THESIS

A SMART-DEVICE BASED MOTOR FUNCTION BATTERY

Submitted by

Patrick G. Monaghan

Department of Health & Exercise Science

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Fall 2018

Master's Committee:

Advisor: Brian L. Tracy

Brett W. Fling
Jaclyn Stephens

ABSTRACT

A SMART-DEVICE BASED MOTOR FUNCTION BATTERY

Growth in the older population will increase the overall impact of age-related neurological disorders. Aging and neurological conditions share features such as impaired motor function and physical dysfunction including reduced muscle strength and power, slowness of movement, increased movement variability and balance dysfunction. Successful performance of daily activities and maintenance of mobility is key to independence and quality of life. Therefore, tracking changes in physical function is critical in gauging quality of life. However truly quantitative measures of physical capacity often require the use of expensive, lab-based equipment. Smart devices contain sensitive tri-axial accelerometers and gyroscopes that measure acceleration and rotation and offer a more cost-effective, portable yet still quantitative means of physical assessment. The purpose is to describe an iPod Touch-instrumented test battery designed to assess features of physical and motor function often shared by normal aging and age-related movement disorders.

We have been assessing the correlation between measures taken from expensive lab devices and the iPod Touch smart device for a variety of movements. We developed and tested a multi-item smart device-based battery of motor tasks that addresses motor variability, slowness and postural instability across a range of young, healthy college students. By changing the location of the device we can assess upper and lower limb movement speed and power, hand tremor, or postural control. We have also used previously validated lab devices concurrently with the smart device, which allows us to correlate the results between devices to assess the extent of

the association between devices. Outcomes such as peak acceleration and variability of movements can be obtained.

Generally, the smart device demonstrated strong correlations with the lab grade sensors for all motor tasks. Furthermore, the smart device was also correlated with the accelerometer across a large range of speed and variability. Strong correlations were seen in ballistic arm and leg tasks, tremor, and postural control assessments. This finding suggests that the smart device can sufficiently assess a broad range of functional capacity.

This battery can then be used to study populations exhibiting motor impairment, ranging from older adults, to neurological patients. Using the sensors on the smart device, this testing can be administered remotely and inexpensively by non-experts, providing cost-effective, mobile, user- and patient-friendly physical function testing. More importantly, accessibility of testing is increased while retaining quantitative precision. This should aid in quantifying disease progression and response to pharmacological or exercise/rehabilitative intervention, with the goal of improved function and quality of life in those with impairment.

ACKNOWLEDGEMENTS

Firstly, I want to give special thanks to Dr. Braun, Dr. Hickey and Dr. Butki for providing me with the opportunity to continue my educational journey within this department. I sincerely appreciate their constant support, guidance and willingness to help, no matter how big or small the questions, an answer or solution was always forthcoming. I would like to thank to entire Health and Exercise Science Department and the entire faculty for creating such a friendly, warm and supportive environment conducive to productive work. I am a firm believer that it is people that make a place great, and that could not be more accurate in this scenario. Of course, I would like to thank Dr. Tracy for his ideas, support and continuous encouragement. Without his support and continuous reinforcement this journey would have been much more difficult. I would like to thank all the Neuromuscular Function Lab (NFL) undergraduate and graduate students who aided in data collection and for all their input throughout the process. I would also like to reach out and thank all the other graduate students across the department, when in need of an answer or help, there was no shortage of wonderfully understanding and supportive students to turn to. I would also like to thank my committee members, Dr. Stephens and Dr. Fling. Their intelligence and cooperativeness have been incredibly beneficial, and I am extremely thankful. Finally, I would like to thank my family for the constant encouragement, motivation and reassurance throughout the process.

TABLE OF CONTENTS

LIST OF FIGURES

1. INTRODUCTION

Western society has experienced and will continue to experience considerable growth in its older population. Currently there are approximately 38.7 million people aged 65 or older, with an expected doubling by 2050 (Seidler et al., 2010). Furthermore, by 2030, more than 20% of US residents will be 65 or older, compared with only 13% in 2010 and 10% in 1970 (Ortman, A. Velkoff, & 2014.). Increased longevity increases the risk of developing neurological disease, many of which increase in prevalence with age (Callixte et al., 2015; Murray et al., 2012). Parkinson's disease (PD), the second most common neurodegenerative disease after Alzheimer's, is one such condition in which the incidence rises steeply with age with peak prevalence typically occurring around 80 years of age (Callixte et al., 2015; Kalia & Lang, 2015; Lees, Hardy, & Revesz, 2009; Pringsheim, Fiest, & Jette, 2014). Similarly, the risk of stroke doubles each decade after the age of 55 (Ovbiagele & Nguyen-Huynh, 2011; Roger et al., 2011). The combination of population aging and the concomitant increase in neurological disease will continue to exert a substantial burden on the health care system and society in general in coming decades.

One of the shared outcomes of the aging process or the development of a neurological condition is the decline in functional capacity or motor performance. This age- or disease-related functional decline can have a significant detrimental impact on physical function in elderly adults. Common motor deficits seen in aging and neurological disease include decreased strength and power output, slowing of movement, and increased movement variability (Beaton, McEvoy, & Grimmer, 2015; Seidler et al., 2010). Similar motor deficits are clinically manifested in neurological conditions such as PD (Kalia & Lang, 2015). Overall, the decline in these systems leads to increased difficulty in performing functional every tasks. Physical function and mobility are crucially important to quality of life (QOL).

The ability to perform everyday activities of daily living (ADLs) and maintain mobility are key to independence and quality of life. However, gait and balance abnormalities are common in aging and neurological impairment (Holtzer, Epstein, Mahoney, Izzetoglu, & Blumen, 2014; Sudarsky, 2001). For example, the incidence of gait impairment increases by 10% between the ages 60-69 and then increases to 80% between the ages of 80-90 (Mahlknecht et al., 2013). Functional disability degrades the ability to perform ADLs such as walking or stair negotiation, and can decrease functional independence and overall quality of life (Schrager, Kelly, Price, Ferrucci, & Shumway-Cook, 2008).

Injuries resulting from falls impact quality of life and independence in aging. Typical aging is associated with an increased risk of falls. For example, one in three people older than 65 years' experience a fall each year and falls are the leading cause of injury in those over 65 years. It is estimated that by 2020, falls will cost the US health care system $54 billion (Lee, Lee, & Khang, 2013). Injurious falls are a major contributor to loss of independence and reduced quality of life and can lead to institutionalization. Mobility impairments are one of the major risk factors contributing to causes of falls in the elderly (Rubenstein, 2006; Rubenstein et al., 2000; Tinetti, Speechley, & Ginter, 1988).

Assessment of motor ability is paramount in addressing the needs of the growing aging population. Physical function and mobility are profoundly important to the quality of life of an individual, thus tracking changes in these outcomes is of importance. Such information is also valuable for assessing decline over time or responsiveness to intervention. Finally, quantitative information on physical function and mobility can also be useful in predicting adverse outcomes such as a fall (Hausdorff, Rios, & Edelberg, 2001).

Existing quantitative measures of physical function and mobility most often require the use of expensive, sophisticated, lab-based equipment. For example, traditional gait assessments are conducted with three-dimensional marker-based analysis systems while many assessments of balance incorporate the use of force plates. These measurements are restricted in terms of space and time and require trained personnel to conduct the assessment (Furrer, Bichsel, Niederer, Baur, & Schmid, 2015; Proessl, Swanson, Rudroff, Fling, & Tracy, 2018). These factors hamper the ability of clinical practitioners to carry out such assessments. Access to testing can be impacted for populations such as the elderly and neurological impaired who may have difficulty visiting a laboratory. Therefore, there is a need for a mobile battery of tests to examine physical function and mobility outside the lab setting.

Smart devices are ubiquitous and offer a means to overcome the current limitations of assessing physical function and mobility. Devices such as smartphones and tablets have become an increasingly popular method of assessment because they are affordable and portable outside the lab setting. For example, smart devices such as the iPod Touch contain MEMS accelerometers which can detect acceleration of the device along three axes continuously (Patterson, Amick, Thummar, & Rogers, 2014). Smart devices also contain a gyroscope sensor which can provide instantaneous information on the orientation of the device at any given time (Yang & Hsu, 2010). Recent research has demonstrated the validity and sensitivity of the tri-axial accelerometer housed within smart devices (Amick, Patterson, & Jorgensen, 2013; Hou, Chiu, Chiang, Chen, & Sung, 2018). The use of the smart device can increase the overall accessibility of physical function and mobility assessment which can help improve functionality and quality of life.

Research using portable smart devices as movement sensors has advanced in recent years. Many features of physical function and mobility are readily detectable using the accelerometer and gyroscope within the device. For example, investigations have incorporated the smartphone in balance assessments (Kuznetsov et al., 2018; Moral-Munoz, Esteban-Moreno, Herrera-Viedma, Cobo, & Perez, 2018; Shah & Aleong, 2016) and features of gait have been measured (Furrer et al., 2015; LeMonye, COROIAN, MASTROIANNI, & GRUNDFEST, 2008; Proessl et al., 2018; Silsupadol, Teja, & Lugade, 2017). Mellone and colleagues demonstrated the reliability and validity of a smartphone-based timed up and go test (Mellone, Tacconi, & Chiari, 2012). Studies assessing the symptoms of PD such as tremor have also incorporated the use of the smartphone (R. Lemoyne, Mastroianni, Cozza, Coroian, & Grundfest, 2010). Overall, the results suggest that the smartphone provides a feasible platform for assessing many features of physical function and mobility.

The purpose is to describe an iPod Touch-instrumented test battery designed to assess features of physical function and mobility often shared by normal aging and age-related movement disorders. The aim was to show the feasibility within a young healthy population for potential use within clinical and motor impaired populations. The overall goal is to increase the quality of information from functional testing above and beyond that of the traditional timed or counted clinical and field tests.

2. METHODS

All testing took place in the Neuromuscular Function Lab at Colorado State University. The procedures were approved by the Colorado State University Institutional Review Board. Prior to participation, written consent was obtained from the subjects that informed them what would be asked of them and any associated risks from taking part in the testing.

2.1 Assessment Devices

2.1.1 5th Generation iPod Touch

A smart device (iPod 5th Generation, Apple, Inc., Cupertino, CA) was used to continuously record accelerometer and gyroscope data during the tasks. These devices house Micro Electro-Mechanical (MEMS) accelerometers which detect instantaneous acceleration. The tri-axial accelerometers permit the detection of acceleration along the X, Y, Z axes of the device. The smart device also contains a gyroscope sensor which measures the orientation of the device around three rotational axes (pitch, roll, yaw). The Sensor Data Application (Wavefront Labs) was used to sample and digitize the data at 100Hz. This sampling rate is the maximum currently allowed by the operating system code. Data is stored on the device as a labeled, delimited text file and subsequently wirelessly transmitted to a computer for analysis. The files on the iPod are accessed remotely via a dedicated URL, renamed, and saved to a secure computer. Each text file was then imported to Spike 2 (Cambridge Electronic Design Limited, UK, Version 7.18) for further analysis.

2.1.2 Lab Grade Accelerometer

For three out of the five functional tasks the smart device was compared with a more expensive lab-based accelerometer, a small, uniaxial, lightweight piezoresistive accelerometer designed for motion studies and other applications requiring high sensitivity (Endevco® 7265A).

The device utilizes two fixed silicon gages and two fixed resistors in a full-bridge circuit, and has a sensitivity of 5 mV/g and a frequency response range from 20Hz to 1000Hz.

The lab accelerometer was attached to the surface of the smart device so that the sensitive axis aligns with the relevant axis of acceleration of the smart device. The accelerometer signal is led through a transducer coupler (Coulbourn, Inc.), digitized at 100Hz (1401 A/D device, Cambridge Electronic Design, UK), recorded on the same computer, and imported to Spike 2 for analysis.

