

Wearable Gait Lab System providing quantitative statistical support for human balance tests



Jiawei Cui^a, Jia Chen^a, Guanzhou Qu^a, James Starkman^a, Xiao Zeng^a, Elizabeth Madigan^b, Miriam Pekarek^c, Wenyao Xu^d, Ming-Chun Huang^{a,*}

^a Department of Electrical Engineering and Computer Science, Case Western Reserve University, Cleveland, OH 44106, United States

^b School of Nursing, Case Western Reserve University, Cleveland, OH 44106, United States

^c Director of Outpatient Therapy, Veale Wellness and Aquatic Center, Willoughby, OH 44094, United States

^d Department of Computer Science and Engineering, University of Buffalo, Buffalo, NY 14260-1660, United States

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ABSTRACT

Sensory devices have the potential to improve monitoring balance tests and providing quantitative supports for activity analysis. The Wearable Gait Lab system is proposed to monitor activities of feet and legs during balance tests. In this system, a wearable underfoot force sensing unit is used to record foot motions and plantar pressure data; a joint angular and EMG sensing unit is used to record leg motions and muscular data; and an android application is implemented to control all units, monitor the data recording process, and upload recorded data to cloud server, which allows health professionals to review it remotely. The system provides adequate data for balance ability analysis and simplifies the scoring processes in balance tests. The proposed system is evaluated with standard balance tests (Limits of Stability, Sit-To-Stand, and Rhythmic Weight Shift), whereas the data collected are analyzed with data mining techniques to verify the reliability of the designated process. Certain parameters are computed such as Center of Gravity (COG), weight transfer time, and sway velocities. The results show that the system is informational and reliable in the process of determining balance status during tests with additional advantages in high portability and efficient review communications.

1. Introduction

Balance is the ability to control muscular energy in the body and maintain an even distribution of weight to remain a stable posture. Balance has been an essential indicator of human health and is realized by the coordination and support from several body systems including the vestibular, visual, auditory, motor, and higher level premotor systems (FB, 1997). Nearly half of the population over age 65 reports certain balance difficulty symptoms. Symptoms of balance disorders include dizziness or blurred vision, feeling of falling, and even lightheadedness and faintness when attempting to stand up or walk (Deafness & Disorders, 2015). The symptoms occur more likely on patients with disorders in neurological or musculoskeletal systems (Mancini, 2010). Furthermore, balance problems are not exclusive to the older population. It has been reported in year 2015 that 18.6 % of children in the United States had certain symptoms of balance difficulties or dizziness, and only 29.9 % of them received treatment from the health-care professionals (Li & Hoffman, 2016).

* Correspondence to: Case Western Reserve University, 10900 Euclid Avenue, 514B Glennan Building, Cleveland, OH 44106, United States.

E-mail addresses: jiawei.cui@case.edu (J. Cui), jxc1135@case.edu (J. Chen), qxq3@case.edu (G. Qu), jas497@case.edu (J. Starkman), xxz258@case.edu (X. Zeng), Elizabeth.Madigan@case.edu (E. Madigan), MPekarek@breckenridge.oprs.org (M. Pekarek), wenyaoxu@buffalo.edu (W. Xu), ming-chun.huang@case.edu (M.-C. Huang).

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To evaluate the patients' balance systems, researchers and clinicians utilize different functional test measures to assist the patients to identify the sources of balance problems. The lab-based tests normally require the presence of patients in a clinic setting to perform balance tests under the supervision of the clinicians. After the tests, a score of the patient's performance is calculated based on certain institution-developed standards, such as Motor Assessment Scale, Berg Balance Scale (AAHF.), and Rivermead Mobility Index (Tyson, 2004). Due to the requirement of clinicians' supervision, most of the tests use qualitative standards to evaluate balance systems for the patients and generate an overall score based on the clinicians' opinion on how well the test subjects complete the tests. For instance, the Berg Balance Scale has 14-item scale designed to measure a patient's balance ability in a lab setting. Each scale has five levels of performance resulting a score ranging from 0–4, and the scores from all the fourteen tests add up to a total score of 56. One example contained in Berg Balance Scale is asking the subject to pick up an object from the floor from a standing position. A 4 is scored when the patient is able to pick up the object safely and easily; a 3 is recorded when the patient can pick up the object but needs supervision; and a 2 is recorded when the person is unable to pick the object up but reaches 2–5 cm from the object and able to keep balance independently. However, it is relatively hard and non-objective for the clinicians to judge the extent of difficulties for the subject to pick the object up. Since those classic balance tests use partially qualitative, semi-subjective standards based on clinicians' personal judgments upon the patients' performances, there may be inaccuracies. In addition, these tests confined in traditional gait lab environment may lead to environmental bias concerns and cannot reflect patients natural behaviors in their usual environment (Lewejohann & Reinhard, 2015).

Wearable sensory accessories and hardware designs have the potential to extend impact of wearable devices in health field, especially applying sensory techniques to quantize human health indicators to better understand body structure and movements. To solve the problems existing in the classical balance tests, especially in poor accessibility, the team implements a solution that the Wearable Gait Lab system will support data recording and upload for human body balance tests at any place that is convenient for the users. The system will only require the user to wear a Myo sensory limb band on each leg and place a smart insole under each foot, while connected to an Android device with Bluetooth Low Energy (BLE). An Android application has been implemented to for the users to control the data collection process. The limb bands on legs will provide electromyography data of the leg muscles and motion data of the leg motions, and the smart insoles will provide feet motion data and plantar pressure data. The users are able to view the plots the collected data in real time and upload them to the cloud server with the Android app. Once the data are uploaded to cloud server, the researchers or the clinicians can review them remotely with a PC user interface the team has built and furthermore provide medical suggestions based on the results reflected in the data. The system eliminates the negative effects caused by semi-subjective standards and environmental bias by providing relatively objective, quantitative data and providing the users with options to perform balance tests at their preferable places.

