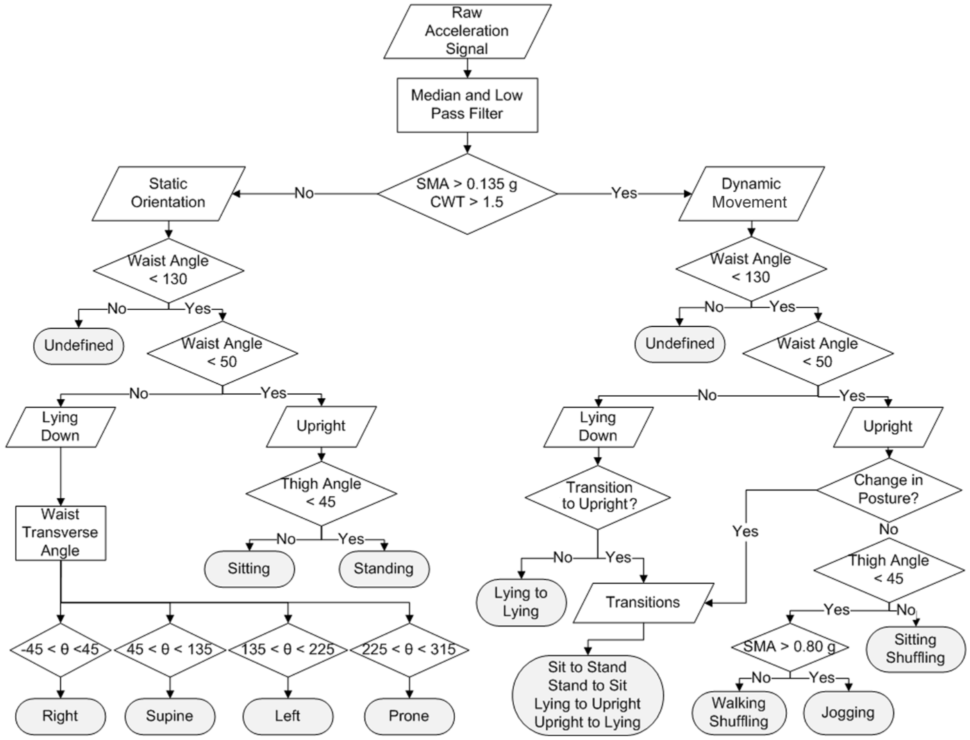

Figure 1.
Decision algorithm for the possible posture and activity classifications determined from the accelerometer data. SMA refers to the signal magnitude area and CWT to the continuous wavelet transform.

