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Assessment of human motion using smartphone sensors: a tutorial for education, research and practice

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Assessment of human motion using smartphone sensors: a tutorial for education, research and practice

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Abstract

Sport science and rehabilitation are naturally evolving towards the implementation of data-driven technology for the analysis of human motion. Analysis of movement has traditionally been taught, researched, and implemented in practice either visually, or using equipment often unavailable outside specialized research centers. The motion sensors in contemporary smartphones can be used to collect acceleration and orientation data, making smartphones widely-available, low-cost devices that may provide useful in the characterization of human motion. The aim of this tutorial is to review basic concepts of how acceleration and orientation data collected with smartphone sensors can be used to assess human motion. We include six examples of data collection and analysis: jump height, balance, jogging cadence, joint range of motion, pelvic orientation during single-leg squat, timed up-and-go test. Acceleration and orientation data related to each example were analyzed using spreadsheet editors; video tutorials provide step-by-step guidance on how to analyze the data. Results are interpreted with respect to biomechanics, performance analysis and potential clinical relevance. We discuss this approach in the context of education, research and practice, hoping that it will help promote data-driven education and practice in fields that may benefit from objective analysis of human motion, such as sport science and rehabilitation.

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Tutorial for 'JMIR mHealth and uHealth'

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Assessment of human motion using smartphone sensors: a tutorial for education, research and practice

Abstract (450 words)

Sport science and rehabilitation are naturally evolving towards the implementation of data-driven technology for the analysis of human motion. Analysis of movement has traditionally been taught, researched, and implemented in practice either visually, or using equipment often unavailable outside specialized research centers. The motion sensors in contemporary smartphones can be used to collect acceleration and orientation data, making smartphones widely-available, low-cost devices that may provide useful in the characterization of human motion. The aim of this tutorial is to review basic concepts of how acceleration and orientation data collected with smartphone sensors can be used to assess human motion. We include six examples of data collection and analysis: jump height, balance, jogging cadence, joint range of motion, pelvic orientation during single-leg squat, timed up-and-go test. Acceleration and orientation data related to each example were analyzed using spreadsheet editors; video tutorials provide step-by-step guidance on how to analyze the data. Results are interpreted with respect to biomechanics, performance analysis and potential clinical relevance. We discuss this approach in the context of education, research and practice, hoping that it will help promote data-driven education and practice in fields that may benefit from objective analysis of human motion, such as sport science and rehabilitation.

Keywords: smartphone; sensor; biomechanics; rehabilitation; sport; education

Introduction

Health and sport professionals often observe how people move to identify suboptimal motor performance, and plan interventions to target these deficits. While motion can be assessed qualitatively simply by looking at how someone performs a task, objective analysis of motion is becoming commonplace in fields such as sports and rehabilitation. Biomechanical and physiological data are often collected using sensors that athletes and patients wear while performing tasks and clinical tests. Two of the barriers that practitioners may face when trying to implement these technologies in their daily practice are: 1) they don't know how to collect and analyze sensor data; 2) they don't have access to the equipment needed to collect and analyze sensor data.

Objective analysis of human motion has traditionally been taught in the classroom. The institutions who have the necessary infrastructure, equipment and staff with expertise in motion analysis also offer demonstrations where the students watch an experienced researcher collect and analyze the data. Unless a student chooses to engage in a thesis research project focused on objective analysis of movement, and the university has the equipment and personnel to support this research, it is likely that the student will graduate without any practical, first-person experience in how to perform objective motion analysis. Alternative solutions that do not rely on dedicated laboratory equipment are needed.

The notion that we carry a portable laboratory in our pockets is not new [1,2], and the use of smartphone sensors in physics education has been implemented successfully [3–5]. To promote engagement in practical exercitations, the team who developed Phyphox [6] has proposed to use smartphone sensors as an educational tool for physics education. Each student uses a dedicated app on their smartphone to record signals such as acceleration and angular displacement, obtaining first-hand, practical experience with demonstration of key physics concepts [3–5]. Similarly, Mathworks has developed Matlab Mobile [7], an app that can collect and display data from smartphone sensors;

the company also provides some examples of how to use these sensors for education in the field of engineering. Even though the sensors used in these physics and engineering applications are similar to those used to assess human movement (e.g.: inertial measurement units, IMU), the possibility to use smartphone sensors to teach motion analysis to rehabilitation and sports science students is still unexplored to our knowledge.