2.2 Assessment Protocols

2.2.1 Hand Tremor

20 young, healthy adults (13 males, 7 females) with no previous diagnosis of neurodegenerative disease or motor impairment took part in this study. Subjects were seated in a chair next to a rigid table. The dominant forearm and hand were placed on the table with the shoulder slightly abducted. Two rigid foam blocks were aligned on the table to permit the full forearm and hand to rest upon them. An iPod Touch 5^{th} generation was firmly attached to the dorsum of the hand using a Velcro strap (**Figure 1A**). The uniaxial lab-grade accelerometer was attached to the screen of the iPod Touch over the location of the internal smart device accelerometer and secured with adhesive tape. Care was taken to secure all wires and ensure the accelerometer was consistently adhered. Both devices collected acceleration data concurrently.

The Sensor Data App was used to record from the iPod's internal sensors at 100Hz and the text files were then downloaded and imported to Spike 2 for analysis (Spike 2, ver. 7.14, Cambridge Electronic Design). The lab-grade accelerometer signal was led trough a transducer coupler (Coulbourn, Inc.), digitized at 100Hz (1401 device, Cambridge Electronic Design, UK) and was also recorded on the same computer and imported to Spike 2 for analysis.

The task was split into three stages consisting of a baseline resting measure, unsupported hand measure, and voluntary simulated tremor measure. Subjects were asked to complete two trials of this task with a one-minute rest period between.

Stage 1: Baseline measure

Subjects rested their dominant forearm/hand on the foam pads and were instructed to rest and remain as still as possible while five seconds of acceleration data was collected from both devices.

Stage 2: Unsupported hand measure

During this stage the distal foam pad upon which the subject rested their dominant hand was removed. The subjects were instructed to keep their hand suspended at the wrist as still as possible. Five seconds of acceleration data was collected from both devices.

Stage 3: Voluntary simulated tremor

With the hand still suspended from the previous stage, subjects were instructed to produce self-paced voluntary hand tremor in a progressive manner- started at the lowest possible amplitude and then increasing to very high amplitude over 60 seconds. Both devices recorded the progressive increases in fluctuations of the acceleration signals.

After acceleration data was collected from both the iPod Touch and the lab-grade accelerometer, data from each device were merged and time –aligned in the Spike2 program (**Figure 1B**). The standard deviation of acceleration was calculated to quantify the amplitude of the tremor. For stages 1 and 2, a single standard deviation value was calculated from a 3 second time interval. Stage 3 was broken down into twelve five second intervals, each representing progressively increasing amplitude of manufactured tremor. Including all stages, a total of 14 SD of acceleration values were obtained across a large range of tremor amplitudes.

For comparison between devices, the SD values were normalized as a percentage of the maximal standard deviation value produced by that device during that trial. This was done to scale the values in the same manner across the large range of amplitudes observed across trials. Pearson correlations and R^2 values were calculated between devices for each trial (n=14 values) and for the normalized data pooled across all subjects and trials.

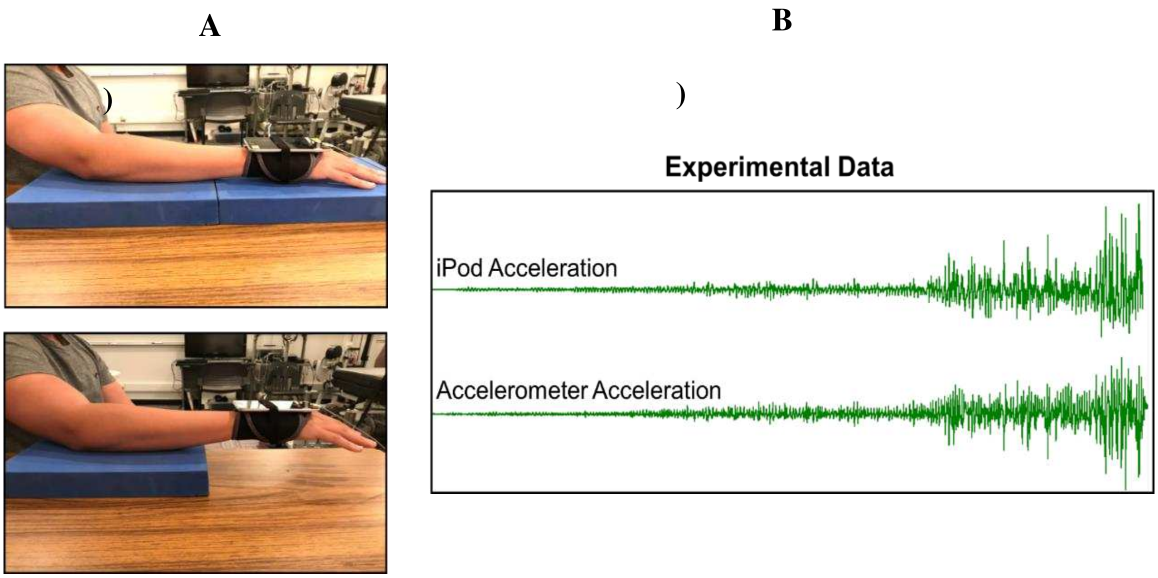


Figure 1. **A)** Experimental set up of the tremor detection assessment. Top picture depicts the position of the iPod on the dorsum of the hand and their hand supported on a foam pad for stage 1 of assessment. **B)** Experimental data traces from voluntary tremor (stage 3). Top trace represents the standard deviation of acceleration from the z-axis of the iPod accelerometer. Bottom trace represents the standard deviation of the lab grade accelerometer.

2.2.2 Ballistic Arm Movement

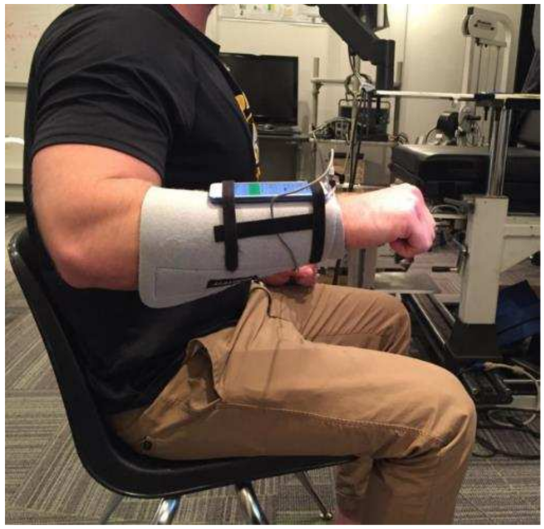
17 young, healthy adults (9 male, 8 female) with no previous history of neurodegenerative disease took part in this task. Subjects were seated in a sturdy laboratory chair with their shoulder slightly abducted, elbow flexed at 90 degrees, forearm in mid pronation and their fingers flexed into a fist (**Figure 2A**).

An iPod Touch 5th generation was firmly secured to a Velcro strap around the distal forearm so that the Y-axis of the device would sense the outward phase of the arm movement. A uniaxial lab-grade Endevco accelerometer was secured to the iPod Touch so that it's sensitive axis was aligned with the Y-axis of the iPod. The lab-grade accelerometer was securely fastened to the iPod Touch using double sided adhesive tape overlying securing tape. All leads were carefully secured as to not interfere with the motion.

The task was an abbreviated outward punch. The shoulder was flexed, and elbow extended in the sagittal plane as rapidly as possible, but not to full extension, and then returned to the starting position. The purpose was to capture the explosive initial phase of limb acceleration. Subjects were instructed to perform three trials of 20 punches with 1-2 seconds rest between repetitions and one-minute rest between trials. Subjects were instructed to begin with a "very slow" punch and perform each of the 20 consecutive punches incrementally faster, so that their final punch was maximal speed. The iPod Touch device and the lab-grade accelerometer both collected acceleration data concurrently.

The iPod Touch device used the Sensor Data App to sample the acceleration values at 100Hz. A brief mechanical artifact was introduced simultaneously to both devices to synchronize the files on the time axis. The data from both devices was then merged into one file for analysis. The peak acceleration from the initial outward punching phase were measured from both devices (Fig 2B). The peak acceleration values from both devices were then normalized as a percent of maximal acceleration value from that trial of 20 repetitions. Bivariate correlations and the R^2 values were then calculated to quantify the correlation between the values obtained from the iPod vs. lab-grade accelerometer for each individual subject's trial. Between-device correlation of the normalized peak acceleration values pooled across all subjects was also examined.

A)



B)

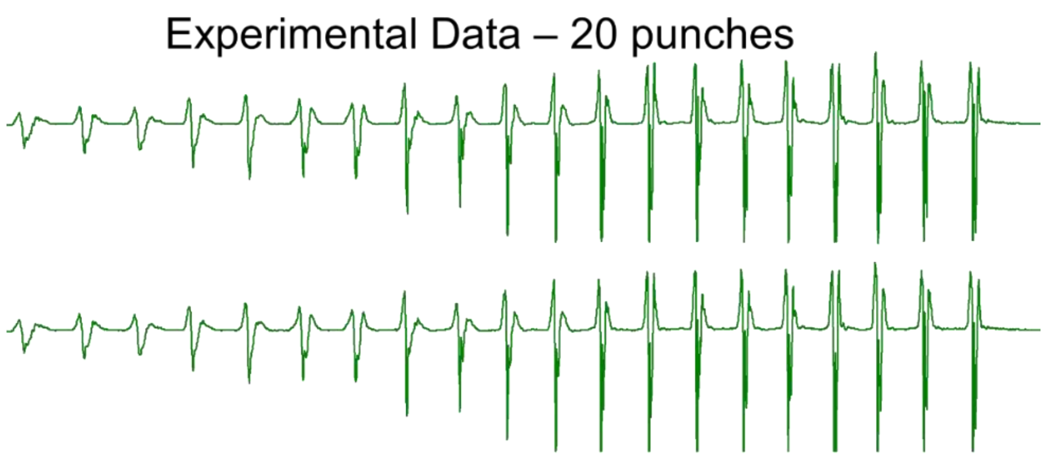


Figure 2: **A)** Experimental set up for the ballistic arm movement task. The iPod was placed on the distal forearm and participants were instructed to rapidly extend their arm horizontally. **B)** Experimental data traces from from twenty ballitic arm movements Top trace is the the y-axis accleration signal from the iPod Touch. The bottom trace represents the accerlation signal from the lab grade acclerometer. The peak accleration values from each movement were measured

2.2.3 Ballistic Leg Movement

Fifteen young, healthy subjects (7 males, 8 females) volunteered and provided written informed consent. They reported no known neurodegenerative disease or motor impairment.

Subjects were seated on a rigid table with their knee at a right angle and the lower leg hanging freely (**Figure 3A**).

An iPod Touch 5th generation was attached to the anterior shank of the dominant leg with the Z-axis perpendicular to the distal lower leg. The iPod was securely fastened to the lower leg with a Velcro strap. A uniaxial lab-grade Endevco accelerometer was attached to the surface of the iPod Touch so that the sensitive axis was in line with the Z-axis of the iPod. The accelerometer was attached with double-sided adhesive tape to ensure it was fastened firmly, so that both devices would undergo the same acceleration while attached to the limb.

Subjects performed one trial of 20 ballistic knee extension movements. Subjects were instructed to perform an arrested kick movement which involved not carrying through full range of motion. Each ballistic leg movement was performed with self-selected increasing velocity, starting at a “very slow” speed and progressing to maximal velocity. The iPod and lab-grade accelerometer sampled acceleration data at the same time.

Acceleration data from both the devices was time-aligned using a simultaneous mechanical artifact in the data stream and then merged into a single data file. The peak acceleration from the initial outward phase of the kick movement was measured from each device (**Figure 3B**). These values were then normalized as a percent of maximal peak acceleration value for that trial to allow for meaningful between-subject and between-device comparisons. Pearson correlations and R^2 values were then calculated for the iPod vs lab-grade accelerometer correlation for each individual trial. Between-device correlation of the pooled normalized values across all subjects was also examined.

