Turn Detection and Characterization with Inertial Sensors

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1 OBJECTIVES

Turn detection and characterization in the home is important for continuous assessment of gait and balance in people with movement disability. Turning often results in falling in individuals with movement disorders. Researchers and clinicians would benefit from a system that identifies and characterizes their daily mobility behavior to predict their risk of falling, benefits or side effects of treatment, and progression of disease. The goal of this study is to develop an algorithm that is capable of reliably detecting turns during gait with the goal of applying it over long periods outside a lab environment. Performance of the algorithm is validated against an optical marker system and video analysis of a subset of the participants.

2 INTRODUCTION

Turning is ubiquitous during activities of daily living. Nearly every task performed during the day requires some amount of turning (Glaister et al., 2007). However, gait research has focused primarily on straight ahead-walking (Studenski et al., 2003; Ganz et al., 2007). Difficulty turning during gait is a major contributor to mobility disability, falls and reduced quality of life in elderly and in people with movement disorders. Falls during turning are particularly dangerous because they usually result in contact of the femur with the ground, which results in eight times more hip fractures compared with falls during straight-ahead walking (Nevitt et al., 1991; Cumming and Klineberg, 1994; Feldman and Robinovitch, 2007). The ability to modify our locomotor trajectory by turning safely is important for functional independence but surprisingly much more difficult for the nervous system to control than straight-ahead walking.

Objective measures of turning mobility are more sensitive than gait speed or clinical measures of mobility to detect impaired mobility. Our studies have shown that people with movement disability may exhibit abnormal turning characteristics even though they have normal straight-ahead walking (Horak et al., 1992; Salarian et al., 2009; King et al., 2011). We found that turning measures in the clinic, such as turning duration and peak turning velocity, can distinguish between people with movement disorders and healthy age-matched controls, even when clinical measures of balance or gait did not (Spain et al., 2010; Zampieri et al., 2010). Other studies found that measurements of turning discriminate elderly fallers from non-fallers (Dite and Temple, 2002). Researchers have suggested that turning-related neural systems may be more vulnerable to impairments than straight-ahead, linear gait. This is due to the fact that turning involves more interlimb coordination, more coupling between posture and gait, and modifications of locomotor patterns requiring frontal lobe cognitive and executive function that plays a role in postural transitions (King et al., 2012; Herman et al., 2010).

In this study, we develop a new algorithms for initial sensors to detect and analyze a wide variety of types of turning activities performed at different gait speeds in the laboratory. We validate our algorithm using a Motional Analysis system as a gold-standard. As a second method of validating our inertial sensor algorithms for turning, two raters review the videos and annotate the beginning and end times of each turn. In the following sections, we present the algorithm and discuss the results and future work.

3 METHODS

We examined 17 healthy control subjects wearing a set of four Motion Analysis reflective markers and an Opal inertial sensor (APDM Inc.) on the lumbar spine. Opal includes triaxial accelerometers, gyroscopes, and magnetometers and record signal data at 128 Hz. Subjects were instructed to walk on a path composed of a mixed route with short straight segments and turns ranging from 30 to 180 degrees. Each subject performed 12 repetitions: 4 at a slow speed, 4 at a preferred speed, and 4 at a fast speed.

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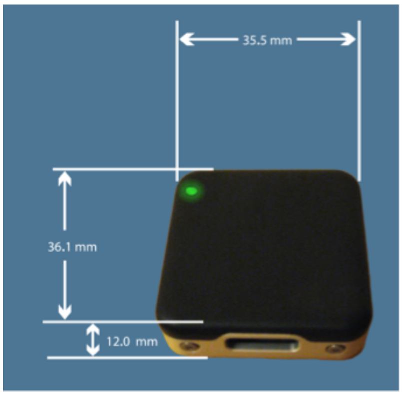

Figure 1: An example of the Opal (APDM Inc.) inertial sensor placed on the lumbar.