The remainder of this paper is structured as follows. Section 2 introduces the background of balance disorders including causes and typical disorder types. Section 3 summarizes related works in the area of balance tests and sensory applications in those tests. In Section 4, the Wearable Gait Lab will be explained, including the hardware of sensory equipments, software implemented, applications of the system, and applied algorithms. In Section 5, the system is evaluated with chosen balance tests, and demonstrations are shown for experiment procedures and data analysis.

2. Balance disorders

The causes of balance disorders include many factors including inner organ dysfunctions due to age, injuries caused by outer forces, and postures the person has. Sometimes the system goes into disorder with no obvious reasons (Deafness & Disorders, 2015). Inner ear or brain conditions caused by medications, ear infections, or a head injury could impact on a person's balance system. Any situations that lead to a person's dizziness would be causes as well, such as alcohol, low blood pressure, and even head spinning. In addition, a person's visual system provides significant aids for a person to keep balance under various conditions. Until today, many balance disorder reasons are not known to researchers, and some balance problems start with no obvious causes. Additionally, the risk of getting balance problems increases as a person gets older in age.

Judgements from the brain to keep one balanced are made by a series of signals from the vestibular system. As shown in Fig. 1, the vestibular system starts at labyrinth in the inner ear. With structures known as semicircular canals containing fluid-filled ducts, the labyrinth is able to tell rotations of the head. A structure called cupula is in each canal, and when the head is rotated to a direction, the fluid in the canal ducts will flow under effect of gravity. The fluid motions will cause the cupula to flex and further make the stereocilia to bend. The nerve signals triggered by the stereocilia bending send information to the brain indicating the turning direction of the head. The utricle and saccule lying between the semicircular canals and the cochlea offer information in the position of the head with respect to the body and report position changes. Once a person moves, the semicircular canals, utricle, and saccule will coordinate with each other and identify the movements. Once the brain receives the signals, it will make corresponding judgements along with the visual and musculoskeletal system to assist the body remaining balance. Any dysfunctions or disorders occurring in the process will cause balance problems.

Balance disorders are mostly classified by their internal organic causes in current medical system. Some of the common ones are Benign paroxysmal positional vertigo (BPPV) or positional vertigo, labyrinthitis, and vestibular neuronitis. The BPPV is normally related to human movement such as spinning the head too fast or intense movements. Those movement would cause the cupula not flex properly and thus send wrong information to the brain. While the information from different organs gets mismatched in the brain, the brain is not able to send correct orders and thus cause balance problems. BPPV could result from an injury caused by outer force or solely regular intense activities, which are mostly mechanical triggering factors. Different from BPPV, labyrinthitis is caused by infection of the inner ear, and sometimes it is associated with infections from other systems as well, such as the respiratory system.

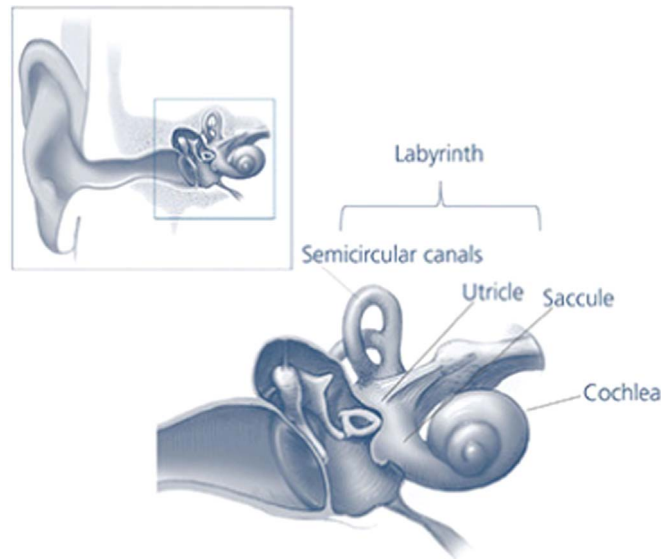


Fig. 1. Structures of the balance system inside the inner ear [Deafness and Disorders, 2015](#).

Similarly, vestibular neuronitis is the effect of inflammation in vestibular nerve and often reacts to an infection due to virus.

3. Related work

3.1. Qualitative balance test

The classic balance tests operated by labs and clinics are mostly based on semi-subjective standards, whereas clinicians are responsible for reporting the quality of a test object's balance status during test activities with scores. Those methods that clinicians implement include Berg Balance Scale and the Mini-BESTest, normally requiring the clinicians to evaluate the test objects' balance ability by their personal preferences and judgments on a number scale ([Ross & Purtill, 2016](#)). Due to balance test differences among clinicians, progress in new technologies has given rise to sensory hardware that are able to evaluate balance test parameters at a more objective scale. The technological devices being developed could be classified as non-wearable sensors and wearable sensors ([Herran & Alvaro, 2014](#)). Non-wearable sensors commonly require the use of controlled research facilities where the sensors are located in the test station statically such as image processing sensors and floor sensors. Compared to non-wearable sensors, the wearable sensors are more diverse and required to be located on parts of the body, such as feet, knees, and thighs; those sensors include IMU sensors, extensometers, goniometers, active markers, electromyography, etc.

3.2. Quantitative balance test

Currently the non-wearable measuring system such as Vicon and GAITrite are widely used in human movement measurements including balance tests. However, the devices are highly expensive and lack mobility. Another option used by the researchers is visual technology devices such as Microsoft Kinect. Researchers choose to use the system in order to acquire human body movement data at a macro-graphic, visual level. To prove its validity, Ross A. Clark made comparisons on the estimated anatomical landmarks obtained by Microsoft Kinect and 3D motion analysis system ([Clark & Pua, 2012](#)). The analysis illustrates that Microsoft Kinect can offer reliable data with lower cost and easier setup process compared to the aforementioned balance systems by providing real-time anatomical landmark position data in three dimensions. On the other hand, the research also shows that the proportional biases and inability of assessing joint rotations. By the research of Phillip A. Gribble, the ankle movements to different directions performs an important part in the balance test ([Gribble & Hertel, 2004](#)). As a result, measurements on joints are essential in balance test data recording process.