A)

B)

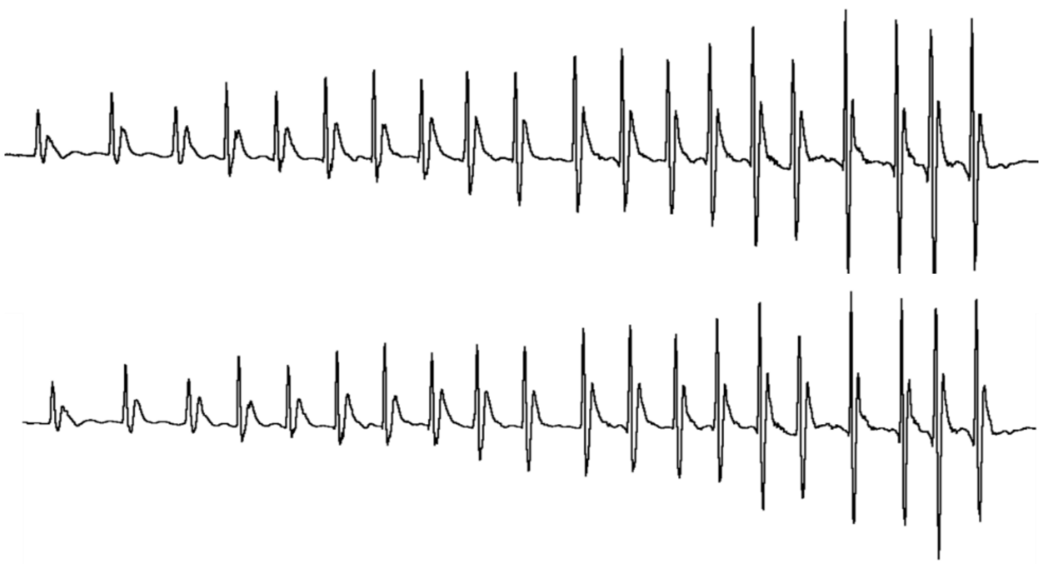


Figure 3 A) Experimental set up for the ballistic leg movement task. The iPod Touch was secured to the anterior lower leg and subjects were instructed to kick outwards progressively faster. **B)** Experimental data traces from the ballistic leg movement task. Top trace is the y-axis acceleration from the iPod Touch. The bottom trace is the acceleration from lag grade accelerometer. The peak acceleration value was obtained from each trial.

2.2.4 Postural Stability

34 young healthy adults (17 male, 17 female) with no previous history of neurological disease or impairment volunteered to take part in this study. A 5th generation iPod Touch was securely attached to the subject's hip with Velcro. The smart device was oriented so that its X-

axis would reflect accelerations in the anteroposterior (AP) direction and the Z-axis provided measures along the medial-lateral (ML) direction. A force platform (Accusway, AMTI) was used to measure center of pressure (COP) excursions. Both devices sampled data concurrently at 100Hz. The signals from the two devices were time-aligned using a simultaneous, small amplitude, sharply applied tap to the iPod and force platform.

The task was separated into three 30-second conditions; 1) Quite Standing Eyes Open (QSEO), 2) Quiet Standing Eyes Closed Neck Extended (QSECE) and 3) Anterior/Posterior Voluntary Sway (APVS) (**Figure 4A and 4B**). The three conditions were chosen to produce significant changes in postural sway to be quantified by the devices. During the QSEO condition subjects were instructed to stand as still as possible with their hands by their side and eyes open. The foot width was calculated as 10% of their height. During the QSECE condition subjects were asked to maintain the same physical posture as the QSEO condition however this time with their eyes closed and neck extended. During the APVS condition, subjects were asked to look forward with their eyes open and then produce slow, voluntary oscillations in sway in the AP direction without the foot sole leaving the ground and with the body as straight and rigid as possible so that the sway occurred mainly at the ankle.

The data from both devices was downloaded and merged into the same Spike2 file and analyzed. The SD of acceleration in the X-axis from the iPod Touch and the SD of AP COP excursion from the force platform was calculated for a 10 second period. Change values between conditions were calculated for both devices. Pearson correlations and R^2 values were used to quantify between-device correlation.

A) **B)**

Figure 4: Postural stability assessment occurred with both eyes open condition **(A)** and eyes closed neck extended condition **(B).** The voluntary anterior posterior sway trial in which subjects manufactured progressively increasing sway, adopted the same position as (A). The iPod Touch was securely fasted to the hip.

2.2.5 Sit-To-Stand (STS)

42 young, healthy adults (21 male, 21 female) who reported no health problems were included in the study and provided written informed consent. Each subject performed three trials of STS movements with 2-3 minutes rest between trials. Subjects were instructed to fold their arms across their chest, stand with their feet at a comfortable width apart (same position for each trial), keep their feet on the ground, and to rise to full standing and return to a full seated position for each repetition. Subjects were asked to first perform 5 STS as fast as they could and then progressively reduce their STS speed over the next 15 repetitions so that by the 20th repetition they were standing and sitting very slowly.

Subjects sat in a rigid chair with their knee angle at 90 degrees. Data was collected concurrently from a 5th generation iPod Touch and electronic goniometer. The iPod Touch was firmly attached with Velcro to the lateral side of the thigh (measured 2/3 distance from greater trochanter to knee). The Sensor Data App on the iPod touch was used to record the pitch, roll and yaw from the iPod's gyroscope at 100Hz. The pitch signal was analyzed as it reflects the sagittal plane thigh tilt during extension and flexion of the knee joint. An electronic goniometer was secured to the lateral side of the left knee joint. The knee angle was digitized at 100Hz and recorded on computer (1401 A/D converter, Spike 2 ver. 7 software, Cambridge Electronic Design, UK). Both signals were merged into the same Spike2 file for analysis.

The signals from the two devices were time-aligned by introducing a sharp tap at the same time to both devices which produced a mechanical artifact in the signal. The peak slope value of the rising phase of the iPod pitch signal and electronic goniometer were calculated for each STS. From all the peak slope values from each trial of 20 repetitions, the maximum value, the minimum value, and the difference between the maximum and minimum value was calculated from each of the 20 repetitions. The overall aim was to assess between-device correlation and agreement in terms of detecting and measuring STS speed. Therefore, correlation values were calculated across a range of speeds for both individual subject trials and the pool of values across all subjects.

2.3 Statistical Analysis

All statistical analysis was completed using SPPS software (IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.). Pearson correlations were used to determine the association between devices. Correlations were classified as very strong (0.9-1.0), strong (0.7-0.9), moderate (0.5-0.9), weak (0.39-0.49) and negligible (<0.30) (Mukaka, 2012).

3. RESULTS

3.1 Hand Tremor

The normalized standard deviation of acceleration values across all subjects and trials demonstrated strong correlation (R^2 =0.89, **Figure 5A**). One individual trial of the voluntary tremor task showed very strong between device correlation (R^2 = 0.92, **Figure 5B**). Figure 5C illustrates how the smart device and accelerometer track each other with increasing accelerations

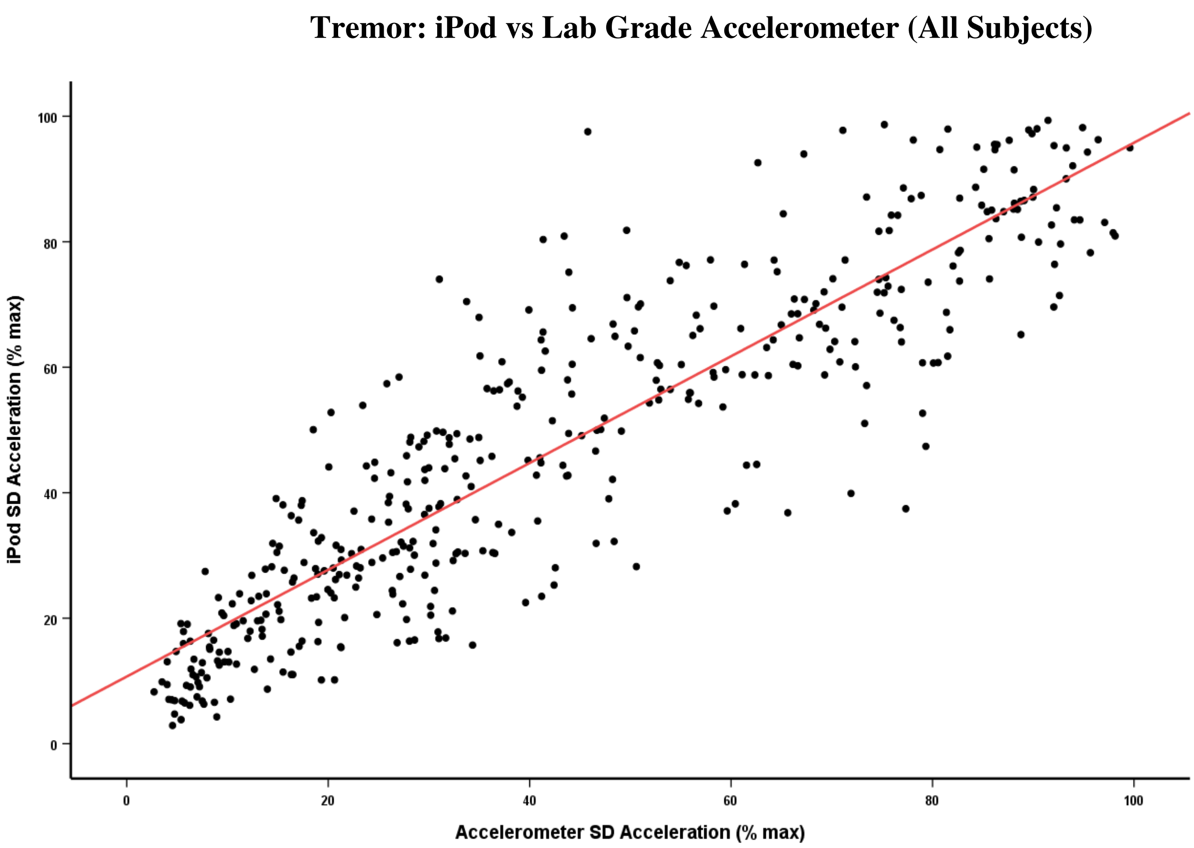


Figure 5A: Between device correlation of the SD of acceleration during the voluntary tremor task for 20 subjects. Each subject completed two trials and was instructed to progressively increase tremor amplitude after each five seconds. (R^2 = 0.89).

(**Figure 5C**). Both devices were able to track the increasing changes in accelerations in a similar manner.