For the purpose of turn detection and characterization, the angular rate about the vertical axis (gravity aligned) is an ideal measurement. A three-axis gyroscope is capable of measuring this vertical axis angular velocity, but aligning the sensor and maintaining accurate alignment is difficult. An accelerometer can be used to measure the direction of gravity during a stationary period and then, the gyroscope measurements could be projected on to that axis throughout the trial.

Orientation angles are commonly estimated using sensor fusing, taking advantage of the accelerometer measurement of gravity to correct drift from integration of angular velocity measurements (El-Gohary and McNames, 2012). We take advantage of the orientation estimates to obtain angular velocity about the vertical axis using appropriate transformation. Opal sensor provide orientation estimates, q, in quaternion form and can be used directly to transform body frame sensor measurements into the inertial frame. We transform the angular velocity measurements in the body frame, ω^b, to that in the inertial frame (with x-y-z axes corresponding to magnetic North, East, and Up), ω^i using the following quaternion multiplication.

$$\omega^i = q * \omega^b * q^{-1} \qquad (1)$$

From the inertial frame angular velocity we extract the z component, w_z about the vertical axis. This angular velocity about the vertical axis can be integrated to obtain an estimate of the relative turn angle.

$$\theta_z = \int \omega_z \qquad (2)$$

This turn angle drifts over time due to integration error, but over short time periods is very accurate. The Opal magnetometer could be used to help compensate for this error. However, since only relative angles during short period while turning are of importance for detecting and characterizing turns, the potential drawbacks of being susceptible to magnetic interference from nearby objects outweigh the benefits of using the magnetometer (Bachmann et al., 2004).

The vertical axis angular velocity (ω_z) is lowpass filtered with a 1.5 Hz cutoff frequency Butterworth filter to remove high frequency components. Candidate turns are then detected from segments where this filtered angular velocity is greater than 15 degrees per second. Start and end of each turn are set to the point where the filtered angular velocity drops below 5 degrees per second. The precise cutoff value has little effect on the total turn duration or angle, and is intended to account for a slight bias which could prevent the angular velocity from dropping exactly to zero. It is difficult for humans to make more than a very slight turn with a duration < 0.5 seconds or to complete an extremely slow turn with a duration > 10 seconds, during gait. Therefore, only turns with duration between 0.5 and 10 seconds, with turn angles over 45 degrees are considered. We combine any turns in the same direction separated by a brief pause < 50 milliseconds.

4 RESULTS

Turn detection was performed on the optical Motion Analysis data. In a subset of trials, a standard video was also reviewed by two raters who annotated beginning and end times of turns. Timing accuracy of the turn detection is important for characterizing turn duration, therefore, we use one based on time intervals rather than a turn by turn accuracy comparison. All turn detection metrics were resampled at 128 Hz, and comparison was calculated on a sample by sample basis, rather than by turns,

Table 1 shows sensitivity of the inertial algorithm detecting turns compared to Motion Analysis and video raters. Sensitivity of the inertial algorithm is 0.86 compared with the optical marker algorithm. Similarly, sensitivity for the inertial algorithm is 0.77 compared to both video rater 1 and 2. The optical algorithm has sensitivity of 0.62 and 0.65 with video rater 1 and2 respectively. Video rater 1 has a sensitivity of 0.89 compared with video rater 2.

Table 1: Sensitivity.

	Optical	Video 1	Video 2
Inertial	0.86	0.77	0.77
Optical		0.62	0.65
Video 1			0.89

Table 2 show specificity of the inertial algorithm detecting turns compared to Motion Analysis and

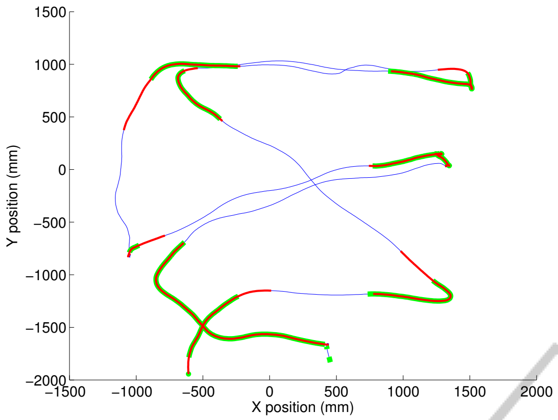

Figure 2: The blue trace is the X-Y position of the center of mass from optical markers. Overlaid in red are the segments detected as turns by the inertial algorithm, and in green the segments detected as turns by the optical algorithm.