To further record joint information during balance tests, many research reports show the wearable sensors' capability of measuring 3-D data to assist in balance tests. Lugade V proved the validity of tri-axial accelerometer in movement detection by identifying postural orientation and movement from accelerometer data against movement video recordings in his experiments ([Lugade,](#)) and Barth et al. validated a system using gyroscopes and accelerometers in order to measure the gait functions ([Barth & Michael, 2012](#)). In addition, Moore ST. et al. explored the use of wearable sensors on ankle to monitor gait activities ([Moore ST1 & MacDougall,](#)). However, only accelerometer and gyroscope data would not provide sufficient information for a reliable balance test system. In Saunders' paper, he mentions that the body sway, another important indicator of balance status and a drawback of the measurement with accelerometers, is difficult to be measured only with accelerometers. In order to accurately predict balance patterns with body sway data, the approximate center of mass (COM) of the subject needs to be computed; however, one may not find the COM position

accurately when performing different actions. Many investigators estimate the change of COM in position over time by measuring changes in the center of applied pressure (COP) on a force plate (Saunders, 2015). Although the estimation has validity only when the subject body behaves as a rigid structure rotating only about the ankle in the sagittal and frontal planes (SS & Robin, 1996), one may use accelerometer, gyroscope and magnetometer sensors to recognize the direction of the ankle and calculate COM in real time. Due to unreliability of determining COM changes solely with changes in COP in order to calculate body sway, the team uses leg orientation data to indicate the sway in legs, which improves the reliability of evaluating the effects on balance states caused by body sway.

3.3. Summary

Nevertheless, the quantitative balance test systems, which mostly concentrate on acquiring macro quantitative data, lack the mobility and portability that are essential to accurate ubiquitous daily balance tests. In addition, quantitative data solely based on macro body statistics such as COM and weight distribution will not fully represent one's balance status. Therefore, electromyography data are introduced to fill the blank to reflect balance statuses at certain parts in human bodies such as lower limbs.

In this paper, the team proposes the Wearable Gait Lab system to perform balance tests and realize data analysis, which utilizes accelerometer sensors, gyroscope sensors, magnetometer sensors, pressure sensors, and electromyography sensors on the human's lower limbs to analyze essential information for balance status and look for unstable patterns. Electromyography sensors are widely used in medical field to assess muscle health and nerve cell information by measuring the strength and speed of nerve signals with electrodes taped to skin surfaces (Staff, 2013). Leg electromyography data are essential in the process of analyzing muscle activities (Nashner, 1977), and studies have shown that related muscles in the legs are activated during stance. In order to improve the portability and ease of use of the system, wireless and Bluetooth connection is the only communication method among devices in the process of data collection and analysis. With the system, the patients will not need to take balance exams in clinics periodically, and the health care professionals do not need to spend time monitoring the balance test process, while relatively objective data are still recorded for analysis.

4. System and methods

In this section, the hardware choices and software implementations of the Wearable Gait Lab are discussed. The section consists of five parts: Wearable Underfoot Force Sensing Unit, Joint Angular and EMG Sensing Unit, Wearable Gait Lab Android Application, JavaFX PC User Interface, and Dynamic Time Warping Algorithm. A system implementation flow chart is shown in Fig. 2.

The complete set of hardware in the system includes the Wearable Underfoot Force Sensing Unit recording feet IMU and pressure data and the Joint Angular and EMG Sensing Unit recording leg EMG and IMU data. Once the test subject wears the system, the two units are connected to an Android device with Bluetooth Low Energy. An Android application is developed by the team to control the data recording process including system data collection initialization and termination, plotting collected data in real time, and uploading the data to the cloud server when the data collection process is completed. Once the data files are uploaded to the cloud server, the researchers or the clinicians are able to view and analyze the data through the PC user interface. The PC user interface includes a 2D plantar pressure map and four line charts to display CSV data files stored on cloud server or local disk. Then the clinicians can provide professional suggestions for the patients after data analysis.

4.1. Wearable underfoot force sensing unit

The key component of the system hardware is the Bluetooth Low Energy controlled Wearable Underfoot Force Sensing Unit, as shown in Fig. 3. Each smart insole in the unit contains a textile pressure array, an inertial motion sensor, a micro control unit (MCU)

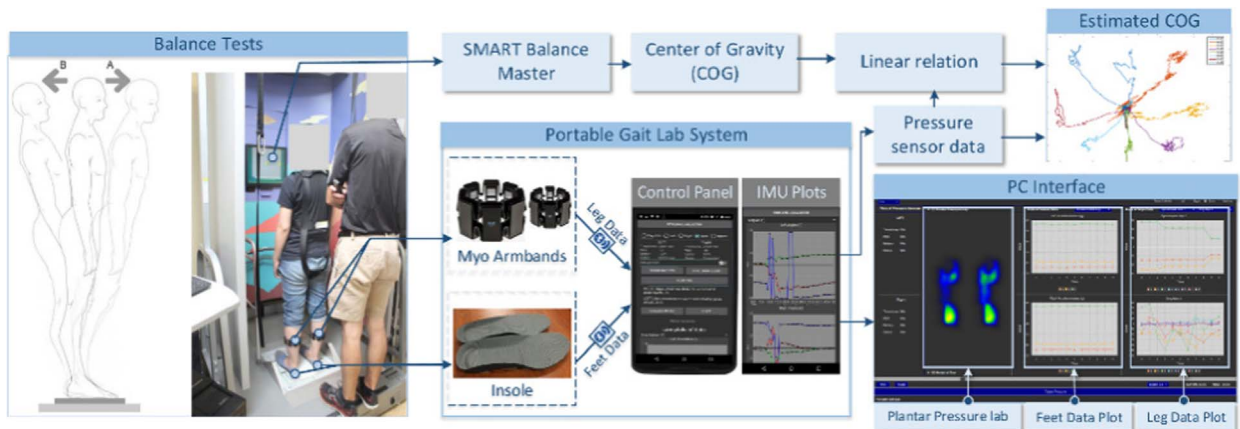


Fig. 2. System implementation flowchart.