This tutorial provides a guide for learning the basics of how to use smartphone sensors to objectively assess human motion; the target audience are students with no or with minimal technical background (e.g.: coding). We illustrate simple ways to use smartphone sensors to assess body acceleration and segment orientation, identify issues during the data collection, visualize the data, and extract information of interest. Examples and applications are mainly focused on the education of health and sport practitioners. To collect the data in this tutorial we used a Samsung Galaxy A5 with Phyphox [6] version 1.1.13 and Matlab Mobile [7] version 6.3.0, as these two applications have been used for education [3–5,8] and have detailed supporting information on their websites. Spreadsheets with the complete datasets are provided, together with videos that illustrate how to use Microsoft Excel (version 2402, Microsoft, Redmond, USA) and Google Sheets (accessed March 2024) to analyze the data without the need of coding. It should be noted that smartphone sensors data may be accessed and analyzed in a variety of ways, and readers are encouraged to find the apps and analysis software that best meet their needs. Throughout this tutorial, smartphone orientation is defined as in Textbox 1.

Textbox 1. Terminology for smartphone orientation used throughout this tutorial.

Flat: the smartphone lays horizontal (e.g.: on a table).

Portrait: the long side of the smartphone is vertical.

Landscape: the short side of the smartphone is vertical.

Note that these orientations are not unique. For instance, landscape orientation can be achieved with the screen facing the user or not, and with the camera on the right or left side. These practical indications are also included in the text.

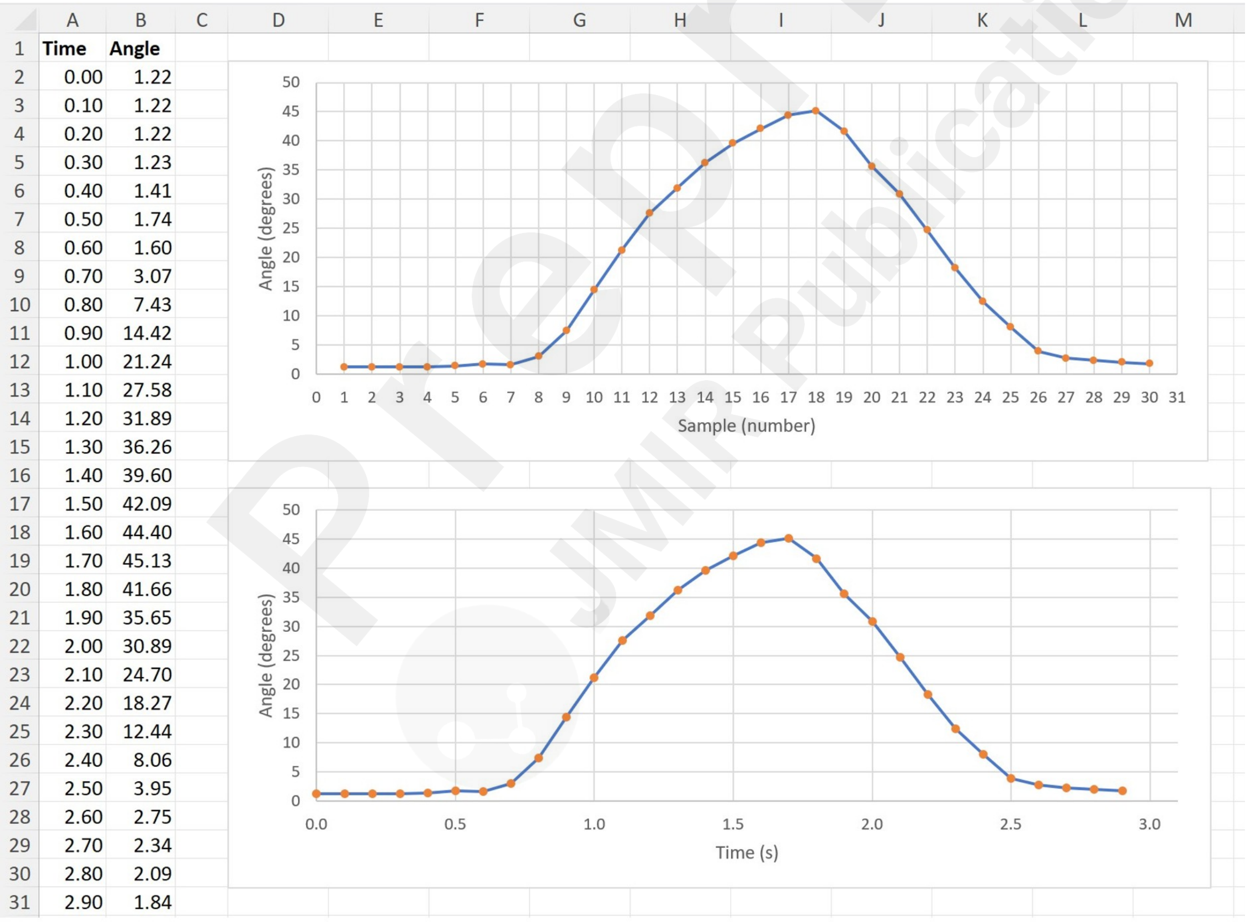
How to access, visualize and export sensor data

