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Validity of using tri-axial accelerometers to measure human movement—Part I: Posture and movement detection

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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 0.1 m/s and 4.8 m/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.

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

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Table 1
Tasks used for validation of acceleration classification.

Task	Description	Duration (s)
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 s 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 m walkway at self-selected slow, comfortable, and fast walking speeds.	600

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 min 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 m walkway at 7–10 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 g with dimensions of 4.7 cm × 2.8 cm × 1.2 cm, 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 (Fig. 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