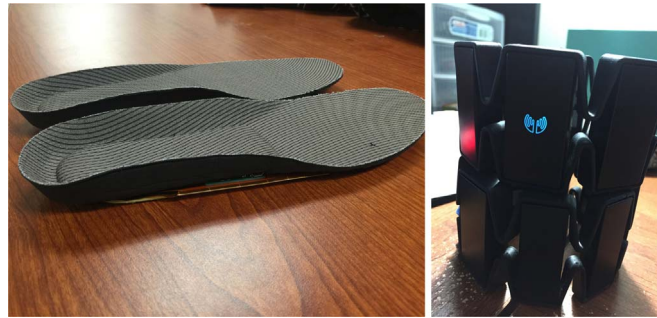


Fig. 3. Left: Wearable underfoot force sensing unit Right: Joint angular and EMG sensing unit.

with Bluetooth Low Energy module, and a battery module. The textile pressure array records data from forty-eight pressure sensors used to obtain a high resolution plantar pressure map. The 9-axis inertial motion sensor records accelerometer, gyroscope, and magnetometer data, whereas the accelerometer and the gyroscope measure the movement of the insole, and the magnetometer provides aids for data calibration. X, Y, Z axis of all three parameters are sampled during the data collection process. The MCU with Bluetooth Low Energy module realizes the system utilization and provides a wireless channel to connect the insole to a smart electronic device. The battery module contains a battery and a micro USB battery connector, allowing the user to recharge the battery when the insole is out of power. In the system, the Wearable Underfoot Force Sensing Unit is placed under feet and functioned to record the plantar pressure data and feet movement data during the balance tests.

4.2. Joint angular and EMG sensing unit

Another component of the system hardware is the Joint Angular and EMG Sensing Unit, as shown in Figure ??, containing a pair of Myo limb bands. Manufactured by the Thalmic Labs, the Myo limb bands are designed to record EMG data while reading the electrical activities of human arm muscles and sending control orders to devices based on motion and gesture information. The team utilizes the Joint Angular and EMG Sensing Unit in the Wearable Gait Lab system due to its functionality of recording IMU and EMG data, and it can be used to better record lower limb activities when worn on legs during the balance tests. X, Y, Z axis of accelerometer and gyroscope data and eight EMG data are recorded at each timestamp in the process. Studies have shown that distal (leg and thigh) muscle activities are important indicators of balance adjustment behaviors (Tang, 1997). The leg EMG data would fill in the gap in current sensory balance tests so that the test results would be more reliable with additional muscle activity indicators. The leg IMU and EMG data are recorded concurrently with the data from the Wearable Underfoot Force Sensing Unit in a balance test for future data analysis.

4.2.1. Myo dual data collector on PC

Since the official Myo SDK for Windows does not provide the option to record both IMU and EMG data from both Myo limb bands in the Joint Angular and EMG Sensing Unit simultaneously, the team has implemented a solution to fulfill data recording purposes in the system so that a CSV data file would be generated for each Myo to record sensory data in the order of timestamp, gyroscope data, accelerometer data, orientation data, and EMG data. Since EMG data are generated with a higher frequency than IMU data, empty IMU data lines are filled with existing IMU data from the previous timestamp to make the generated data a complete matrix for ease of data analysis. The Myo Dual Data Collector program is used in the data collection process only as a supplement to the Android application and is the second choice for Myo data recording due to portability.

4.3. Wearable Gait Lab android application

The Wearable Gait Lab Android application is implemented for the purposes of displaying and recording the sensor data from the left, right, or both of the lower limbs by bridging the data to xPC host-target system through BLE. As shown in Fig. 4, the Android application uses a single pane structure whereas all functionalities are found by simple scrolling actions. The data types that would be recorded are feet accelerometer, feet gyroscope, feet magnetometer, feet pressure, leg accelerometer, leg gyroscope, leg orientation, and leg electromyography accordingly. The top of the application interface locates the control panel, containing the device information including timestamp, RSSI, connectivity and battery. In the control panel, the user initializes data collection process and uploads recorded data to the cloud server. Currently the team has acquired and managed a secured cloud storage space from Case School of Engineering Information Technology Department with a feasible capacity. Under the control panel, the interface contains line charts to plot IMU (accelerometer, gyroscope, and magnetometer) and electromyography data in real time, and a plantar pressure map to visualize pressure map under each foot.

4.4. JavaFX PC user interface

The JavaFX program is a user interface on PC for ease of display and analysis of the data collected from Wearable Gait Lab system.