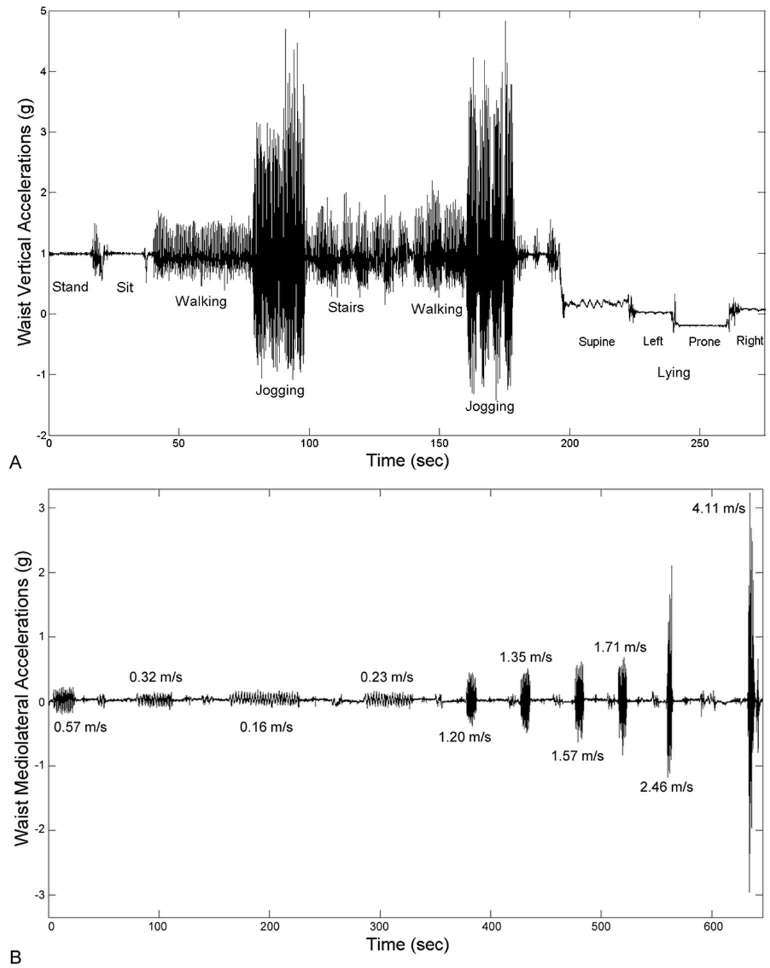

Figure 2.
Sample data of the waist accelerations ($g = 9.81$ m/s^2) collected for a subject while performing a series of tasks (A) and walking at a range of gait speeds (B).

