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Analysis of dual-task elderly gait in fallers and non-fallers using wearable sensors

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ABSTRACT

Dual-task (DT) gait involves walking while simultaneously performing an attention-demanding task and can be used to identify impaired gait or executive function in older adults. Advancment is needed in techniques that quantify the influence of dual tasking to improve predictive and diagnostic potential. This study investigated the viability of wearable sensor measures to identify DT gait changes in older adults and distinguish between elderly fallers and non-fallers. A convenience sample of 100 older individuals (75.5 ± 6.7 years; 76 non-fallers, 24 fallers based on 6 month retrospective fall occurrence) walked 7.62 m under single-task (ST) and DT conditions while wearing pressure-sensing insoles and tri-axial accelerometers at the head, pelvis, and left and right shanks. Differences between ST and DT gait were identified for temporal measures, acceleration descriptive statistics, Fast Fourier Transform (FFT) quartiles, ratio of even to odd harmonics, center of pressure (CoP) stance path coefficient of variation, and deviations to expected CoP stance path. Increased posterior CoP stance path deviations, increased coefficient of variation, decreased FFT quartiles, and decreased ratio of even to odd harmonics suggested increased DT gait variability. Decreased gait velocity and decreased acceleration standard deviations (SD) at the pelvis and shanks could represent compensatory gait strategies that maintain stability. Differences in acceleration between fallers and non-fallers in head posterior SD and pelvis AP ratio of even to odd harmonics during ST, and pelvis vertical maximum Lyapunov exponent during DT gait were identified. Wearable-sensor-based DT gait assessments could be used in point-of-care environments to identify gait deficits.

1. Introduction

Dynamic stability is a property of a body that causes it when disturbed from a condition of equilibrium or steady motion to develop forces or moments that restore the original conditions. During walking, an individual must control center of mass displacements with respect to a changing base of support (Priest et al., 2008), using sensorimotor and cognitive processes (Woollacott and Shumway-Cook, 2002), particularly executive function and attention (Hsu et al., 2012; Ijmker and Lamoth, 2012). Links between impaired executive function, mobility control issues, and increased fall risk can be revealed during dual-task (DT) walking (Ijmker and Lamoth, 2012; Lamoth et al., 2011; Hausdorff et al., 2008; Montero-Odasso et al., 2014).

DT gait involves walking while performing an attention-demanding task, often verbal or mathematical. In older adults, DT gait can result in reduced walking speed (Lamoth et al., 2011; Hausdorff et al., 2008; Montero-Odasso et al., 2014; Hollman et al., 2007; Bock and Beurskens, 2011a,2011b; Oh-Park et al., 2013; Springer et al., 2006; van Iersel et al., 2008; Wild et al., 2013), stride frequency (Lamoth et al., 2011), and center of force stance velocity (Howcroft et al., 2014); increased percentage of missteps (Krampe et al., 2011), step duration (Bock and Beurskens, 2011a), stride time (Lamoth et al., 2011), stance time (Wild et al., 2013; Howcroft et al., 2014); increased (Wild et al., 2013; Howcroft et al., 2014) or decreased (Hausdorff et al., 2008; Springer et al., 2006) swing time; increased variability for swing time (Hausdorff et al., 2008; Springer et al., 2006), stride-to-stride gait velocity (Hollman et al., 2007), stride time (Lamoth et al., 2011; van Iersel et al., 2008), stride length (van Iersel et al., 2008), and phase variability index (Lamoth et al., 2011); decreased root mean square and peak anterior–posterior (AP) and medial–lateral (ML) trunk accelerations (Lamoth et al., 2011); and increased local stability exponent

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for AP and ML trunk accelerations (Lamoth et al., 2011), and sample entropy for AP trunk accelerations (Lamoth et al., 2011). The attention demanding task could also be disrupted during the DT (Beauchet et al., 2009).

Opinions are mixed regarding DT potential for predicting future falls or diagnosing underlying problems (Menant et al., 2014; Zijlstra et al., 2008). Some DT measures for differentiating elderly fallers from non-fallers are lower gait speed (Faulkner et al., 2007; Verghese et al., 2002; Beauchet et al., 2008a), and higher swing (Springer et al., 2006; Herman et al., 2010) and stride (Kressig et al., 2008) time variability. However, other studies found no fall prediction improvement after adding a second task (Beauchet et al., 2008b; Bootsma-van der Wiel et al., 2003). Individuals tend to prioritize motor tasks over cognitive tasks in a DT scenario (Oh-Park et al., 2013; Wild et al., 2013), but prioritization across participants can vary and negatively impact fall risk prediction. In addition, task selection and standardization (both cognitive and walking tasks) can impact DT cost (percent difference between single and dual task performance) (Menant et al., 2014). The inability of some studies to improve faller identification with a DT assessment suggests a need for further examination of factors such as: task standardization, selection and quantification of cognitive task performance, and selection and refinement of gait measures. The current study focussed on the latter, examining gait measures to better reveal gait changes associated with DT performance. A primary determinant of DT cost may be dynamic stability control, with impaired control causing greater attentional demand and greater DT cost. Measures associated with dynamic stability control may be more sensitive to DT gait changes.