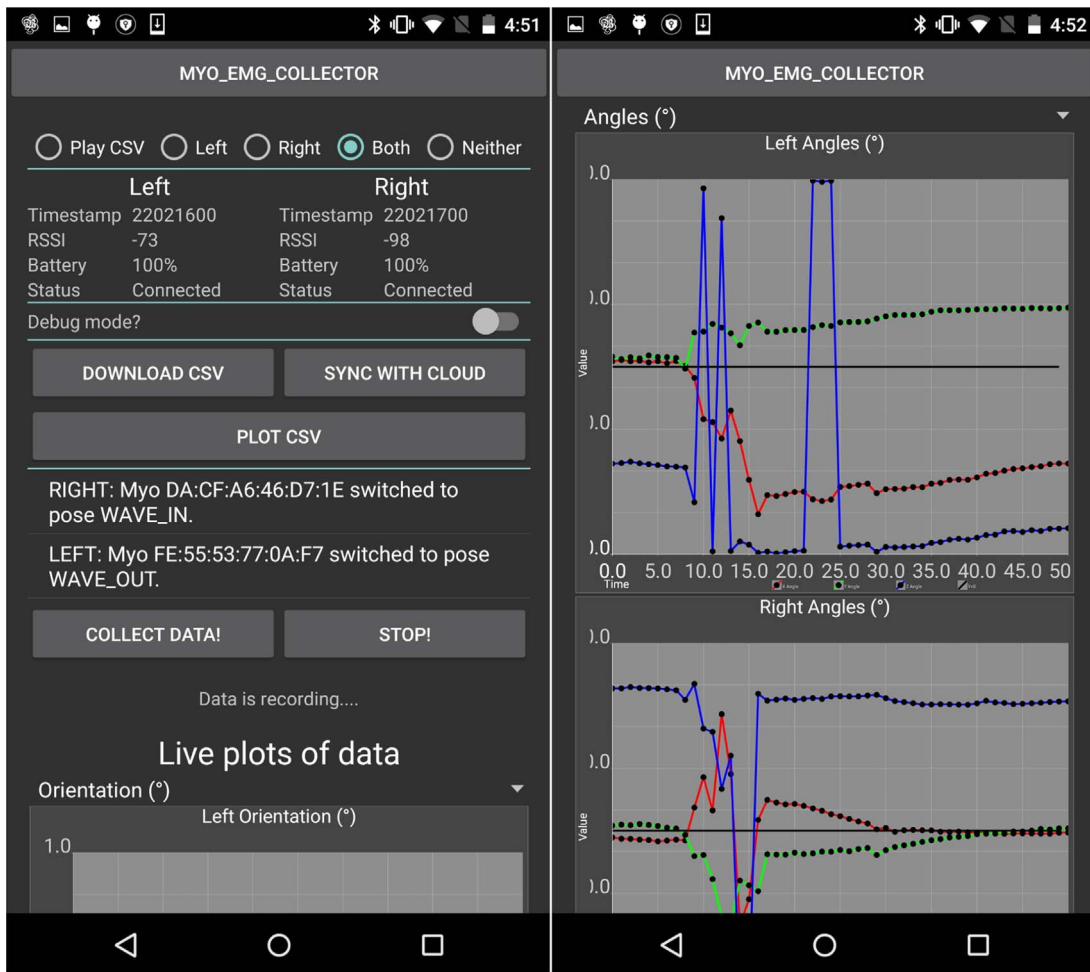


Fig. 4. Wearable Gait Lab android application control panel and plotting interface.

The software is designed for the researchers or the clinicians to read CSV data generated from Wearable Gait Lab Android application and display sensor information the same as the Android application. Correspondingly, the software is optimized to share similar interface style and include charts and graphs in a similar structure of sections for operation affinities while switching between the PC software and the Android application. In the Wearable Gait Lab system, both of the Wearable Gait Lab units are calibrated and the smartphone with the Android application is able to receive the corresponding real-time movement and pressure sensor data and process the data into CSV files. The user interface of the PC software is built with JavaFX, whereas the control functions are contained in controller functions written in Java, and the interface is written in FXML and optimized with CSS, as shown in Fig. 5.

The JavaFX PC user interface reads in CSV data exported from the Android user application from the cloud server or the local disk, whereas between every timestamp, the CSV data contain information of foot side, the timestamp, nine IMU sensor data including three each from accelerometer, gyroscope, and magnetometer, and forty-eight pressure sensor data on the Wearable Gait Lab. Similar to the Android application, the PC user interface can be chosen to display underfoot force sensing data information from the left insole, the right insole, both of them, or neither of them. The PC user interface displays the data in four line charts and one 2D plantar pressure map. The interface would read in the file and display the data in a chronological order in a continuous video form, meaning that it displays the data in the first line of the data as the user imports the file and data in the following lines correspondingly until the last line. Clinicians are also able to adjust the speed of playing, pause the data display process, and manually choose display time, and save screenshots for future record.

4.5. Dynamic time warping algorithm

The Wearable Gait Lab system might collect data at a slightly different frequency. In order to find a more accurate time series, the Dynamic Time Warping algorithm (DTW) is implemented to map right and left Wearable Gait Lab's data (Keogh & Ratanamahatana, 2005). Known as a delicate technique to perform an optimal alignment and discern for connections between two time-dependent sequences of different lengths, the Dynamic Time Warping technique is able to support building traceable patterns between right and

Plantar Pressure Map Insole Data Line Charts Myo Data Line Charts

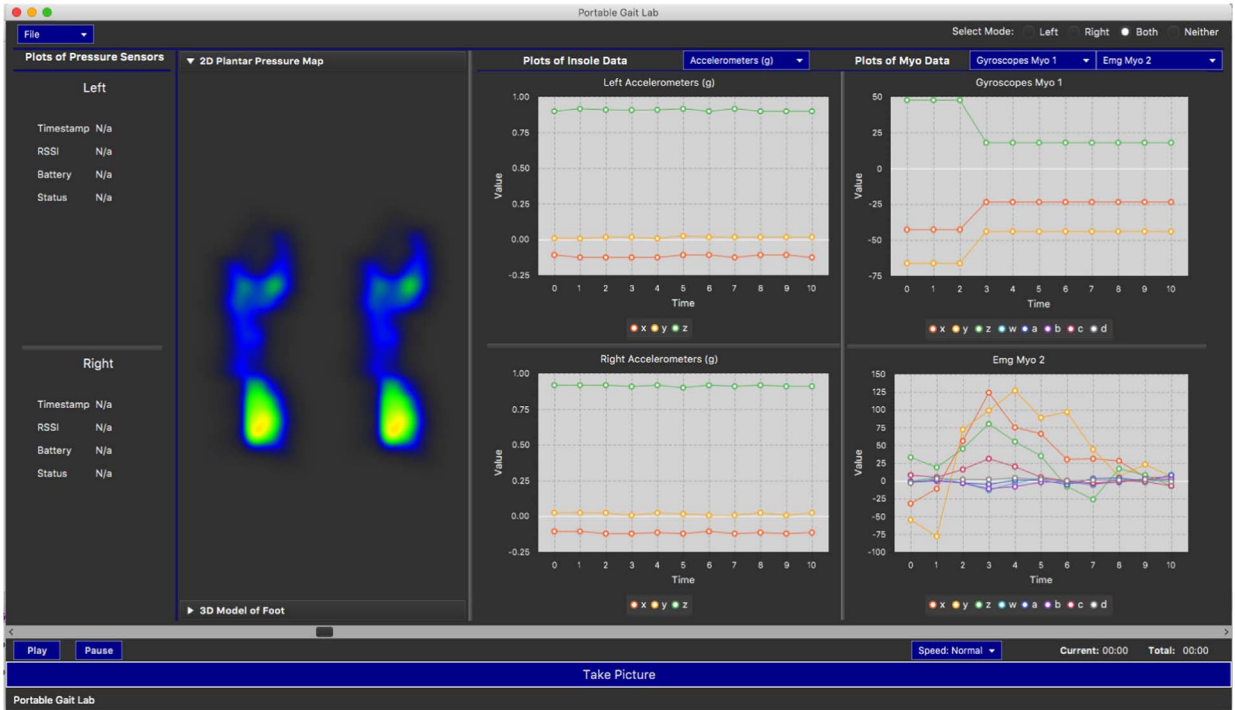


Fig. 5. JavaFX PC user interface for data review.

left insole's sensor data, even if their timestamps do not match (Müller, 2007). In addition, the DTW algorithm is used to synchronize data between the Wearable Underfoot Force Sensing Unit and the Joint Angular and EMG Sensing Unit to realize data fusion, so that the timestamps between different sensors would match accordingly.