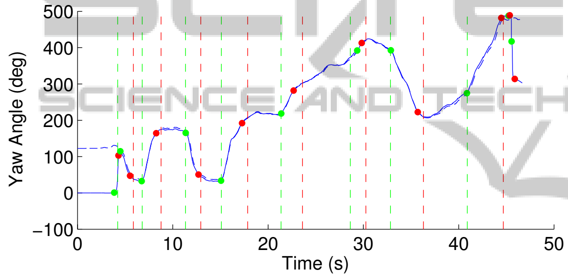

Figure 3: The blue trace is the yaw angle from the optical system. The dashed blue line is relative yaw angle from the inertial algorithm. The dots represent onset (green) and end (red) of turns detected by the optical algorithm. The vertical dashed lines represent onset (green) and end (red) of turns detected by the inertial algorithm.

video raters. Specificity of the inertial algorithm is 0.70, 0.66 and 0.54 with the optical marker algorithm, video rater 1 and 2 respectively. The optical marker algorithm has specificity of 0.77 and 0.68 with video rater 1 and 2. Rater 1 has a specificity of 0.64 compared with video rater 2.

Table 2: Specificity.

	Optical	Video 1	Video 2
Inertial	0.70	0.66	0.54
Optical		0.77	0.69
Video 1			0.64

The number of detected turns for the inertial algorithm averaged 9.6 (sd = 1.4) across all subjects and trials. The algorithm based on optical markers detected an average of 10.4 turns (sd = 3.4). The prescribed pattern had 10 turns larger than 45 degrees, including one pair of 90 degree turns to pick up a basket. Table 3 shows turn metrics detected by the inertial algorithm, including average number of terms, turn peak and mean velocity in degrees per seconds, and turn duration in seconds.

Table 3: Turn metrics.

Metric	Slow (sd)	Normal (sd)	Fast (sd)
# of turns	9.6 (1.1)	9.6 (0.9)	8.3 (1.3)
Peak Vel.	112.2 (16.8)	131.2 (19.4)	169.7 (27.8)
Mean Vel.	56.8 (6.6)	64.0 (8.2)	76.8 (10.7)
Duration (s)	2.2 (0.3)	2.1 (0.3)	2.1 (0.4)

5 DISCUSSION

Turning is ubiquitous during activities of daily living. Nearly every task performed during the day requires some amount of turning (Glaister et al., 2007). However, gait research has focused primarily on straight ahead walking. In this study, we use inertial sensors including gyroscopes and accelerometers to characterize turns during gait. We validated our inertial algorithm using Motional Analysis system and turn data from 2 raters analyzing video recordings of healthy subjects.

Inertial sensors can be used to detect turns during walking at least as well as an optical marker system. Subjects were very inconsistent with the basket turns, with some avoiding it altogether by picking up the basket without any turning at the waist. In this close pattern with the rapid series of turns it is sometimes the case that multiple turns become blended together, where a subject will transition fluidly from one to the next rather than following the line precisely. Both of these factors contribute to variability in the number of detected turns, especially in the fast trials.

Turn detection and characterization in the home is important for continuous assessment of gait and balance in people with movement disability. Asking an individual to execute a turn in a clinical environment often does not reveal their impairments. We hypothesis that we can use the algorithm developed in this study to measure locomotor activities and to distinguish turning characteristics in healthy subjects and individuals with movement disorders, in the home throughout the day, using wearable inertial sensors.

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