Smartphone sensors can be accessed through dedicated apps or web apps. These apps can be designed to access one specific sensor, bundle different sensors in packages, or provide users with the option to manually select which sensor is activated every time data collection starts. Custom apps can also be designed, for instance using the Phyphox experiment editor [9], Simulink [10], or various frameworks that provide access to smartphone sensors. A key parameter that needs to be carefully considered before data collection is the sampling rate (or sampling frequency), which is the number of data points that a sensor collects in a second. This value needs to be set manually in some apps, whereas it is fixed in others. A potential, critical issue is that low sampling rates may provide biased estimates of motion, especially when assessing fast movements. On the other hand, high sampling rates may capture potentially sensitive information (e.g.: voice conducted through vibrations) and result in unnecessarily large files that need large amounts of storage, or that can only be opened in spreadsheet editors in high-performance computers. Based on the data in the Phyphox database [11], most of the smartphone sensors discussed in this tutorial can sample at least 100 samples per second, which is a rate sufficient for most applications for human motion. It may be necessary to use lower sampling rates to collect data over an extended period of time (e.g.: slow postural sways over one hour), or higher sampling rates to collect data during highly dynamic motion (e.g.: some ballistic tasks). A potential approach to determine an appropriate sampling rate is to review the literature to find the maximum frequency of the test condition and set the sampling rate at least twice that value, as defined by the Nyquist theorem. Another parameter that should be considered before the start of the data collection is what happens if the smartphone screen turns off, or if the app runs in background. Matlab Mobile allows to collect data in the background, although this option needs to be activated manually and it may lead to potential security concerns (see ‘Privacy and data security’). If the app is not allowed to record data when running in the background or when the screen turns off, it may be necessary to change the settings of the smartphone to delay or remove the screen lock to allow for sufficient time to collect the data. Finally, if the smartphone vibrates during data collection (for instance due to a call or an app notification), this vibration may affect the sensors readings. If it is important to avoid this, it may be necessary to turn off the vibration while recording data.

During data collection, data can be visualized in different ways. Most apps display the current value a sensor measures as a number on the screen of the device. This visualization is simple and effective when measuring a static position, for instance how the gravity acceleration is measured across the different axes of the accelerometer, or when determining the inclination of the smartphone in a static position. Instead, data that changes relatively quickly over time is best visualized as a graph. Some apps offer the option to visualize the data as a line graph, with time on the X axis and different sensor values on the Y axis. However, if the smartphone is in motion during data collection, data visualized on the device itself can only be effectively reviewed after the movement has ended since it is difficult to look at graphs on a smartphone that is, for instance, strapped to an arm during an exercise. In this case, it may be possible to livestream the data to a computer through network connection. This allows to see the data collected from the smartphone sensors on a different screen in realtime. Currently, this can be achieved using both Matlab Mobile (the app stores the data on the Mathworks Cloud service, which can be accessed in real time from a Matlab software on a computer connected to the user account) and Phyphox (if the smartphone and the computer are on the same wireless network).