During the computing process, a warping path is defined to be the alignment between the two sequences by assigning elements in one sequence to the elements in the other. The warping path is constructed by the following equations of W_k ,

$$W_k = (i, j) \tag{1}$$

and

$$W_{k+1} = (i', j'), i \leq i' \leq i + 1, j \leq j' \leq j + 1 \tag{2}$$

where i and j are timestamps found in left and right Wearable Gait Lab data. The distance of the warping path can be calculated by

$$Dist(W) = \sum_{k=1}^{k=K} [Dist(w_{ki}, w_{kj})] \tag{3}$$

where $Dist(W)$ is the distance of the wrapping path W , and $Dist(w_{ki}, w_{kj})$ is the k th element's distance between two data timestamps of the warping paths.

5. Experiment and calculation

To evaluate the reliability of proposed system, existing balance systems on market including NeuroCom SMART Balance Master system is used as references. Four standard balance tests using Balance Master Systems are applied: 1) Limits of Stability (LOS); 2) Sit-To-Stand (STS); and 3) Rhythmic Weight Shift (RWS). These three tests are semi-static balance tests, which means among all gesture the subject is asked to do, the monitored feet/foot is not leaving the ground. The following Table 1 lists all parameters calculated in

Table 1
Summary of experiments and calculated parameters.

Exp 1 LOS	COG	Sway Velocity	
Exp 2 STS	Wt Time	Sway Velocity	L/R Wt Symmetry
Exp 3 RWS	On-Axis V		



Fig. 6. Left: A Demonstration of displacing COG from center to front and from center to back. Right: Equipment set up. The test subject is wearing Wearable Gait Lab while standing on dynamic force plate of the Smart Balance Master system.

each experiments, including center of gravity (COG), sway velocity (SV), left/right sway velocity differences (L/R SV difference), weight transfer time (Wt time), left/right weight transfer symmetry(L/R Wt symmetry), and On-Axis Velocity(On-Axis V). These three experiments do not involve joint motions; thus the data collected by Joint Angular and EMG Sensing Unit are not evaluated in this paper.

5.1. Limits of Stability (LOS)

The Limits of Stability test is aimed to analyze the human's ability to maintain balance at the maximum distance one can displace Center Of Gravity (COG) (Mobility, 2016). The participant was required to stand on dynamic force plate of the Smart Balance Master system and wear the Wearable Gait Lab system. Based on the instructions shown on a screen in front of the test subject, after hearing a tone, the test subject is instructed to shift his/her center of gravity to one of the eight cardinal and diagonal directions without lifting his/her heels and toes. During the process, both feet of the test subject must stay on the ground. Fig. 6 shows two conditions of the LOS experiment: moving COG from the standing phase to front (arrow A) and moving COG from the standing phase to back (arrow B), and the figure on the right in Fig. 6 shows the equipment set up including the test subject. Five subjects participated in this test.

The team found linear relations between the pressure data collected by sensors in the Wearable Gait Lab System and COG given by the SBM, for each trial, using multiple linear regressions between the pressure sensor data and computed COG, from which a linear correlation between the two has been concluded. Fig. 7 shows that one of the participants' residual plots under Condition 2 as an example, during which the test subject was requested to move COG to the front-right direction. The upper plot in Fig. 7 named “residual case order plot (x axis)” refers to the test subject's instability statistics on x-direction on the Balance Master (test subject's center to left and to right). Accordingly the plot “residual case order plot (y axis)” refers to data on the test subject's center to front and to back. The x-axes of two plots refer to the case number, which are the data collected from the Wearable Gait Lab the test subject wore, and the y-axes refer to the residuals in each case. According to the plots, the majority of the cases fit in the linear relation well, presented in green. The outliers, presented in red, are relatively sparse compared to the data fitted to the relation. The coefficient of determinations R^2 and p-values of five subjects are listed in Table 2. All p-values are much smaller than 0.05, therefore, statistically strong linear correlations hold.

Each pressure sensor data is multiplied by their weights to compute the COG. Fig. 8 intuitively illustrates the trends of COG transfer under each condition when the test subject is requested to move COG to different directions. The traces in the figure indicate that the test subject moves his/her COG from the original stance place to the destination gradually. The fluctuations represent the test subject's self adjustments to keep balance while switching COG to the left or to the right.

The sway velocity at each direction is also calculated based on COG to illustrate how fast one can change their COG in the test environment. A bigger value in sway velocity means a faster speed (a shorter time) one can react to keep balance. The sway velocities can be calculated by