Tremor: iPod vs Lab Grade Accelerometer (Single Subject)

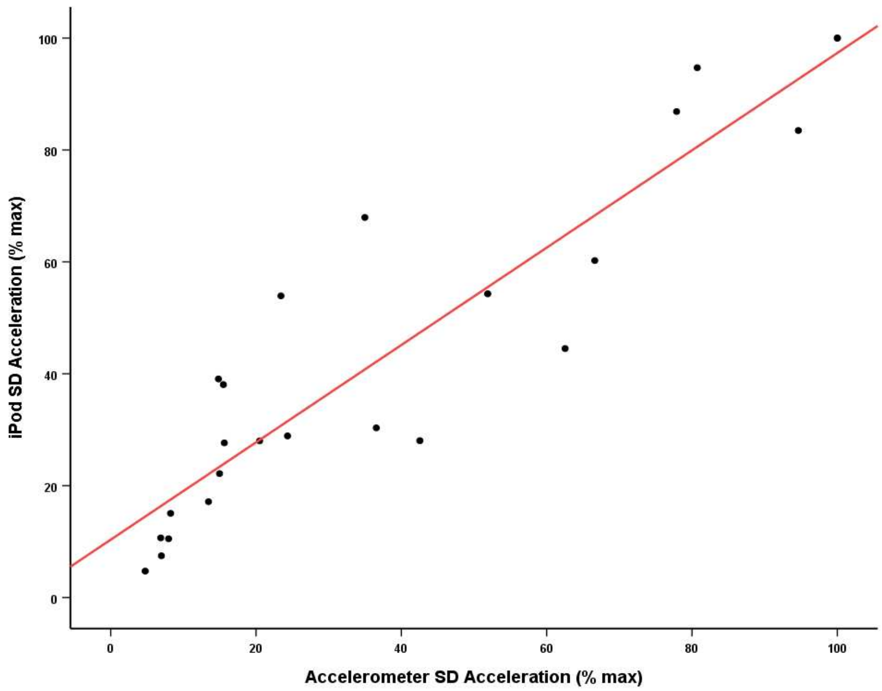


Figure 5B: Example of between-device correlation for the standard deviation of acceleration across a large range of tremor amplitude. Data from two trials of voluntary tremor from a single subject that produced 28 pairs of values. (R^2= 0.84)

Voluntary Tremor Across Repetitions

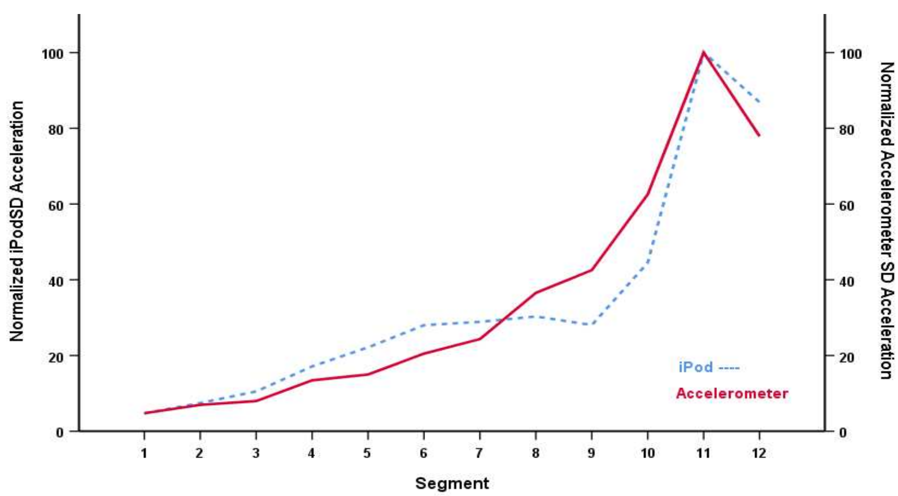


Figure 5C: Line graph depicting one trial from one subject's voluntary tremor task. Subjects were instructed to progressively increase their tremor each five seconds. This graph depicts how the smart device and lab grade accelerometer track each other at increasing accelerations during one trial.

3.2 Ballistic Arm Movement

The normalized peak acceleration values across all subjects demonstrated very strong correlation between devices (R^2=0.98, **Figure 6A**). For the 60 repetitions pooled from a single subject's three trials, the between device correlation was also very strong (R^2= 0.97, **Figure 6B**). The maximum and minimum single peak acceleration values from a 20-repetition trial were also strongly correlated between devices across subjects (both R^2 = 0.98, **Figure 6C and D**). Similarly, there was a strong correlation between the two devices for the value that represented the change in ballistic arm movement from the slowest to fastest repetition (**Figure 6E**).

Ballistic Arm Movement Peak Acceleration: iPod vs Lab Grade Accelerometer (All Subjects)

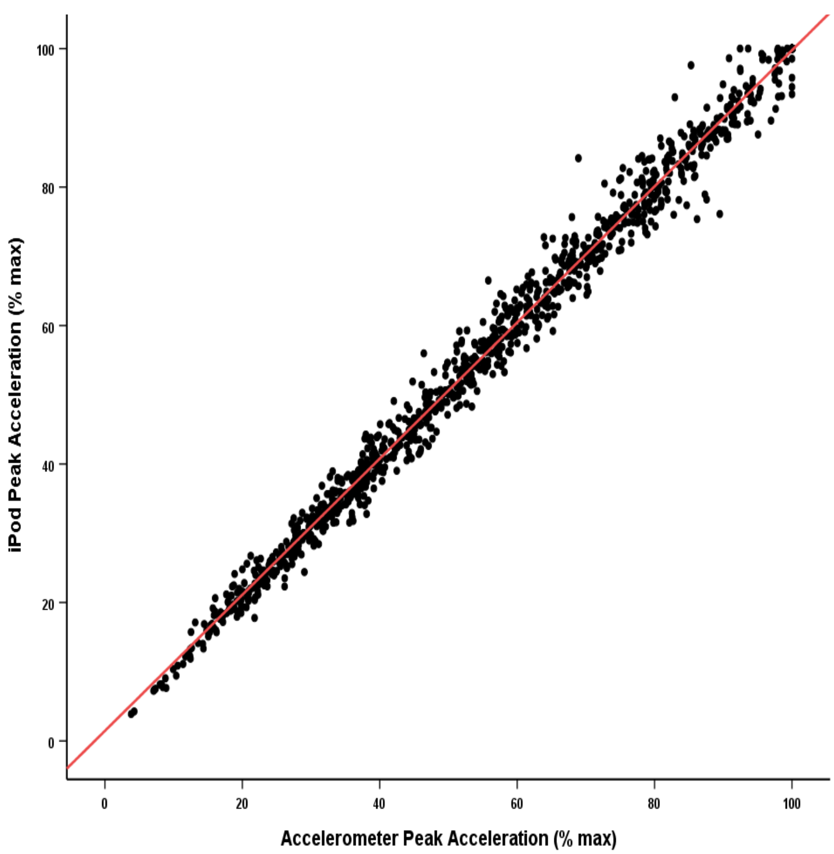


Figure 6A: Between-device correlation of the peak accelerations during the ballistic arm movement task for 20 subjects. Each subject completed three trials and was instructed to progressively increase speed of movement each rep. (R^2 = 0.98).

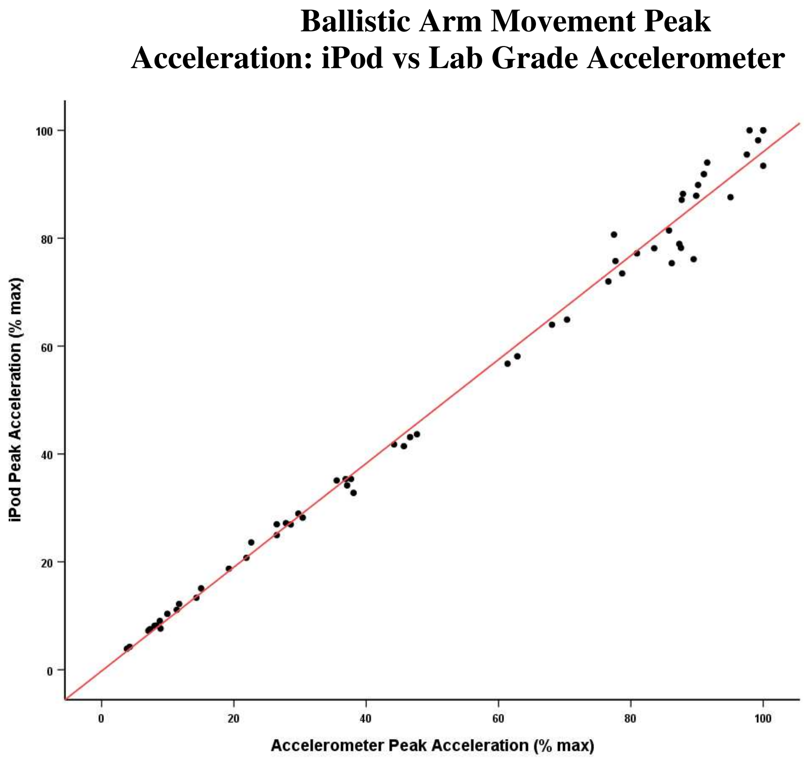


Figure 6B: Example of between device correlations of one subject's three trials of 20 progressively increasing ballistic arm movements ($R^{2=}$ 0.97).

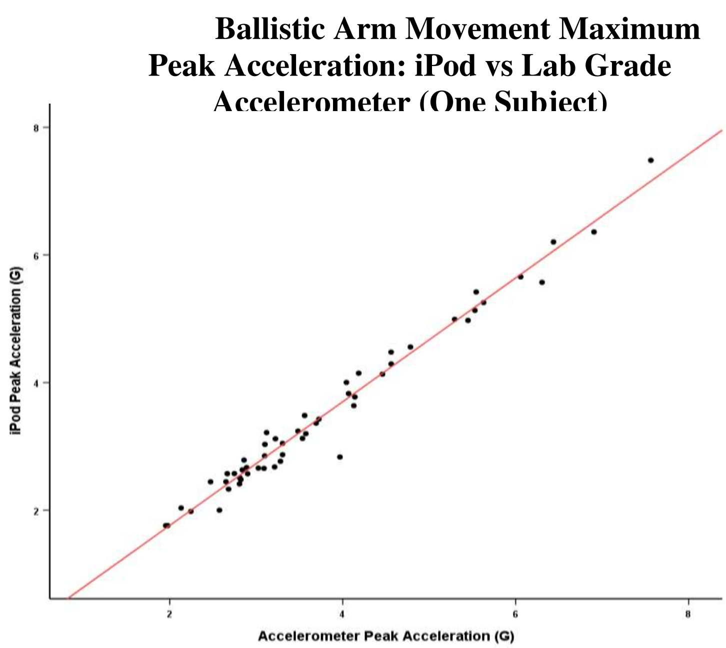


Figure 6C: Between-device correlation of the maximum peak acceleration values from each trial of the ballistic arm movement. Each subject performed three trials of 20 movements, this graph depicts the 60 maximum peak acceleration values detected from each device (R^2=0.98).

Ballistic Arm Movement Minimum Peak Acceleration Values: iPod vs Lab Grade Accelerometer

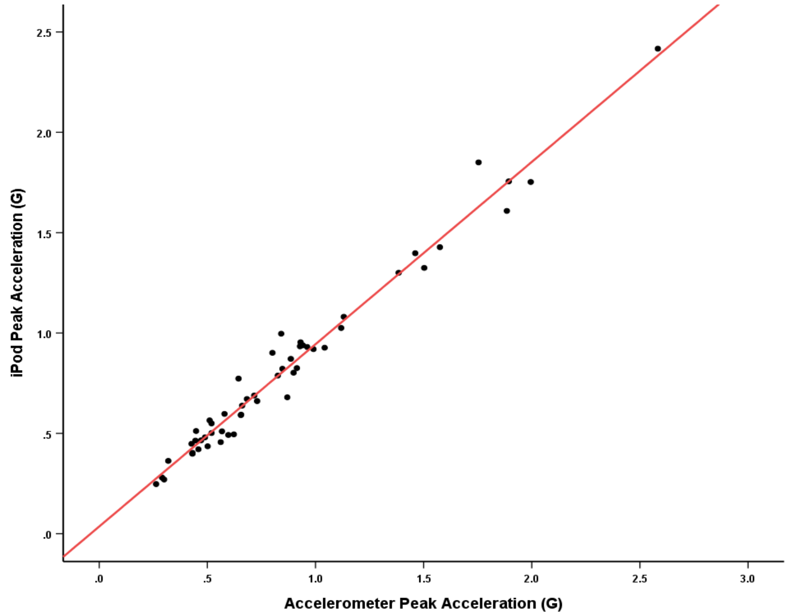


Figure 6D: Between-device correlation of the minimum peak acceleration values extracted from each trial of 20 repetitions of arm movement. Each subject performed three trials of 20 movements. Depicted here are the 60 minimum peak acceleration values detected from each device (R^2 =0.98).