Sensor data are usually stored as arrays of numerical values, where each value corresponds to the estimate from the sensor in a specific time instant, as defined by the sampling frequency set (Figure

1). For instance, if the acceleration sensor collects data for 10 s at 100 samples per second, the array will contain 1000 numerical values that correspond to the smartphone acceleration every 10 ms within the 10 s registration period. If the sensor collects data over different axes (for instance, three-dimensional acceleration), the values will be organized in different arrays. A simple way to think about this data is as a table, with time samples in consecutive rows, and different sensor axes in different in the columns. In the example above, the table would have 1000 rows, and 3 columns since acceleration sensors collect data along 3 axes. An additional column with the timing of each sample and a header row with a description of the data in each column are usually included in the data table.



	A	B
1	Time	Angle
2	0.00	1.22
3	0.10	1.22
4	0.20	1.22
5	0.30	1.23
6	0.40	1.41
7	0.50	1.74
8	0.60	1.60
9	0.70	3.07
10	0.80	7.43
11	0.90	14.42
12	1.00	21.24
13	1.10	27.58
14	1.20	31.89
15	1.30	36.26
16	1.40	39.60
17	1.50	42.09
18	1.60	44.40
19	1.70	45.13
20	1.80	41.66
21	1.90	35.65
22	2.00	30.89
23	2.10	24.70
24	2.20	18.27
25	2.30	12.44
26	2.40	8.06
27	2.50	3.95
28	2.60	2.75
29	2.70	2.34
30	2.80	2.09
31	2.90	1.84

Figure 1: Data in table form (left) and plot (right). Each row of the table (sample) corresponds to the Time instant (column A, in seconds) at which an Angle value (column B, in degrees) has been sampled. For instance, the first sample (row 2) was time 0.0 s and measured 1.2 degrees; since the

sampling frequency was 10 Hz, the second sample (row 3) was collected 0.1 s after the first one, and also measured 1.2 degrees since the smartphone was stationary. The top plot has Samples on the X *axis, and Angle on the* Y *axis; the orange dots are the Angle values at every sample plotted against their row number (excluding the header). This graph shows that the movement peaked close to sample 18, therefore the peak value is in cell B19 (not B18 because of the header in cell B1). The bottom plot shows the same data, but with time values on the* X *axis. Here it is possible to see that movement started at 0.7 s and ended at 2.6 s, therefore it lasted about 1.9 s.*

A common way to store this data is to save it as a '.csv' file. These files can be easily opened as spreadsheets using commercial software such as Microsoft Excel, open applications such as Google sheets, or imported in programming environments such as Matlab and Python. Some apps (e.g.: Phyphox) allow to share these files via email or to upload them to cloud services through other apps installed on the smartphone. Matlab Mobile instead allows to upload the data to the account logged in during data collection. The data can be accessed through Matlab Drive (cloud-based storage) as a '.mat' file to be processed in Matlab directly, or to be converted in a '.csv' format, although this requires custom-written code (example of code provided as supplementary material). Alternatively, if the data is livestreamed to a computer, it can be downloaded on the computer directly as a '.csv' file (e.g.: using Phyphox) or saved in the Matlab workspace.

Data collection

Smartphones have a number of physical sensors relevant for the assessment of human motion. In March 2024, data from more than 34,000 users who submitted their device data to the Phyphox database [11] show that the device of more than 99.9% of the users have accelerometers, almost 90% have gyroscopes, and over 90% have magnetometers. Note that this data includes not only smartphones, but also other devices such as laptops and tablets that are less likely to have a complete set of built-in sensors. This tutorial focuses on the use of smartphone sensors to estimate body acceleration and orientation, therefore common uses and issues with the acceleration and orientation data are presented in detail below. Other sensors of potential interest for motion analysis but outside the scope of this tutorial are acknowledged as well.