$$\text{Sway Velocity} = \frac{\arcsin(\theta_i - \theta_{i-1})}{t} \tag{4}$$

whereas

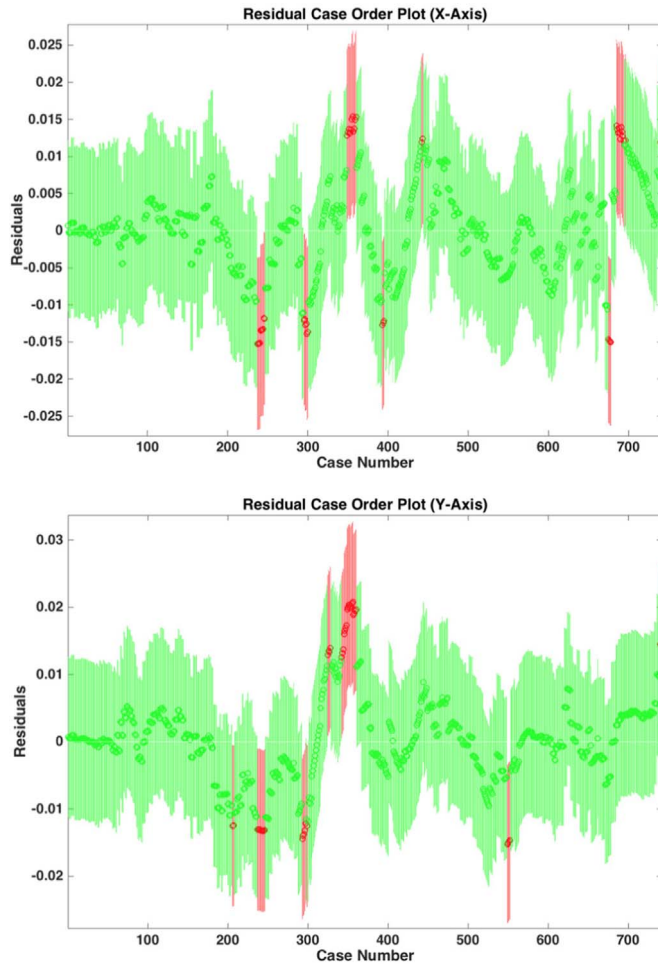


Fig. 7. Linear regression analysis: moving COG to front-right in LOS experiments. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\theta_i = \arcsin\left(\frac{\text{abs}(\text{COG}_i - \text{COG}_{i-1})}{\text{height} \times 55\%}\right) \tag{5}$$

in which θ is the angle between the human body and the vertical direction orthogonal to the ground. As an example, the result of Subject 5 is shown in the Table 3.

Reaction Time (RT) is the time in seconds it takes for the participant to initiate adjusting COG (to reach the target) after the starting signal. However, since it is extremely difficult to start collection from both the Wearable Gait Lab system and SMART Balance

Table 2

R^2 , F statistic, p-values, and error variances of five subjects. All p-values are smaller than 0.05, which proves the linear correlation of pressure data collected by our system and COG collected by SBM.

Subject #	x axis R^2	x axis F	x axis p-value	x axis error var
1	0.8714	1858	1.24e-58	2.67e-05
2	0.8567	12981	2.41e-75	7.26e-06
3	0.9229	3487	2.62e-282	1.76e-05
4	0.7817	1822	1.25e-83	5.61e-05
5	0.8045	1808	8.73e-32	3.81e-05
Subject #	y axis R^2	y axis F	y axis p-value	y axis error var
1	0.8574	1164	5.08e-168	1.75e-05
2	0.9023	2950	3.51e-218	8.72e-06
3	0.9358	2860	2.87e-261	1.50e-05
4	0.7685	790	8.50e-49	1.59e-05
5	0.8349	449	1.05e-146	2.42e-05

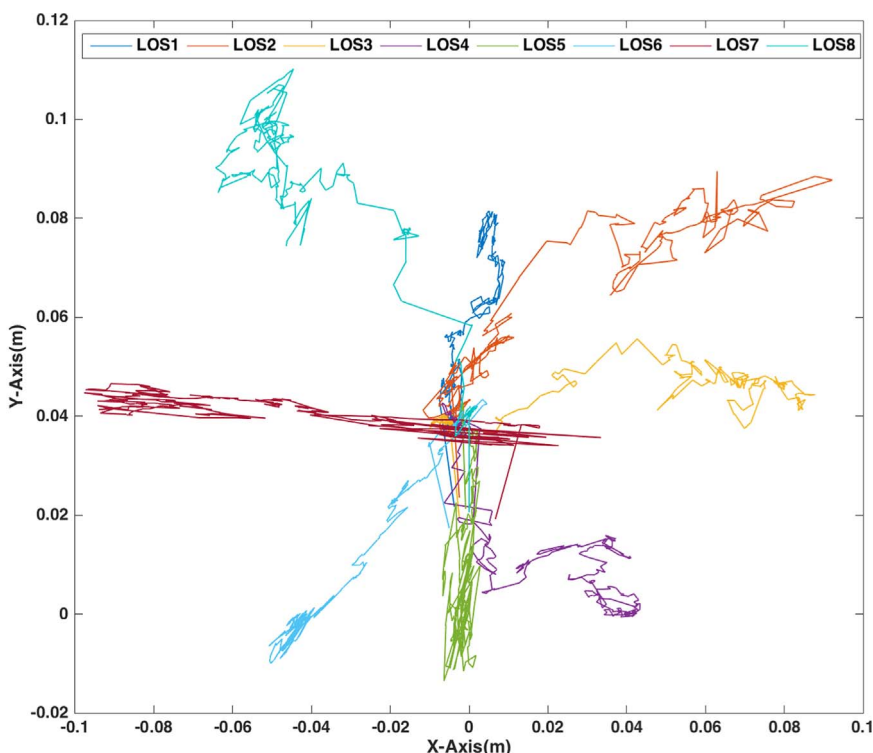


Fig. 8. Center of Gravity (COG) of LOS experiments.

Master system at the same time manually, there is certain time error that could not be entirely eliminated. The results can be collected accurately, if both systems can be bound and initialized together. Nevertheless, the results from statistical analysis have indicated strong correlation between the data from the Wearable Gait Lab system and the SMART Balance Master system.

5.2. Sit-To-Stand (STS)

Sit-To-Stand test is designed to quantify the test subject's balance status when he/she stands up from seated posture (Mobility, 2016). Key parameters measured during the test include weight transfer time, sway velocity during the rising phase, and left/right symmetry of the rising force. During the test, the test subject is asked to wear the Wearable Gait Lab and sit on a wooden stool placed on long force plate of the Smart Balance Master system as shown in the right image of Fig. 9. The participant is requested to stand up as soon as possible after hearing an alert tone, as shown in the left two figures in Fig. 9. This procedure is repeated three times. During this test, the harness set was not required. Eight volunteers participated in this test.

