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Good agreement between smart device and inertial sensor-based gait parameters during a 6-min walk

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ABSTRACT

Background: Traditional laboratory-based kinetic and kinematic gait analyses are expensive, time-intensive, and impractical for clinical settings. Inertial sensors have gained popularity in gait analysis research and more recently smart devices have been employed to provide quantification of gait. However, no study to date has investigated the agreement between smart device and inertial sensor-based gait parameters during prolonged walking.

Research question: Compare spatiotemporal gait metrics measured with a smart device versus previously validated inertial sensors.

Methods: Twenty neurologically healthy young adults (7 women; age: 25.0 ± 3.7 years; BMI: 23.4 ± 2.9 kg/m^2) performed a 6-min walk test (6MWT) wearing inertial sensors and smart devices to record stride duration, stride length, cadence, and gait speed. Pearson correlations were used to assess associations between spatiotemporal measures from the two devices and agreement between the two methods was assessed with Bland-Altman plots and limits of agreement.

Results: All spatiotemporal gait metrics (stride duration, cadence, stride length and gait speed) showed strong ($r > 0.9$) associations and good agreement between the two devices.

Significance: Smart devices are capable of accurately reflecting many of the spatiotemporal gait metrics of inertial sensors. As the smart devices also accurately reflected individual leg output, future studies may apply this analytical strategy to clinical populations, to identify hallmarks of disability status and disease progression in a more ecologically valid environment.

1. Introduction

Gait is an important clinical biomarker for disease status and quality of life. In many neurological disorders and even healthy aging, the ability to walk is one of the main determinants of disability status and disease progression [1–3]. Self-selected gait speed, and the underlying kinematics that contribute to gait speed such as stride length, are functional vital signs for overall health in a variety of populations [2,4–6]. The ability to extract these features of gait from simple mobility measures is clinically relevant because it enables tracking of disease progression or rehabilitation efficacy.

Traditional kinematic and kinetic gait outcomes are measured using highly accurate lab-based systems such as 3-dimensional motion analysis and force plates [7,8]. However, these systems are impractical for common clinical use because they are often difficult to access and require time intensive procedures, trained personnel, and large spaces. Also, gait laboratories are limited by room size and the use of treadmills, which limits the study of real-world ambulation. Importantly, the expense of these systems further reduces accessibility to gait laboratories.

To move away from laboratory settings, to improve the portability of gait measures, and importantly to reduce costs associated with traditional lab-based systems, body-worn tri-axial accelerometers, or inertial measurement units (IMU) such as the APDM Opal have gained popularity in mobility research [9]. Inertial sensors offer valid and reliable quantification of gait [10,11]. However, even these portable systems can be costly and require significant training, thus limiting access for investigators, educators, and clinicians. Better access to investigators and clinicians therefore presents a potential opportunity to improve quality of care.

Recently, smartphones have been employed to provide quantitative assessments in gait laboratories and clinical settings [12]. The

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smartphone is a ubiquitous and practical platform that can be used to measure acceleration in three axes (x, y, z). The built-in sensors can detect the periodic changes in acceleration during gait cycle transitions. Although research has been conducted assessing the capability of smart devices to accurately measure acceleration during a sit-to-stand [13], timed-up-and-go test [14], or short bouts of walking (≤ 10 m) [15] limited research exists with regard to continuous walking, such as the widely used 6-minute walk test (6MWT). To our knowledge, only Capela et al. [16] compared the distance covered and number of steps assessed with a BlackBerry smartphone application to video during a 2-minute walk test. In a subsequent study, the same authors demonstrated the ability of the smartphone to assess clinically relevant gait metrics during a 6MWT [17]. Despite promising results regarding the accuracy of the smartphones' internal accelerometer, neither study compared the gait metrics analyzed from the smartphone to a validated and reliable gait measurement system and instead used video for comparison. As a consequence, the gait analysis was limited to number of steps, cadence and distance covered, lacking comparisons of other widely used gait variables.

Thus, the purpose of this project was to compare spatiotemporal gait measures as detected by a smart device versus a previously validated and reliable inertial sensor/software system, the APDM Opal wireless inertial sensors in conjunction with APDM Mobility Lab software (Version 2).

2. Methods

Twenty neurologically healthy young adults provided written informed consent and were oriented to the procedures. The procedures were approved by the Colorado State University Institutional Review Board, in accordance with the Declaration of Helsinki.

2.1. Screening

Participants were screened by the same investigator and were excluded if they had any history of a medical condition that would impair cognition or mobility, any injuries or surgeries that would affect their gait within the prior 6 months, any neurological disease, or were outside the ages of 18–35.