Acceleration

Smartphone accelerometers can measure the acceleration acting on the device. This sensor has been used to estimate parameters related to human motion, including number of steps [12,13], gait and balance [14–17], jump characteristics [18,19], tremor [20], heart rate [21], and breathing pattern [22,23]. Research shows that some of the metrics computed from smartphone accelerometers are valid compared to laboratory equipment and reliable between days [15–17,24].

Technical considerations when working with smartphone acceleration

Although the principle through which acceleration is measured depends on the type of accelerometer used (e.g., piezoelectric, capacitive), accelerometers measure acceleration by detecting displacements of an internal mass (the proof mass). If someone holds a smartphone in the palm of the hand while standing quietly, the reference frame (smartphone case) has an acceleration of 0 m/s^2 because the device weight is compensated by the normal force provided by the hand. Even though there is no smartphone acceleration, the proof mass displaces from its resting position in the direction of its weight vector component (i.e., in the absence of smartphone acceleration the accelerometer detects an acceleration in a direction opposed to that of gravity). The accelerometer will, therefore, provide a reading equal to $-\vec{g}$. If a person holding a smartphone is in free fall, for instance jumps while recording acceleration with a smartphone on their body, during flight and in the absence of changes in the smartphone orientation, the magnitude of the acceleration measured is close to 0 m/s^2 because there is no displacement of the proof mass from the resting position.

Acceleration sensors measure, therefore, the linear acceleration acting on the device along three orthogonal axes (Figure 2). The two main contributors to the acceleration measured by the device are gravity and forces resulting from the interaction between the smartphone and the body segment it is secured to. Gravity leads to an acceleration vector directed towards the ground, whose magnitude is approximately 9.81 m/s^2. When no forces are applied to the device, acceleration readings along the three axes will depend mainly on gravity and on the orientation of the smartphone. For instance, if a smartphone is placed flat on a table, with the screen facing up, the reading will approximate 9.81 m/s^2 on the Z axis and 0 m/s^2 on the X and Y axes. If the smartphone is held in portrait orientation with the camera on top, the Y axis will detect an acceleration of 9.81 m/s^2, with opposite polarity if the smartphone is held upside-down. If the smartphone is held at an angle, the magnitude of the total (resultant) acceleration reading will still be a constant value, nearly 9.81 m/s^2, following the equation:

$$Acc_{RES} = \sqrt{Acc_X^2 + Acc_Y^2 + Acc_Z^2}$$

where Acc_X, Acc_Y and Acc_Z are the magnitude of the gravity acceleration components on the X, Y and Z axes, respectively. If a smartphone is in a static position or moves linearly at constant speed, the magnitude of the resultant acceleration will approximate 9.81 m/s^2 regardless of its orientation. It should be noted that the magnitude of gravity acceleration may vary slightly depending on the latitude, altitude and the density of the geological structure where it is measured, and depending on the smartphone brand and model [11].