Ballistic Arm Movement Peak Acceleration Across Repetitions

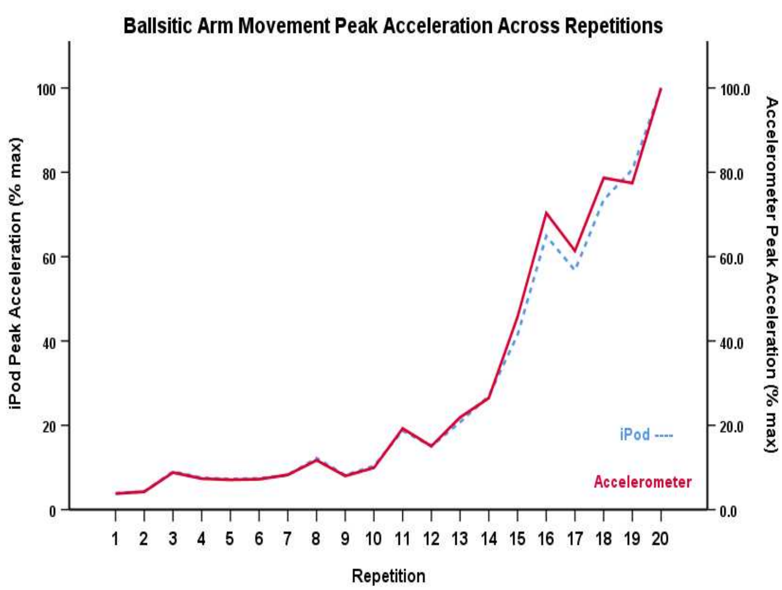


Figure 6E: Line graph depicting one trial from one subject's ballistic arm movement task. Subjects were instructed to progressively increase the speed of their movement each repetition. This graph depicts how the smart device and lab grade accelerometer track each other at increasing accelerations

3.3 Ballistic Leg Movement

When the normalized peak acceleration values were pooled across all trials from all subjects, the two devices were very strongly correlated (R^2=0.97, **Figure 7A**). When examining an individual trial the between device correlation was also very strong (R^2=0.99, **Figure 7B**). The ability of the devices to similarly capture both the maximum peak acceleration values (R^2=0.88) and minimum peak acceleration values (R^2=0.97) from each trial demonstrated strong correlation (**Figure 7C and D**). The two devices detected changes in increasing acceleration in a similar manner (**Figure 7E**).

Ballistic Leg Movement: Peak Acceleration:
iPod vs Lab Grade Accelerometer (All Subjects)

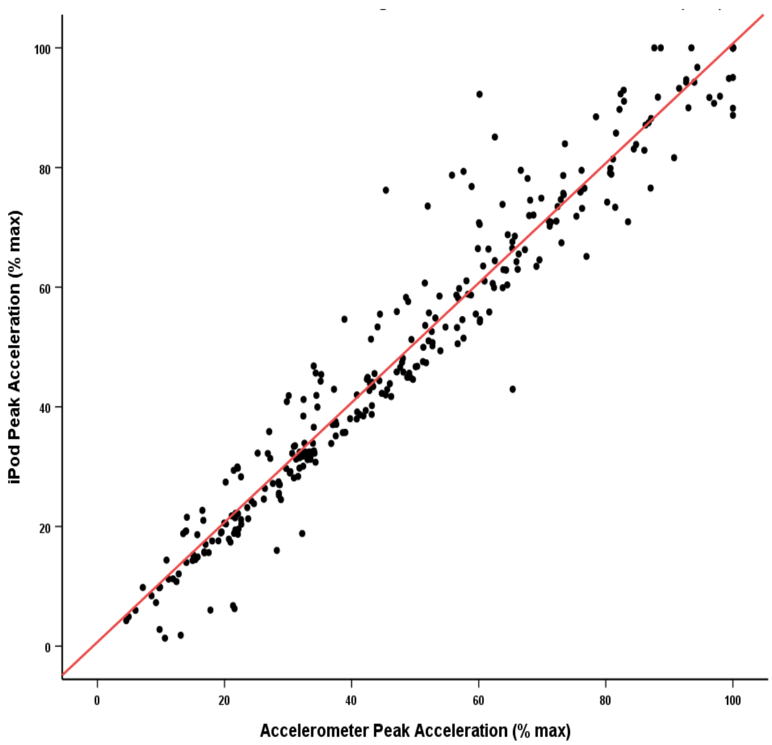


Figure 7A: Between device correlation of the peak acceleration values during the ballistic leg movement task for 15 subjects. Each subject completed one trial and was instructed to progressively increase speed of movement with each successive repetition (R^2 = 0.97).

Ballistic Leg Movement: Peak Acceleration: iPod vs Lab Grade Accelerometer (One Subject)

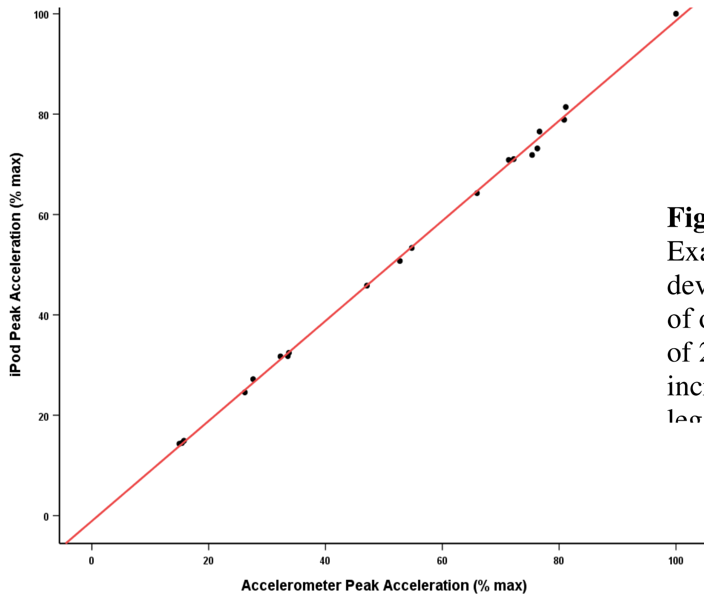


Figure 7B: Example of between device correlations of one subject's trial of 20 progressively increasing ballistic leg movement task

Ballistic Leg Movement: Maximum Peak Acceleration iPod vs Lab Grade Accelerometer

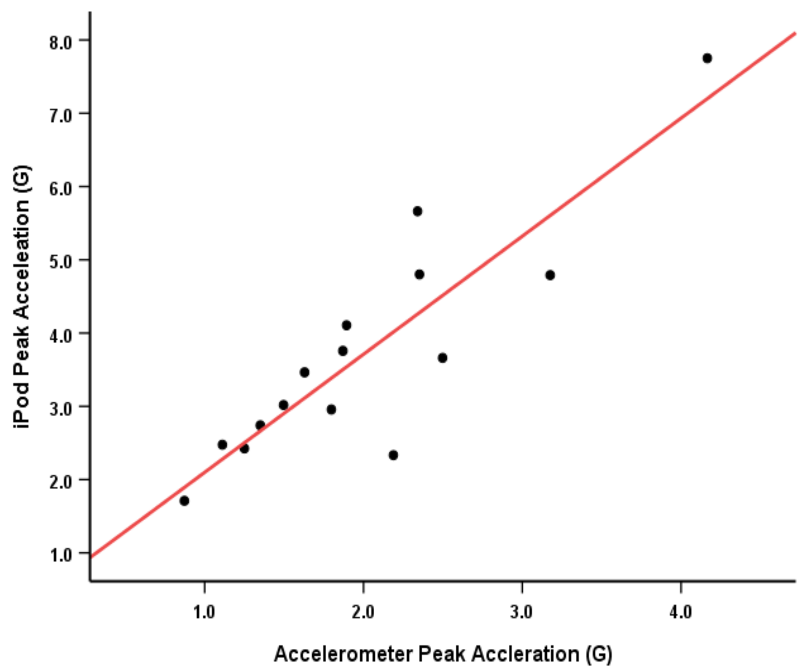


Figure 7C: Between device correlation of the maximum peak acceleration values from each trial of the ballistic leg movement. Each subject performed one trial of 20 movements, this graph depicts the minimum peak acceleration values detected from each device (R^2 =0.98).

Ballistic Leg Movement: Minimum Peak Acceleration iPod vs Lab Grade Accelerometer

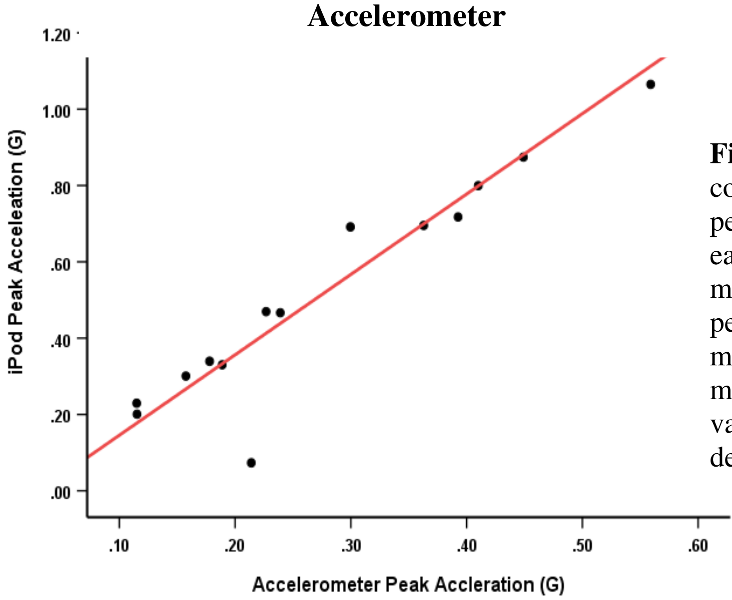


Figure 7D: Between device correlation of the minimum peak acceleration values from each trial of the ballistic leg movement. Each subject performed one trial of 20 movements, this graph depicts minimum peak acceleration values detected from each device (R^2 =0.98).

Ballistic Leg Movement Peak Acceleration Across Repetitions

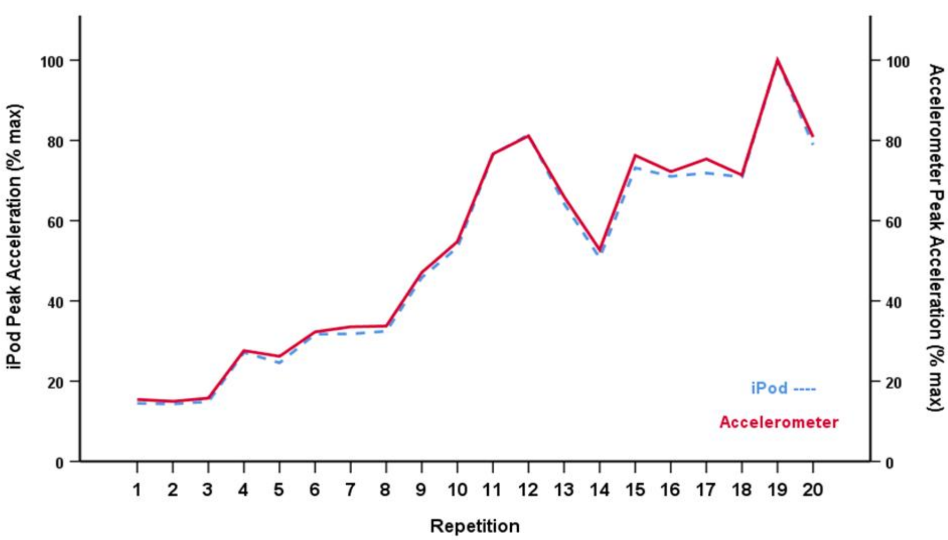


Figure 7E: Line graph depicting one trial from one subject's ballistic leg movement task. Subjects were instructed to progressively increase the speed of their movement each repetition. This graph depicts how the smart device and lab grade accelerometer track each other at increasing accelerations during one trial.