The results are shown in the Table 4. If the left/right weight symmetry is negative, the participant puts more weight on left foot; if it is positive, it means that the participant puts more weight on right foot. It has also been confirmed that the results from the Wearable Gait Lab agree with those from SMART Balance Master system.

5.3. Rhythmic Weight Shift (RWS)

Rhythmic Weight Shift (RWS) is a test to evaluate one's ability of shifting their weight distribution between left and right or between backward and forward rhythmically. There are two parallel bars shown on the screen of SMART Balance Master system, both vertically or horizontally at different times. The participant is required to shift their COG following a cursor moving between the bars on the screen. The cursor shifts in three speeds on each direction. During this test, the harness set was not required. Eight subjects participated in this test. On-axis velocity, which is the sway velocity along the direction of the participant shifts, is calculated (Table 5). Trial 3 is the fastest, and Trial 1 is the slowest.

Table 3
Sway velocities of Subject #5 in LOS Experiments.

Condition #	LOS1	LOS2	LOS3	LOS4
Sway Velocity (deg/sec)	1.94	3.51	1.81	2.29
Condition #	LOS5	LOS6	LOS7	LOS8
Sway Velocity (deg/sec)	3.79	2.08	5.37	2.16

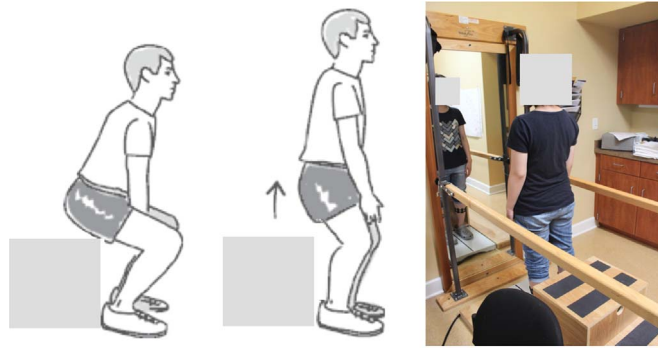


Fig. 9. Left: Sit-To-Stand illustration right: Sit-To-Stand experiment setup.

In Table 5, On-Axis Velocity for each trial by each subject has been included in both horizontal and vertical directions. Due to policies at Breckenridge Village, the team is not allowed to release the unprocessed data from the SMART Balance Master system even anonymously. However, it is confirmed with the results that the On-Axis Velocities collected from the Wearable Gait Lab system and the SMART Balance Master system agree with each other with large similarity.

6. Conclusion and future work

In this paper, the Wearable Gait Lab is proposed for balance tests data collection and remote data analysis in order to simplify balance tests procedures and improve result accuracies. The system allows the user to connect all the wearable sensors wirelessly through a smart device, and the data collection procedures can be simply controlled by an Android application. Accordingly the data collected during the process can be conveniently reviewed remotely by researchers or clinicians. In the experiments, the system has been verified with standard balance tests including Limits of Stability test, Sit-To-Stand test, and Rhythmic Weight Shift test. Certain status indicators are computed and compared to verify the proposed system with existing balance systems on the market, including COG, sway velocity, weight transfer time, reaction time, and so on. It has been confirmed that the proposed Wearable Gait Lab system has advantages in data collection and review process simplification and high portability compared to existing balance systems, while keeping test results accurate.

In the future, more data samples will be collected by the team, so that the team can compare test results among different groups and better serve balance test purposes. The system would be more advantaged with additions of functionalities in real time monitoring and analysis with statistics. Due to vigorous development of wireless sensory industry today, additional components can also be added to the system to better achieve desired sensory data for gait and balance experimental purposes.

Table 4
Statistical data in Sit-To-Stand tests.

Sit To Stand								
Subject	Trial	WT time (sec)	Sway velocity (deg/sec)	% L/R Wt symmetry	Trial	WT time (sec)	Sway velocity (deg/sec)	% L/R Wt symmetry
1	1	0.13	26.08	-4.61	2	0.91	20.60	3.25
	3	0.67	26.07	-6.12	mean	0.57	24.24	-2.49
2	1	0.13	14.07	-2.42	2	0.16	14.55	-58.84
	3	0.6	21.43	-47.3	mean	0.30	16.68	-36.21
3	1	0.13	25.03	-26.95	2	0.73	14.73	20.23
	3	0.17	31.59	20.70	mean	0.34	23.78	4.66
4	1	0.31	24.53	-38.33	2	0.46	17.29	-35.31
	3	0.40	21.25	-25.24	mean	0.39	21.02	-32.96
5	1	0.15	17.43	11.94	2	0.25	15.20	-0.06
	3	0.35	7.00	29.21	mean	0.25	13.21	13.69
6	1	0.28	9.10	5.93	2	0.09	14.89	-6.09
	3	0.18	13.81	-5.49	mean	0.18	12.60	-1.89
7	1	0.53	28.67	22.02	2	0.12	27.74	-62.19
	3	0.35	14.92	4.88	mean	0.33	23.78	-11.76
8	1	0.36	2.06	-10.38	2	0.51	2.06	-25.96
	3	0.53	1.93	-24.93	mean	0.47	2.06	-20.42

Table 5
On-axis velocities in rhythmic weight shift tests by Wearable Gait Lab system.

On-axis velocity (deg/s)						
Subject #	Horizontal			Vertical		
	Trial1	Trial2	Trial3	Trial1	Trial2	Trial3
1	1.45	5.77	9.46	0.54	0.47	1.36
2	1.63	5.12	3.63	0.39	0.40	0.67
3	2.13	2.33	6.40	0.76	0.96	2.17
4	4.49	4.60	6.72	0.41	0.49	0.91
5	2.86	3.93	8.89	0.49	1.00	1.41
6	2.44	4.75	4.92	0.57	0.97	2.17
7	2.67	5.78	6.95	0.24	0.35	1.21
8	3.94	5.13	6.16	0.60	0.61	1.23

Conflict of interest

None declared.

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