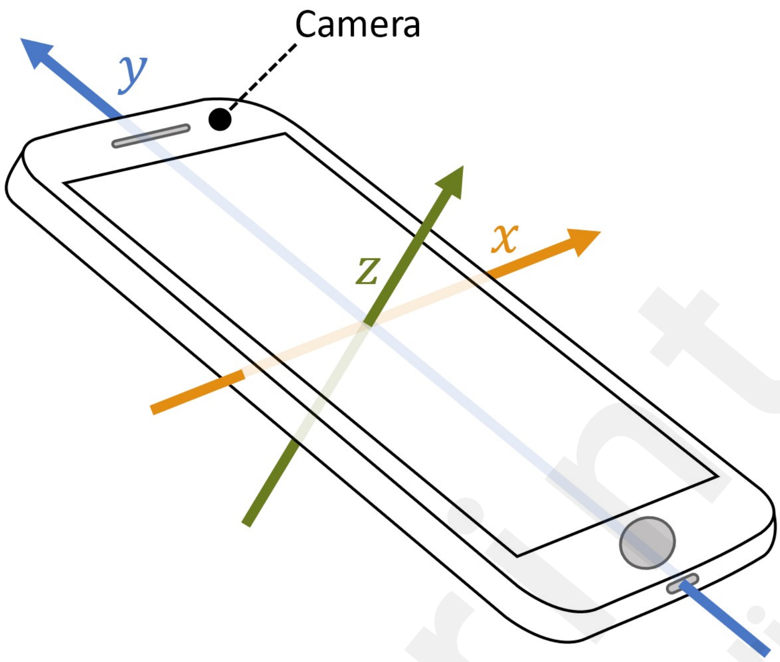


Figure 2: Drawing of smartphone axes. The X axis extends along the short side of the smartphone, the Y axis extends along the long side of the smartphone, and the Z axis extends out of the screen. Throughout this tutorial, practical references to the orientation of the smartphone (e.g.: camera on the left) are provided assuming that the association between smartphone axes and camera is consistent with what illustrated in this figure.

Assessing body acceleration using smartphone sensors

Accelerometers can estimate the acceleration resulting from the application of external forces to the smartphone. For instance, if a smartphone is placed flat on a table (Figure 3A), sliding it along its shorter side at varying speed will result in acceleration on the X axis, sliding it along its longer side will result in acceleration on the Y axis, and lifting it up from the table will be detected as changes in the Z axis. Moving the smartphone along a curvilinear path with varying speed will result in acceleration readings as well, with the magnitude of acceleration components in the three axes depending on the path direction. Slightly tapping the screen, top or side of the smartphone will also result in acceleration along different axes. Faster movements or stronger impacts (i.e.: larger changes in velocity) will result in larger acceleration.