2.2. 6-min walk test

Participants wore six wireless inertial sensors (APDM Opal) placed on the sternum, on each wrist, the lower back (at the level of L5), and on the dorsum of each foot. The sensors were attached to the respective body part using elastic straps adjusted to fit snugly and to reduce unwanted movement, but not too tight to be uncomfortable for the participant. The participants also wore two smart devices strapped just proximal to the lateral malleolus using an elastic strap, Velcro, and two smaller reinforcing straps (Fig. 1). Subsequently, participants performed a 6MWT in a linoleum-tiled hallway with floor tape placed 30 m apart. Participants did not wear shoes and were instructed to walk at their self-selected pace and turn as naturally as possible. At the end of the 6MWT total distance covered was recorded based on the number of lengths completed plus the remaining distance.

2.3. APDM Opal

Inertial sensors (Opal, APDM Inc., Portland, OR) have been previously found to provide valid and reliable ($r > 0.9$ for all metrics compared, relative to an instrumented force plate treadmill; intraclass correlation coefficient > 0.9) [10] quantification of mobility measures in healthy and clinical populations [18–21]. The accompanying software, Mobility Lab (Version 2) provides a number of gait metrics including but not limited to: cadence (*steps/min*), gait speed (*m/s*), stride length (*m*), step duration (*s*), and stride duration (*s*).

2.4. Smart device

A smart device (iPod Touch 5th Generation, Apple, Inc., CA), running the Sensor Data application (Wavefront Labs), was used to detect heel strikes. The application continuously sampled tri-axial acceleration from the internal micro electro-mechanical systems (MEMS) accelerometer. All heel strike acceleration peaks during walking were readily visually identifiable and well within the 8 g maximum of the smart device's internal accelerometer. Accelerometer positioning and axes orientation are shown in Fig. 1A.

2.5. Data processing

Upon completion of the 6MWT, the Opal sensors wirelessly streamed data to a laptop using the Mobility Lab software. Wireless sensor data was recorded at a sampling rate of 128 Hz and did not undergo additional processing. Instead, the Mobility Lab software automatically calculated gait metrics. For the smart device, data was sampled via the Sensor Data application at 100 samples/s, saved as a text file, and wirelessly transferred to a computer. Data from the left and right leg smart device was exported separately and then merged (time-aligned) into one Spike 2 (Cambridge Electronic Design Limited, Version 7.18) data file for further analysis.

2.6. Calculation of gait features from smart device data

To calculate the gait variables from the smart device, the peak detection tool in Spike 2 was used to identify and record a time stamp the gait cycle of each leg (Fig. 1B). Detection of peaks was accomplished with user-entered amplitude threshold and time step values. The peak detection tool algorithm automatically detects x-axis acceleration peaks above the threshold after each time step. The threshold and time step values were entered based on brief visual inspection of the data. To ensure accurate algorithm detection of the peak x-axis acceleration (heel strike) of each gait cycle, all data was visually inspected after it was processed. For clearly identifiable peaks which were not detected based on acceleration threshold, a time stamp was manually added. For cases of mistaken peak detection, the time stamp was removed. Manual addition/removal was based on the obvious features of the repetitive gait cycle pattern and typically involved editing of less than 2% of the trial. Previous studies with the Opal sensors have excluded gait cycles before and after a turn [16,22] in order to account for the reduction in gait speed and stride length. We therefore manually removed the two gait cycles associated with a turn from the smart device data to allow for a fair comparison between devices. These gait cycles were not included in the subsequent analysis. Turns were visually identified and confirmed using the pitch derived from the gyroscope. The individual time stamps and their associated gait cycles were carefully visually inspected and exported for analysis.

Stride duration (*s*) was calculated by subtracting the time stamp of one gait cycle from its preceding gait cycle. Step duration was derived by dividing stride duration by two. Based on each individual stride duration, cadence (*steps/min*) was calculated. We divided each individual stride duration by 60 s, calculated the average, and subsequently added both legs to derive cadence. To compare additional gait features to the inertial sensors, we calculated gait speed (distance covered/360 s; *m/s*) independent from the output of the smart device. By multiplying gait speed and mean stride duration, mean stride length (*m*) was derived. The same formulas were applied to produce gait variables for each leg.

2.7. Statistical analysis

All statistical analysis was completed using R software (Rstudio, Boston, MA). Pearson correlations were used to determine the association between cadence, stride length, stride duration and gait speed