3.4 Postural Stability

During the voluntary sway phase in which subjects were asked to manufacture increasing sway in the anterior posterior direction, strong correlation (R^2= 0.86) was noted in the SD of acceleration and the SD of COP between devices (**Figure 8A**). Change values were also calculated in order to assess how the two devices were correlated in detecting a change in stability between conditions. Fold change values were calculated from each device comparing the eyes open and eyes closed conditions and then correlated with each other. **Figure 8B** depicts the strong correlation observed between devices.

AP Voluntary Sway: iPod vs Force Plate

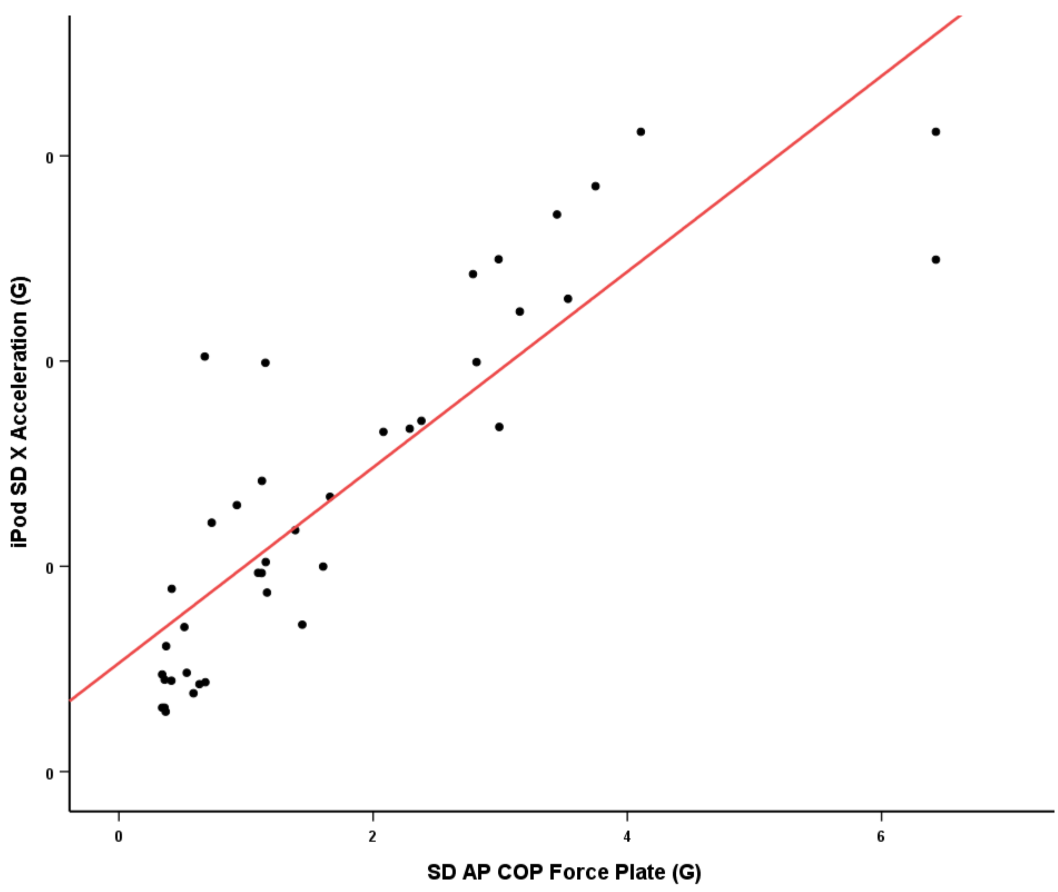


Figure 8A: Pearson correlation of the standard deviation of the x-axis Acceleration of the iPod with the SD of change in in A/P COP from the force plate (R^2=0.74).

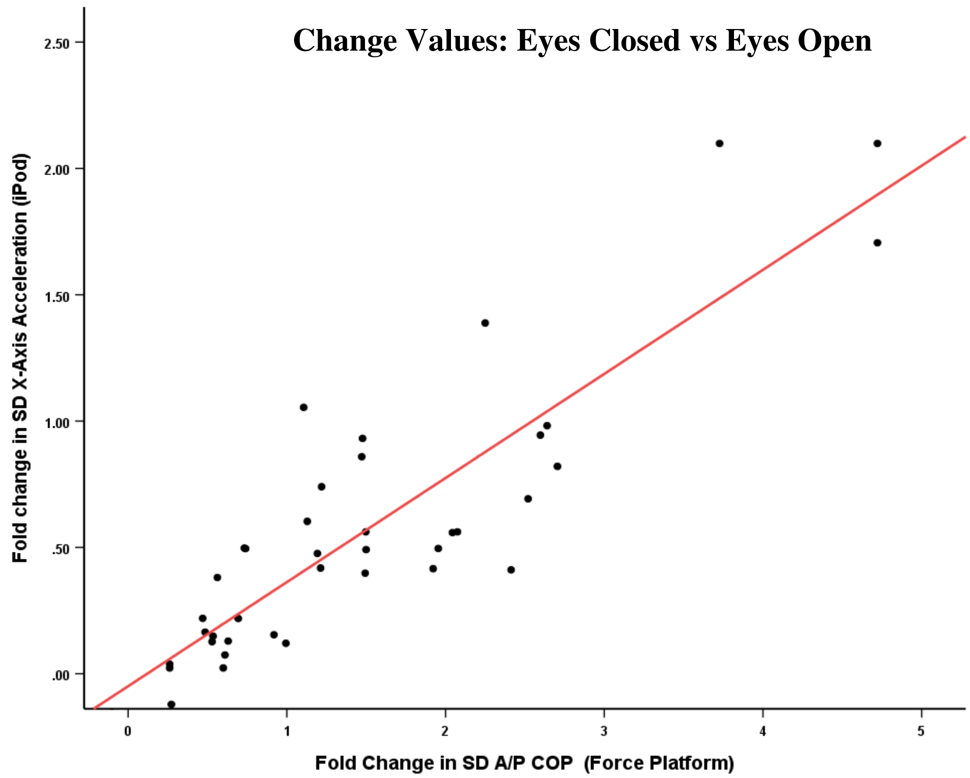


Figure 8B: The change in the SD of iPod x-axis acceleration was correlated with the change in SD of AP COP between the eyes and eyes closed conditions. (R^2=0.76)

3.5 Sit-To-Stand

The between-device (iPod vs. eGONI) correlations of peak slope revealed consistently high correlation values (**Figure 9A**). The mean peak slope R^2 value across all trials was 0.95 for iPod vs eGONI. The distribution of R^2 values was strongly positively skewed with 88% over 0.9 (**Figure 9B**). To determine the ability of the iPod to detect specific outcome parameters, the minimum, maximum and the maximum minus the minimum was extracted from each trial of 20 repetitions. Correlation values between the iPod and eGONI for the minimum peak slope value were R^2= 0.83, for the maximum peak slope R^2= 0.78 and the max-min change value in peak slope R^2= 0.78. (**Figures 9 C, D, and E**).

iPOD vs eGONI

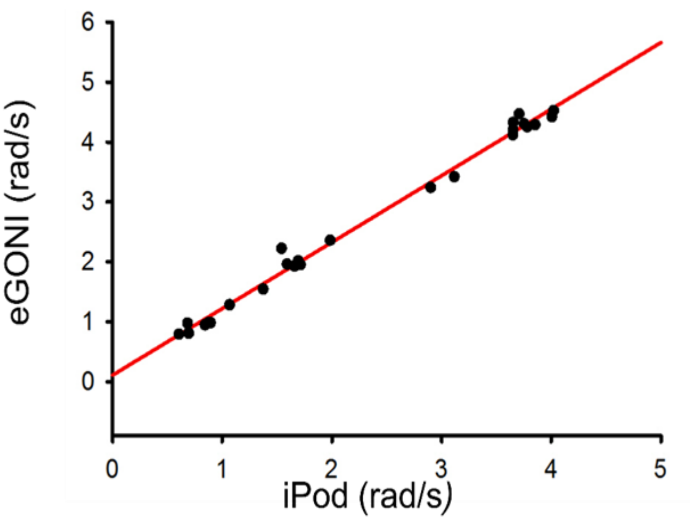


Figure 9A: Example of between-device peak slope correlations for one trial of 20 repetitions from four different participants. iPod peak slope vs. eGONI peak slope (R^2= 0.99).

iPOD vs eGONI: R^2 Values (All Trials)

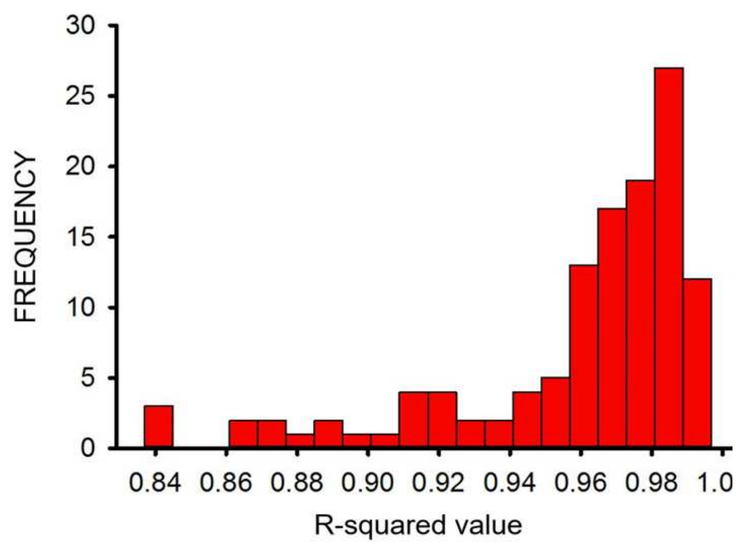


Figure 9B: Distribution of the R^2 values from all 126 individual participant trials for A) the correlations between iPod peak slope vs. eGONI peak slope (Mean R^2 value =0.95)

iPOD vs eGONI: Maximal Single Repetition

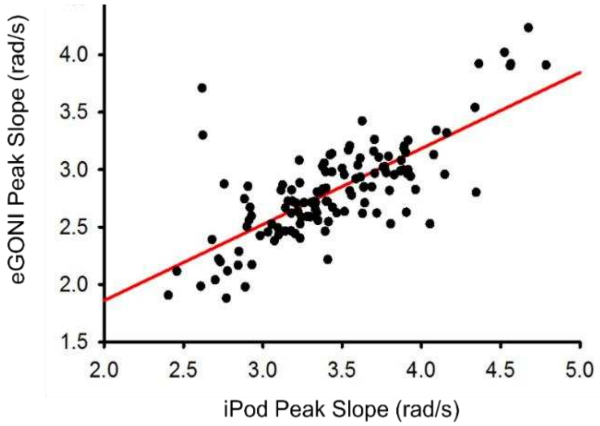


Figure 9C: Between-device correlations for the maximal peak slope from the fastest single repetition from each trial of 20 repetitions. The maximal peak slope from the iPod was positively correlated with the maximal peak slope from the eGONI (R^2 =0.78)

iPOD vs eGONI: Minimal Single Repetition

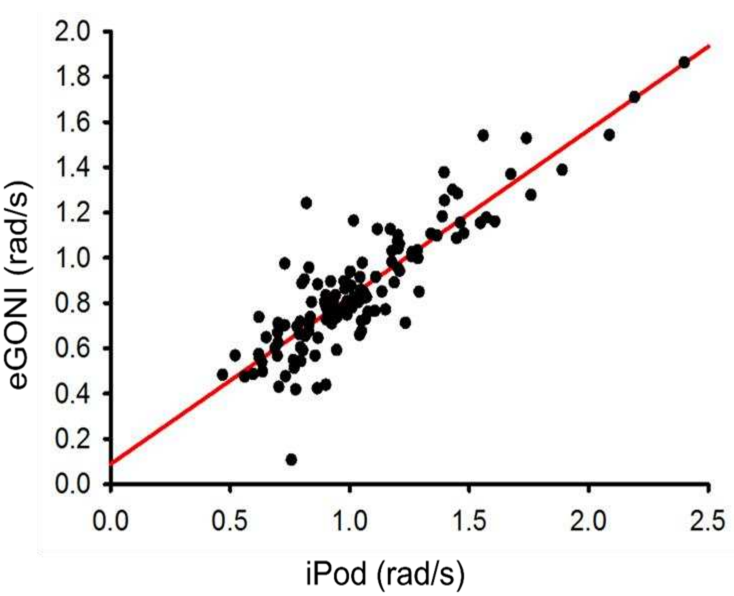


Figure 9D: Between-device correlations for the minimal peak slope from the slowest single repetition from each trial of 20 repetitions. The minimal peak slope from the iPod was positively correlated with the minimal peak slope from the eGONI (R^2 = 0.83)