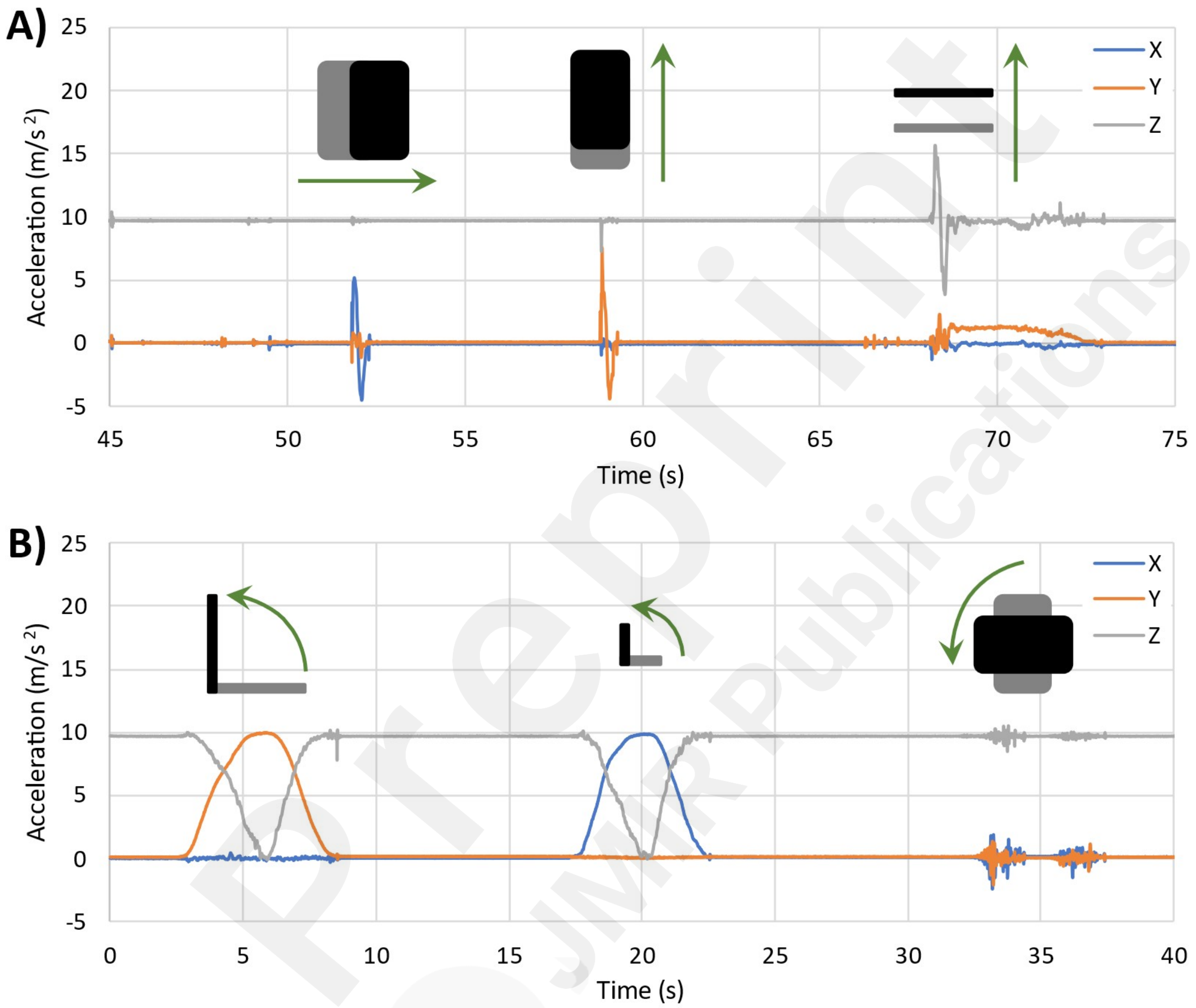


Figure 3: A) Changes in acceleration due to smartphone linear motion. When the smartphone is flat on the table, the Z component reads 9.81 m/s^2. Moving the smartphone sideways (along the X axis) and away (along the Y axis) results in changes in acceleration on the X and Y axes respectively. Lifting the phone off the table results mainly in changes on the Z axis; the small, prolonged increase in acceleration on the Y axis is due to a small change in smartphone orientation while off the table. B) Changes in acceleration due to changes in smartphone orientation. As the smartphone rotates

toward portrait orientation (around the X axis), the gravity acceleration is less represented on the Z axis, and more on the Y axis. Similarly, as the smartphone rotates from flat toward landscape orientation (around the Y axis), the gravity acceleration is less represented on Z and more on the X axis. Rotation around the Z axis does not result in changes in acceleration due to gravity, since gravity is always measured on the Z axis throughout the motion.

In addition to measuring acceleration during smartphone translation, the acceleration sensor also measures changes in acceleration when the smartphone is rotated in space as described in Figure 3B. Changes in smartphone orientation result in different acceleration readings because of changes in the projection of the gravity acceleration on the three axes, as well as from centripetal and tangential accelerations. For instance, a smartphone placed in landscape orientation over the sacrum (Figure 4) records fluctuations of the medio-lateral acceleration signal both when the pelvis is shifted sideways (e.g.: linear acceleration due to mediolateral pelvic translation) and when the pelvis tilts in the frontal plane (e.g.: change in orientation due to pelvic drop). If one is interested in recording linear acceleration of the body segment the smartphone is secured to, compensation for changes in acceleration due to gravity is necessary. Centripetal and tangential acceleration may be neglected, when the smartphone sensor is placed close to the axis of segment rotation or when the angular speed is small. Gravity compensation can be achieved with appropriate filtering [25] or subtraction of the gravity components based on the other sensors' readings [26,27]. Some apps allow to compensate for the gravity acceleration (e.g.: Phyphox, 'Acceleration without g' experiment), returning mainly the acceleration due to user motion while limiting the influence of gravity. In the example above, compensation for gravity would mean recording acceleration changes mainly associated with postural sways, and less with changes in pelvic orientation.