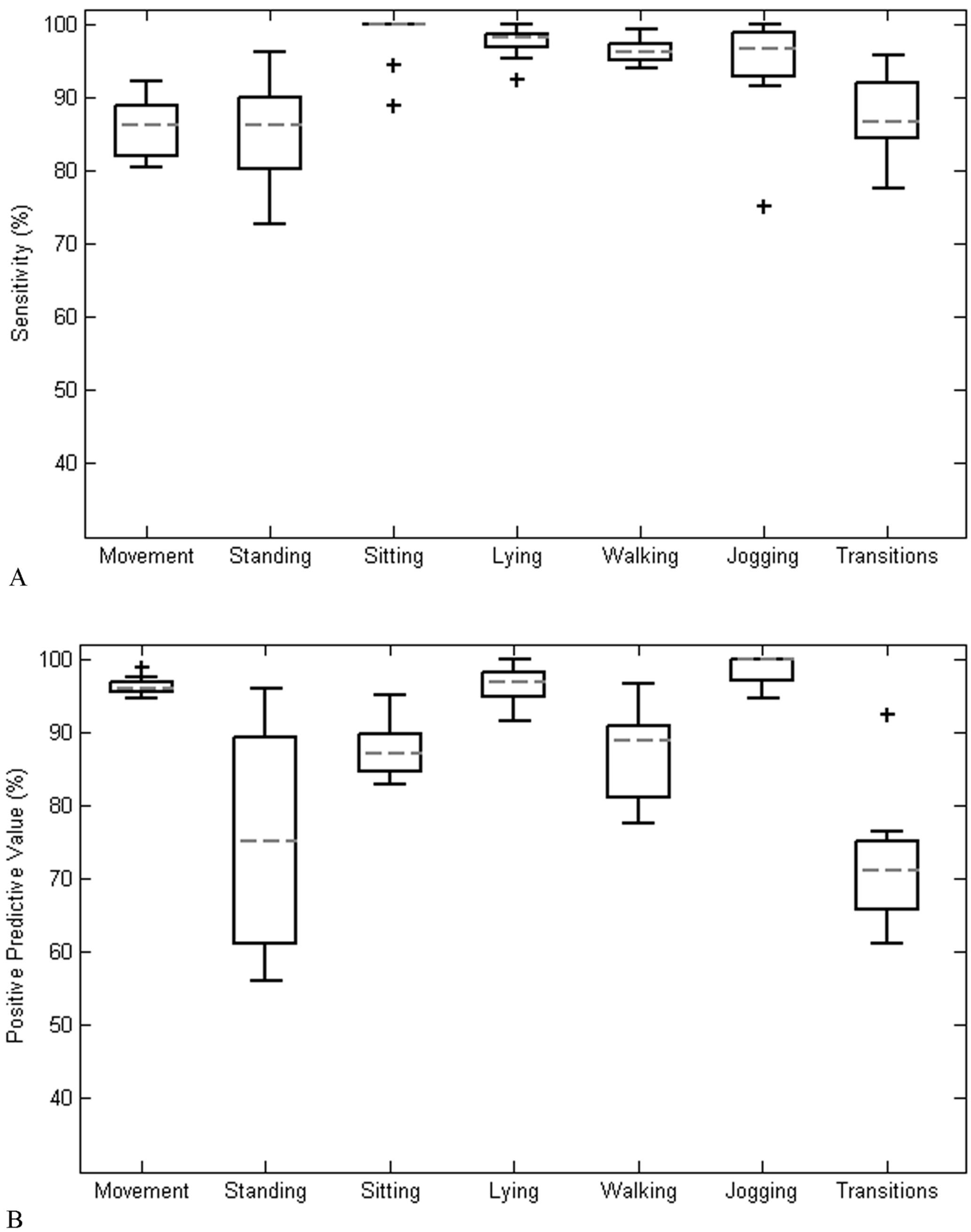

Figure 3.

Sensitivity (A) and positive predictive value (B) when identifying static orientations and dynamic movements with accelerometer data compared to video identification among all subjects. The central line represents the median, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to ± 1.5 of the interquartile range. Outliers beyond this range are labeled as +. For the PPV of jogging, the median value is equal to 100%.

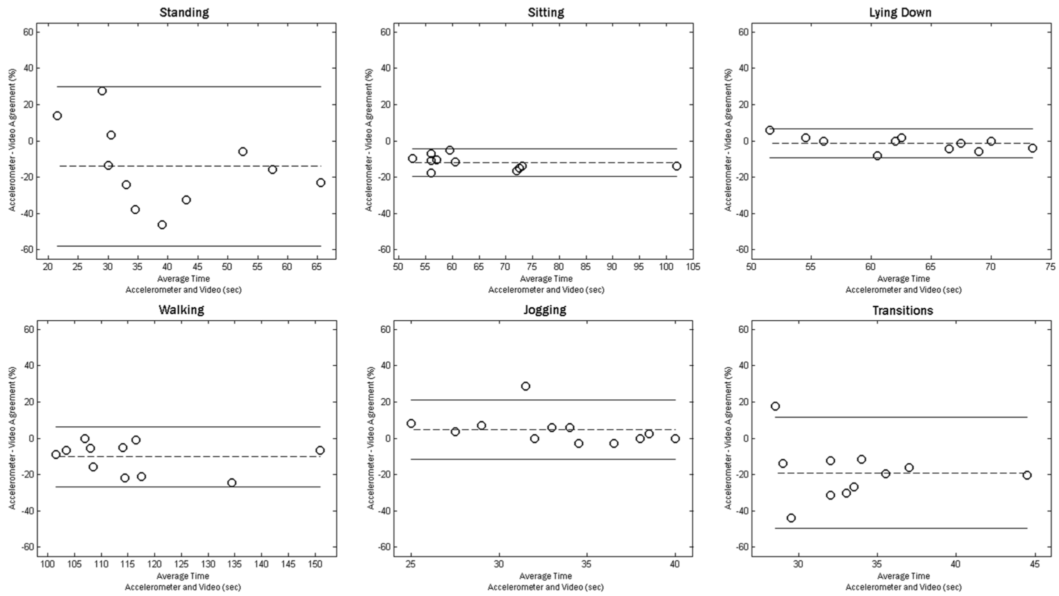

Figure 4.
Bland-Altman plots demonstrating error in identifying each of the static and dynamic activities when using accelerometer compared to video identification. The data for each of the 12 subjects studied includes fidgeting while sitting or standing. The dashed line is the average, while the solid lines represent the repeatability coefficient (± 1.96 SD).