iPOD vs eGONI: Maximal – Minimal Repetition

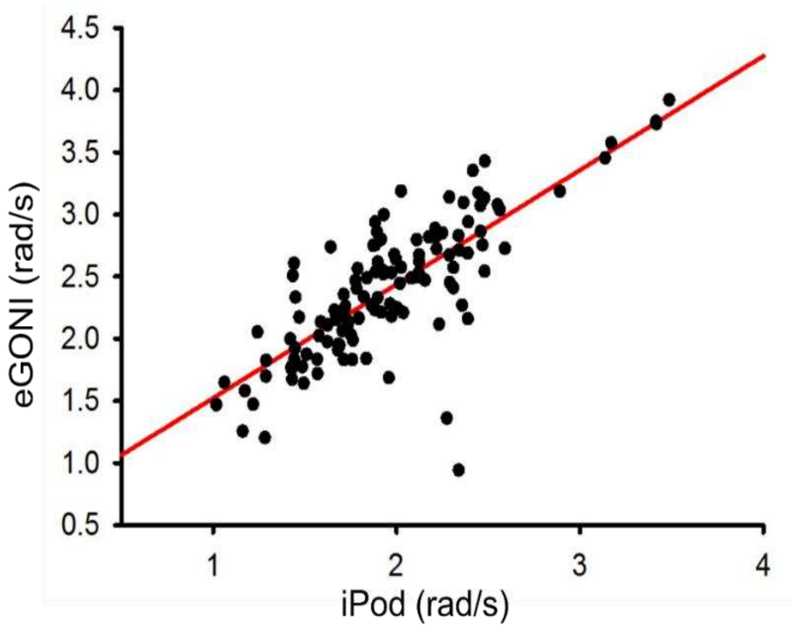


Figure 9E: Between-device correlations for the difference in peak slope between the fastest single repetition and the slowest single repetition in a trial of 20 repetitions. The iPod peak slope difference (Max-Min) was positively correlated with the eGONI peak slope difference (Max-Min) ($R^2 = 0.78$).

.

4. DISCUSSION

The goal of this paper was to examine and compare quantitative measures of movement taken during a battery of physical function tasks between a cost-effective, portable smart device (iPod Touch) and a validated and reliable lab grade accelerometer (Endevco 625A). Tasks were deliberately chosen to reflect key physical and functional capacity measures that previous research has shown degrade with age or the development of neurological disease. Furthermore, tasks were performed across a large range of performance (e.g., slow to fast speed, small to large variability) to further demonstrate the capability of the smart device to accurately measure accelerations at slow and fast speeds.

The results indicate that the iPod Touch-based assessment can accurately reflect output variables from the lab grade accelerometer or lab-based force platform. From each of the tasks, raw signal output traces from both devices displayed high similarity. Across the five tasks, the main finding was that across a range of performance values, there was very strong between-device correlations in the outcome measures. The voluntary tremor task produced strong between device correlations for the standard deviation of acceleration, a measure of the average amplitude of motor variability (**Figures 5A and 5B**). The ballistic arm movement task demonstrated very high correlation of peak acceleration values between the smart device and lab grade accelerometer (**Figures 6A and 6B**). Comparison of peak acceleration values from the ballistic leg movement task also demonstrated very strong correlation (**Figures 7B and 7B**). When varying amounts of postural sway were produced during different tasks, the SD of the X-axis acceleration and the standard deviation of COP from the force plate were strongly correlated (**Figure 9A**) and between-condition changes in those values were also correlated. The measure of peak knee joint rotation rate from the iPod Touch was highly correlated between the smart device and electronic goniometer (**Figures 9A and 9B**). Other specific performance parameters extracted from the STS such as the maximum speed, minimum speed and change in speed (max-min) was strongly correlated between devices (**Figures 9C, 9D and 9E**).

4.1 Ballistic Arm Movement

For the ballistic arm movement task, the iPod Touch and accelerometer were placed on the forearm (**Figure 2A**) and the peak acceleration value in the horizontal axis was obtained. This reflects the maximum speed at which at which an individual can extend their arm outward. This movement reflects actions such as rapid reaching which can be an important component of activities of daily living. Previous research has shown that older individuals produce movements with 30-70% lower peak velocity compared with younger adults. Ketcham and colleagues found that for a short distance movement older adults peak velocity was 15.9 cm/s compared to young adults whose peak velocity was 29 cm/s (Ketcham, Seidler, Van Gemmert, & Stelmach, 2002). This finding has been reinforced through numerous other investigations (Bellgrove, Phillips, Bradshaw, & Gallucci, 1998; Cooke, Brown, & Cunningham, 1989; Pratt, Chasteen, & Abrams, 1994). Furthermore, as previously described, fall risk increases with age (Tinetti et al., 1988). This consistent finding of markedly reduced movement speed can therefore have huge negative implications for an elderly individual. For example, the ability of an individual to extend their arms outwards to a nearby support surface as they fall or to break a fall to the ground is important to reduce the severity of injury. The strategy to land with outstretched arms can reduce the likelihood of injuries such as hip fractures, which present a severe risk in the aging population. A unique approach for this protocol was to test the sensitivity and association of the smart device and lab grade accelerometer at progressively increasing peak accelerations across a large range of performance, which to our knowledge has not yet been studied. Further, very strong correlation was observed when the absolute maximum and minimum peak accelerations from each trial were correlated between devices. This depicts the capability of the smart device to be used as a diagnostic and rehab tool to subjectively quantify upper limb movement speed.

4.2 Ballistic Leg Movement

For the ballistic leg movement task, the iPod Touch was placed on the anterior shin and the peak acceleration during the outward phase of knee extension was measured (**Figures 3A and 3B**). This task provides a quantitation of unloaded leg movement speed, which significantly degrades with age (Seidler et al., 2010). (Seidler et al., 2010). Furthermore, this knee extension is physically similar to the stepping action commonly executed for protection against falling in response to a trip or perturbation (Maki & McIlroy, 1997; Rogers, Hedman, Johnson, Martinez, & Mille, 2003). The initiation of this protective stepping mechanism involves the complex integration and interaction of sensorimotor, neuromuscular and other cognitive systems. However, age and disease related declines in these systems leads to impaired control of balance and postural stability (Stelmach & Worringham, 1985). For example, much research has shown that aging delays the initiation of voluntary movements such as in reaction time stepping (Patla et al., 1993). Therefore, the longer latency to initiate voluntary stepping is a marker for increased fall- risk (Lord & Fitzpatrick, 2001).

Further research has shown that perturbation training using external perturbations can lead to improvements in protective stepping (Barajas & Peterson, 2018). Previous research has demonstrated that within an older population, perturbation training resulted in fewer falls within the community while Pai et al. showed that older adults who participated in a single session experienced a 50% reduction in falls within the next year (Mansfield, Peters, Liu, & Maki, 2010; Pai, Bhatt, Yang, & Wang, 2014).

This training paradigm is an example of a situation where the smart device could be implemented as an effective and reliable rehabilitation device. The smart device would permit for an easy and accessible method of measuring lower limb movement speed at various times throughout an intervention, whether the measures were performed in the rehabilitation clinic or even the home setting.

4.3 Hand Tremor

The results obtained from the tremor task support previous work carried out by LeMonye and colleagues (R. Lemoyne et al., 2010). Their study investigated tremor amplitude between healthy control subjects and PwPD. Acceleration signals were used to detect tremor amplitude with the use of a smart device. PwPD demonstrated significantly increased tremor as represented by increased acceleration fluctuation values. This study depicts the ability of the smart device to differentiate between a clinical population and healthy controls. Our hand tremor data provides support for and expands upon these findings. Firstly, acceleration data was collected 1) concurrently with a lab grade device and 2) over a progressively increasing tremor amplitude. High correlation values were obtained between devices and at both low and high tremor amplitudes, demonstrating that the smart device is capable and sensitive enough to measure and detect a large range of tremor, whether it be subtle and low amplitude or the type observed in more severe stages of disease. This further supports the notion that the smart device could be integrated in a clinical or rehabilitation setting to enhance diagnosis or track intervention efficacy.

.

4.4 Postural Stability

Improvement in balance function has been shown to reduce the overall risk of injury, aid in the recovery from injury and improve functional performance in elderly individuals (Moral-Munoz et al., 2018). There is thus a need to have the ability to quickly and reliably assess balance outside of a hospital or laboratory setting. Our results demonstrate the capability of the iPod to be readily and reliably used as an objective balance assessment in a field setting. The implications of this could increase the resources available to a clinician and have a beneficial impact on the clinical environment. The outcome of our testing supports pervious research completed in this area. Hou et al. utilized a smart device in six different postures and assessed whether the device can note any significant differences between conditions or postures. . As with our results, they showed the ability of the smart device to detect a change in conditions (eyes open vs eyes closed), Hou and colleagues also found that the smart devices were sensitive enough to detect the expected differences in postural stability between healthy controls and stroke patients (Hou et al., 2018). Likewise, Patterson and colleagues showed that balance measures obtained from a smart device were consistent with measurements obtained using an already validated system, demonstrating concurrent validity of the smart device-based balance measurement (Patterson et al., 2014). The totality of this work suggests that the iPod Touch is an assessment tool that can be feasibly used to measure balance. This device can fulfill the need for a cost-effective, convenient and easy to use measure of balance. The development and validation of such a protocol is beneficial, whether it be as a rehabilitative tool in injury recovery, aiding in injury prevention or enhancing the functional performance of an individual ultimately resulting in increased QOL.

4.5 Current Limitations in Assessment

Current assessment of motor function, physical function, and mobility have some limitations. They are either confined to laboratory settings with expensive, fixed equipment, or they are relatively crude timed or counted measures in the field. For example, the lab grade equipment necessary to provide quantitative motor function measures is usually heavy, expensive, prone to damage with moving, and requires power. This severely limits the ability to conduct testing in field settings and thus reduce accessibility to such testing. Aside from the lack of portability, laboratory grade equipment is often costly. For example, the least expensive lab grade force platforms used to assess postural stability can cost upwards of $5000, and full systems for measuring ground reaction forces can be > $40K. Again, this expense impacts the ability to carry out assessments. Furthermore, tests using this type of equipment require significant training and must be conducted by a skilled researcher. Finally, a number of the more traditional assessments, while easy to perform, involve relatively crude outcome measures. For example, the number of sit-to- stand repetitions a subject can complete in a given time, or the time taken to complete a timed up-and-go or simple walking task. This outcome measure is rudimentary and does not provide the clinician with the precision of information necessary to track progression or and target specific rehabilitation strategies.

4.6 Novelty and Utility of Smart Device Motor Battery

The evidence that supports our novel collection of motor assessments expands on previous data from work on other portable movement sensors and together demonstrates that the smart device appears to be a feasible and reliable movement sensor. There is a need for the ability to report on an individual's mobility and physical function outside of a laboratory or a hospital setting. The results of our study indicate that the iPod Touch could be a potential tool to fill this void. It could be a valuable resource for a clinician whether it be aiding in diagnostic decision making or evaluating interventions. Furthermore, the iPod Touch is relatively inexpensive, it is portable and easy to use and can provide in depth and quantitative information concerning movement behavior. . The notion of the utility of these devices in this type of testing is supportive of views put forward by Culhane and colleagues which suggest that the accelerometers housed within the smart devices have potential use in a clinical setting (Culhane, O'Connor, Lyons, & Lyons, 2005). Despite heavy use within the research realm, these inexpensive, miniature, non-invasive accelerometers are ideal for potential use in clinical monitoring situations.