Wearable sensors enable point-of-care gait assessments that can be easily and quickly implemented in clinical care and older-adult living environments. Inertial wearable sensors (Lamoth et al., 2011; Bock and Beurskens, 2011a,2011b; Howcroft et al., 2014) and force-sensing insoles (Hausdorff et al., 2008; Springer et al., 2006; Herman et al., 2010) have been successfully used to detect elderly-gait changes between single task (ST) and DT walking. In these studies, inertial sensors were applied to the lower leg (Bock and Beurskens, 2011a,2011b), head (Bock and Beurskens, 2011a), lower back (Howcroft et al., 2014), and trunk (Lamoth et al., 2011), but only Bock and Beurskens (2011a) assessed movement using more than one inertial sensor. Multiple inertial sensors, including the lower back location since it approximates the body center of mass (Howcroft et al., 2013), would allow a more complete movement assessment.

Relevant parameters must be extracted from the sensor signals. Lamoth et al. (2011) and Howcroft et al. (2014) found non-temporal, acceleration-based changes under DT conditions in older adults; however, most wearable-sensor-derived measures for DT walking have been temporal. A complete assessment should include non-temporal and temporal measures, to potentially identify non-temporal gait changes associated with movement frequency, abnormal body segment movements, and abnormal movement in a particular direction. Gait variability has been associated with dynamic stability control and has been used to successfully identify differences between fallers and non-fallers under DT conditions (Springer et al., 2006; Herman et al., 2010; Kressig et al., 2008).

The current study expands on previous research by exploring new non-temporal measures and advancing gait variability investigation using wearable plantar pressure sensors and tri-axial accelerometers at multiple locations, during DT walking for elderly fallers and non-fallers. Such multifaceted gait-characteristic differentiation could lead to better identification of dynamic stability control impairment during DT walking and distinguish between elderly fallers and non-fallers. The objectives of this study were to use wearable sensors to: (1) detect gait differences between fallers and non-fallers for ST walking, (2) detect gait differences between fallers and non-fallers for DT walking, (3) detect differences between ST and DT walking for fallers, and (4) detect differences between ST and DT walking for non-fallers.

2. Methods

2.1. Participants

A convenience sample of 100 people, 65 years or older, were recruited from the community (Table 1). Participants were identified as fallers if they reported at least one fall during the six months prior to study participation. Falls were defined as an event that results in a person coming to rest unintentionally on the ground or other lower level, excluding falls resulting from a stroke or overwhelming hazard (Tinetti et al., 1988). Participants were excluded if they had a cognitive disorder (self-reported) or were unable to walk for six minutes without an assistive device. The University of Waterloo Research Ethics Committee approved the study and all participants gave informed written consent.

2.2. Protocol

Participants reported six month retrospective fall occurrence, age, and sex. Body weight and height were measured.

Pressure-sensing insoles (F-Scan 3000E, Tekscan, Boston, MA) were equilibrated using multi-point calibration (137.9, 275.8, and 413.7 kPa), fit to the shoes, and calibrated. Accelerometers (X16-1C, Gulf Coast Data Concepts, Waveland, MS) were attached to the posterior head with a band, posterior pelvis with a belt, and lateral shank, just above the ankle, with a band. Plantar pressure data were collected at 120 Hz and accelerometer data at 50 Hz. Participants completed a 7.62 m walk with and without a cognitive load with completion times recorded via a stopwatch. Participants started walking approximately 1 m before the start of the 7.62 m course and stopped walking approximately 1 m after the end of the course. These 1 m distances allowed for participant acceleration and deceleration and were excluded from analysis. The cognitive load was a verbal word fluency task requiring the participants to say words starting with A, F, or S (Rende et al., 2002). The starting letter and order of walking activities were randomized.

2.3. Data processing

Gait velocities for ST and DT trials were calculated as 7.62 m divided by the stopwatch recorded time. The positive vertical accelerometer axis was upwards, positive AP axis anterior, and positive ML axis toward the participant's right. Plantar-pressure and accelerometer data were exported to Matlab v2010a to calculate outcome variables:

- **Center of Pressure (CoP) path**:
  a. Number, length, and duration of posterior deviations (PD) per stance phase. Since the CoP path should advance monotonically and anteriorly, posterior CoP path movements were identified as irregular.
  b. Number, length, and duration of ML path deviations per stance: first derivative of the CoP ML signal exceeding a dual threshold of ± 0.5 mm/frame (Biswas et al., 2008). Smooth medial and lateral movements were expected.
  c. Minimum, maximum, mean, and median CoP path velocities, normalized by stance time.
  d. AP and ML coefficients of variation (CoV) for the stance phase CoP path: Mean and standard deviation (SD) of CoP path positions at 1% intervals, determined using ensemble averaging (Egret et al., 2003), for the entire

Table 1
Participant characteristics.

	Participants (#)	Age (years)	Height (cm)	Weight (kg)	6MWT (m)
Fallers	13 male, 11 female	76.3 ± 7.0	165.2 ± 10.3	71.9 ± 14.3	446.6 ± 101.4
Non Fallers	31 male, 45 female	75.2 ± 6.6	165.1 ± 9.9	73.1 ± 13.4	455.8 ± 102.4