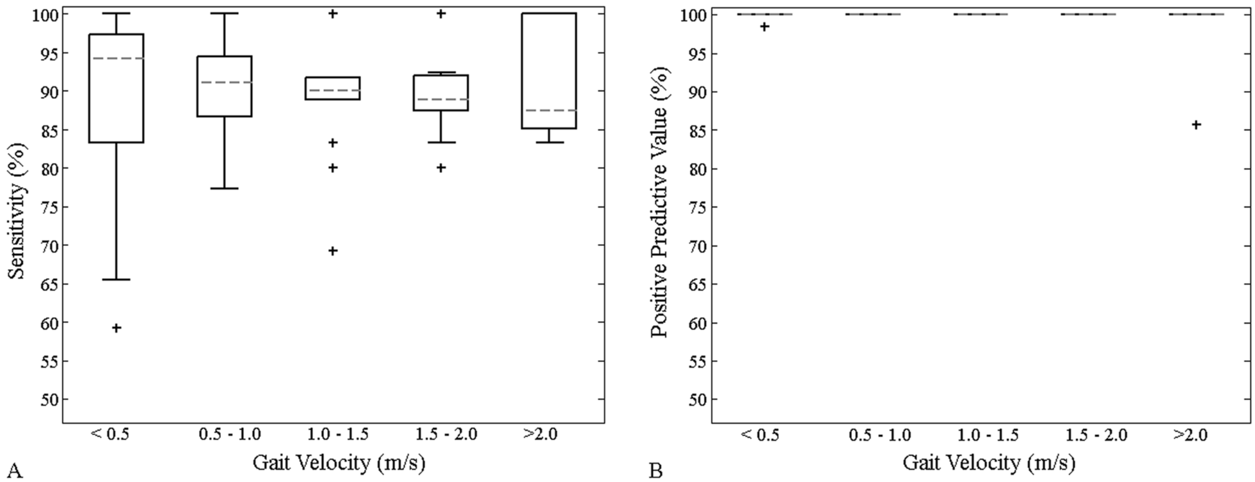

Figure 5.
Boxplot of activity detection when walking at a range of gait velocities. The median sensitivity (A) was greater than 84% and the median PPV (B) 100% at all velocities. The central line represents the median, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to ± 1.5 of the interquartile range. Outliers beyond this range are labeled as +.

Table 1

Tasks used for validation of acceleration classification.

Task	Description	Duration (sec)
	First Protocol - Static and Dynamic Tasks	
Jumping	Perform three consecutive standing jumps	5
Quiet Standing	Subject stands on two feet	15
Quiet Sitting	Subject sits down in a chair and remains seated	15
Walking	Subject stands up and walks at a self-selected pace	30
Jogging	Subject jogs at a self-selected pace	20
Stair Climbing	Subject walks up and down a 7 step staircase	30
Walking	Subject walks at a self-selected pace	20
Jogging	Subject jogs at a self-selected pace	15
Lying Down	Subject lies down supine, left, prone and right for 15 seconds each	60
Quiet Sitting	Subject sits on the floor cross-legged or straight-legged	15
Standing	Subject stands up and is asked to sway/shuffle feet slightly	15
Sitting	Subject sits in a chair and fidgets legs and arms as if working at a desk	15
	Second Protocol - Walking Speeds	
Walking	Subject asked to walk across a 10 meter walkway at self-selected slow, comfortable, and fast walking speeds.	600

Table 2

Duration spent in each task and the intraclass correlation coefficient (ICC) for two raters.

Task	Rater 1 [a] (Sec)	Rater 2 [a] (sec)	ICC [b]
Dynamic Movement[c]	175 (18)	178 (18)	0.96 (0.80, 0.99)
Walking	109 (13)	107 (13)	0.95 (0.82, 0.99)
Jogging	34 (4)	35 (5)	0.94 (0.55, 0.99)
Transitions	31 (5)	34 (7)	0.47 (−0.04, 0.80)
Standing	57 (13)	56 (13)	0.96 (0.86, 0.99)
Sitting	61 (13)	61 (13)	1.00 (0.99, 1.00)
Lying	63 (6)	61 (6)	0.92 (0.65, 0.98)

[a]Values provided are the mean and standard deviation

[b]Values provided are the ICC(A,1) along with the lower and upper bounds for the 95% confidence interval.(McGraw and Wong, 1996)

[c]Dynamic movement included walking, jogging and transitions.