4.7 Future Exploration

For the tests described as part of this motor protocol, data was collected on the iPod Touch through means of a straightforward data collection application that simply logs the values from the sensors and produces a text file. Data was stored temporarily on the device and then transferred to computer for subsequent analysis. Use of the common smart device is ubiquitous amongst the public, thus an application onboard the device with an algorithm capable of quantifying the parameters and producing the outcome measures as outlined in our protocol would be very useful. This would serve to contain the entire measurement and analysis process on the device and increase the access to outcomes for investigators and patient alike. The development of smart device apps for self-managed or professional health assessment is developing rapidly. For example, Munoz and colleagues conducted a review of smartphone applications used to assess the performance of body balance (Moral-Munoz et al., 2018). They found that the app called ‘Sway’ had the highest number of scientific publications validating their use. Authors used a clinically reliable and valid force platform to compare the data obtained by a mobile app using the mobile accelerometers, concluding that the results were consistent and valid between devices (Patterson et al., 2014; Roeing, Hsieh, & Sosnoff, 2017). Similar applications have also shown a degree of feasibility with the sit-to-stand task. For example, a feasibility study was carried out by Lummel and colleagues using the gyroscope of the smart device during a 5x STS study to assess whether an automatic algorithm detection is sensitive and capable enough to capture angular velocity. They concluded that the automated algorithm was capable and feasible in detecting the angular velocity during a STS and clearly demonstrates clinical utility (Van Lummel et al., 2013).

The results of our findings show that the iPod Touch is a valid and reliable movement sensor, displaying high correlation when compared to lab grade apparatus. Therefore, the next logical and practical step is to develop a simple app, with a user-friendly interface, capable of measuring our outcome parameters such as peak acceleration values or motor variability. This will permit for more efficient and effective assessment of motor function, physical function, and mobility in almost any setting.

4.8 Study Limitations

Throughout the study there were several limitations identified. One such being that the lab grade accelerometer (Endevco 625A) is only a uniaxial accelerometer and therefore had to be aligned specifically during each task so that the desired axis was sensitive to acceleration direction. The findings would likely have been enhanced with the use of a tri-axial lab grade accelerometer. A second potential limitation was the outcomes quantified for the postural stability task. The iPod Touch outcome measure of sway was the standard deviation of x-axis acceleration which is reflective of the variability of body movement in the A/P direction. The outcome measure of postural stability from the force platform was the SD of the excursion of the anteroposterior center of pressure. Subjects were instructed to stand with a straight body during the quiet standing portions and to produce the active voluntary A/P sway at the ankle with a straight body. However, there might have been subtle deviations from this form which could have introduced differences in the amplitude of the fluctuation between the iPod (hip) and force platform (COP). Another limitation was that throughout all the tasks, the iPod Touch was compared and correlated with another accepted measure of assessment but not necessarily directly with the accepted gold standard for that outcome.

5. CONCLUSION

This study showed that a smart device (iPod Touch) can assess a range of upper and lower limb movement speeds, the variability of movements and postural stability by means of a battery of motor function tasks. This testing can be administered remotely and inexpensively by non-experts, providing cost-effective, portable means of motor function testing while still retaining precise quantitative assessment.

REFERENCES

1. Seidler, R.D., et al., *Motor control and aging: links to age-related brain structural, functional, and biochemical effects.* Neurosci Biobehav Rev, 2010. **34**(5): p. 721-33.

2. Ortman, J.M., Victoria, a.H.H. A. Velkoff, and *An Aging Nation: The Older Population in the United States,* U.S. Census Bureau,, 2014.(Current Population Reports,): p. 25-1140.

3. Callixte, K.-T., et al., *The pattern of neurological diseases in elderly people in outpatient consultations in Sub-Saharan Africa.* BMC Research Notes, 2015. **8**: p. 159.

4. Murray, C.J., et al., *Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010.* Lancet, 2012. **380**(9859): p. 2197-223.

5. Lees, A.J., J. Hardy, and T. Revesz, *Parkinson's disease.* Lancet, 2009. **373**(9680): p. 2055-66.

6. Pringsheim, T., K. Fiest, and N. Jette, *The international incidence and prevalence of neurologic conditions: How common are they?* Neurology, 2014. **83**(18): p. 1661-1664.

7. Kalia, L.V. and A.E. Lang, *Parkinson's disease.* The Lancet, 2015. **386**(9996): p. 896-912.

8. Roger, V.L., et al., *Heart disease and stroke statistics--2011 update: a report from the American Heart Association.* Circulation, 2011. **123**(4): p. e18-e209.

9. Ovbiagele, B. and M.N. Nguyen-Huynh, *Stroke Epidemiology: Advancing Our Understanding of Disease Mechanism and Therapy.* Neurotherapeutics, 2011. **8**(3): p. 319-329.

10. Beaton, K., C. McEvoy, and K. Grimmer, *Identifying indicators of early functional decline in community-dwelling older people: a review.* Geriatr Gerontol Int, 2015. **15**(2): p. 133-40.

11. Holtzer, R., et al., *Neuroimaging of mobility in aging: a targeted review.* J Gerontol A Biol Sci Med Sci, 2014. **69**(11): p. 1375-88.

12. Sudarsky, L., *Gait disorders: prevalence, morbidity, and etiology.* Adv Neurol, 2001. **87**: p. 111-7.

13. Mahlknecht, P., et al., *Prevalence and burden of gait disorders in elderly men and women aged 60-97 years: a population-based study.* PLoS One, 2013. **8**(7): p. e69627.

14. Schrager, M.A., et al., *The effects of age on medio-lateral stability during normal and narrow base walking.* Gait Posture, 2008. **28**(3): p. 466-71.

15. Lee, A., K.W. Lee, and P. Khang, *Preventing falls in the geriatric population.* Perm J, 2013. **17**(4): p. 37-9.

16. Rubenstein, L.Z., et al., *Effects of a group exercise program on strength, mobility, and falls among fall-prone elderly men.* J Gerontol A Biol Sci Med Sci, 2000. **55**(6): p. M317-21.

17. Rubenstein, L.Z., *Falls in older people: epidemiology, risk factors and strategies for prevention.* Age Ageing, 2006. **35 Suppl 2**: p. ii37-ii41.

18. Tinetti, M.E., M. Speechley, and S.F. Ginter, *Risk factors for falls among elderly persons living in the community.* N Engl J Med, 1988. **319**(26): p. 1701-7.

19. Hausdorff, J.M., D.A. Rios, and H.K. Edelberg, *Gait variability and fall risk in community-living older adults: a 1-year prospective study.* Arch Phys Med Rehabil, 2001. **82**(8): p. 1050-6.

20. Proessl, F., et al., *Good agreement between smart device and inertial sensor-based gait parameters during a 6-min walk.* Gait Posture, 2018. **64**: p. 63-67.

21. Furrer, M., et al., *Validation of a smartphone-based measurement tool for the quantification of level walking.* Gait Posture, 2015. **42**(3): p. 289-94.

22. Patterson, J.A., et al., *VALIDATION OF MEASURES FROM THE SMARTPHONE SWAY BALANCE APPLICATION: A PILOT STUDY.* International Journal of Sports Physical Therapy, 2014. **9**(2): p. 135-139.

23. Yang, C.C. and Y.L. Hsu, *A review of accelerometry-based wearable motion detectors for physical activity monitoring.* Sensors (Basel), 2010. **10**(8): p. 7772-88.

24. Hou, Y.R., et al., *Feasibility of a smartphone-based balance assessment system for subjects with chronic stroke.* Comput Methods Programs Biomed, 2018. **161**: p. 191-195.

25. Amick, R., J. Patterson, and M. Jorgensen, *Sensitivity of Tri-Axial Accelerometers within Mobile Consumer Electronic Devices: A Pilot Study*. Vol. 3. 2013. 97-100.

26. Kuznetsov, N.A., et al., *Validity and reliability of smartphone orientation measurement to quantify dynamic balance function.* Physiol Meas, 2018. **39**(2): p. 02NT01.

27. Moral-Munoz, J.A., et al., *Smartphone Applications to Perform Body Balance Assessment: a Standardized Review.* J Med Syst, 2018. **42**(7): p. 119.

28. Shah, N. and R. Aleong, *Novel Use of a Smartphone to Measure Standing Balance.* 2016. **3**(1): p. e4.

29. Silsupadol, P., K. Teja, and V. Lugade, *Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket.* Gait Posture, 2017. **58**: p. 516-522.

30. LEMOYNE, R., et al., *ACCELEROMETERS FOR QUANTIFICATION OF GAIT AND MOVEMENT DISORDERS: A PERSPECTIVE REVIEW.* Journal of Mechanics in Medicine and Biology, 2008. **08**(02): p. 137-152.

31. Mellone, S., C. Tacconi, and L. Chiari, *Validity of a Smartphone-based instrumented Timed Up and Go.* Gait Posture, 2012. **36**(1): p. 163-5.

32. Lemoyne, R., et al., *Implementation of an iPhone for characterizing Parkinson's disease tremor through a wireless accelerometer application.* Conf Proc IEEE Eng Med Biol Soc, 2010. **2010**: p. 4954-8.

33. Mukaka, M.M., *Statistics corner: A guide to appropriate use of correlation coefficient in medical research.* Malawi Med J, 2012. **24**(3): p. 69-71.

34. Rogers, M.W., et al., *Triggering of protective stepping for the control of human balance: age and contextual dependence.* Brain Res Cogn Brain Res, 2003. **16**(2): p. 192-8.

35. Maki, B.E. and W.E. McIlroy, *The role of limb movements in maintaining upright stance: the "change-in-support" strategy.* Phys Ther, 1997. **77**(5): p. 488-507.

36. Stelmach, G.E. and C.J. Worringham, *Sensorimotor deficits related to postural stability. Implications for falling in the elderly.* Clin Geriatr Med, 1985. **1**(3): p. 679-94.

37. Patla, A.E., et al., *Age-related changes in balance control system: initiation of stepping.* Clinical Biomechanics, 1993. **8**(4): p. 179-184.

38. Lord, S.R. and R.C. Fitzpatrick, *Choice stepping reaction time: a composite measure of falls risk in older people.* J Gerontol A Biol Sci Med Sci, 2001. **56**(10): p. M627-32.

39. Barajas, J.S. and D.S. Peterson, *First-trial protective step performance before and after short-term perturbation practice in people with Parkinson's disease.* J Neurol, 2018. **265**(5): p. 1138-1144.

40. Mansfield, A., et al., *Effect of a perturbation-based balance training program on compensatory stepping and grasping reactions in older adults: a randomized controlled trial.* Phys Ther, 2010. **90**(4): p. 476-91.

41. Pai, Y.C., et al., *Perturbation training can reduce community-dwelling older adults' annual fall risk: a randomized controlled trial.* J Gerontol A Biol Sci Med Sci, 2014. **69**(12): p. 1586-94.

42. Culhane, K.M., et al., *Accelerometers in rehabilitation medicine for older adults.* Age Ageing, 2005. **34**(6): p. 556-60.

43. Roeing, K.L., K.L. Hsieh, and J.J. Sosnoff, *A systematic review of balance and fall risk assessments with mobile phone technology.* Arch Gerontol Geriatr, 2017. **73**: p. 222-226.

44. Van Lummel, R.C., et al., *Automated approach for quantifying the repeated sit-to-stand using one body fixed sensor in young and older adults.* Gait Posture, 2013. **38**(1): p. 153-6.