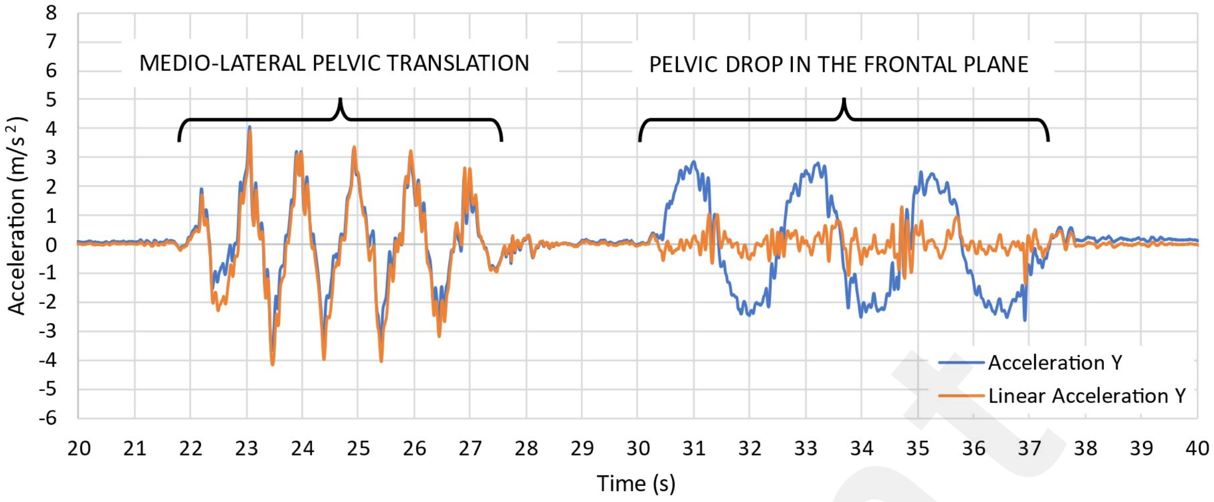


Figure 4: Smartphone acceleration during linear motion (pelvis mediolateral translation) and angular motion (pelvic tilt in the frontal plane). 'Acceleration with g' (blue line) measures large changes in acceleration due to both linear and angular motion. 'Acceleration without g' (orange line) measures a similar acceleration during linear motion, but smaller fluctuations during the pelvic tilt.

Potential issues when collecting acceleration data

Potential issues observed when collecting smartphone acceleration data include insufficient sampling rate, saturation and artefacts, as illustrated in Figure 5. Insufficient sampling rates may bias acceleration estimates (Figure 5A); this is especially critical when assessing peak acceleration during ballistic tasks. Saturation occurs when the signal reaches the extreme values defining the range of measurement of the sensor (Figure 5B). For instance, if an accelerometer has a range of ±10 m/s^2, and the acceleration applied to the device is 15 m/s^2, the accelerometers will only read 10 m/s^2. Saturation can be as a 'clipped' signal with a plateau of values equal to the sensor range. Accelerometers in most devices have a range close to ±80 m/s^2 [11], which is large enough even for highly dynamic tasks. Saturation may occur during ballistic, maximal contractions (Figure 5B) or during very forceful impacts. Artefacts may be defined as accelerations recorded by the device due to factors other than the motion of interest. For instance, a smartphone strapped around the calf of an individual can be used to record acceleration due to the jumping and landing while hopping; however, if there is any movement between the smartphone and the body segment during the task, for instance the smartphone slides over the skin, the sensor will record an acceleration that is unrelated to jumping or landing. In this case, the acceleration introduced by the relative motion between the smartphone and the body can be considered an artifact. Artefacts can also have a physiological origin. For instance, body acceleration due to postural sways during quiet standing can be characterized using smartphone sensors (Figure 5C). A smartphone is placed on the chest in landscape orientation will record low-frequency fluctuations of acceleration z, which denote antero-posterior postural sways. Superimposed to these fluctuations are some high-frequency disturbances (‘spikes’) which repeat approximately once per second; these are due to heartbeats since the smartphone was placed close to the heart. Since cardiac activity is not of interest when measuring trunk acceleration during quiet stance, these peaks can be considered an artifact. Some artefacts can be prevented or limited by carefully choosing where to place the smartphone, for instance away from the heart in the quiet stance example. Depending on their frequency content, some artefacts may be removed using digital filters.

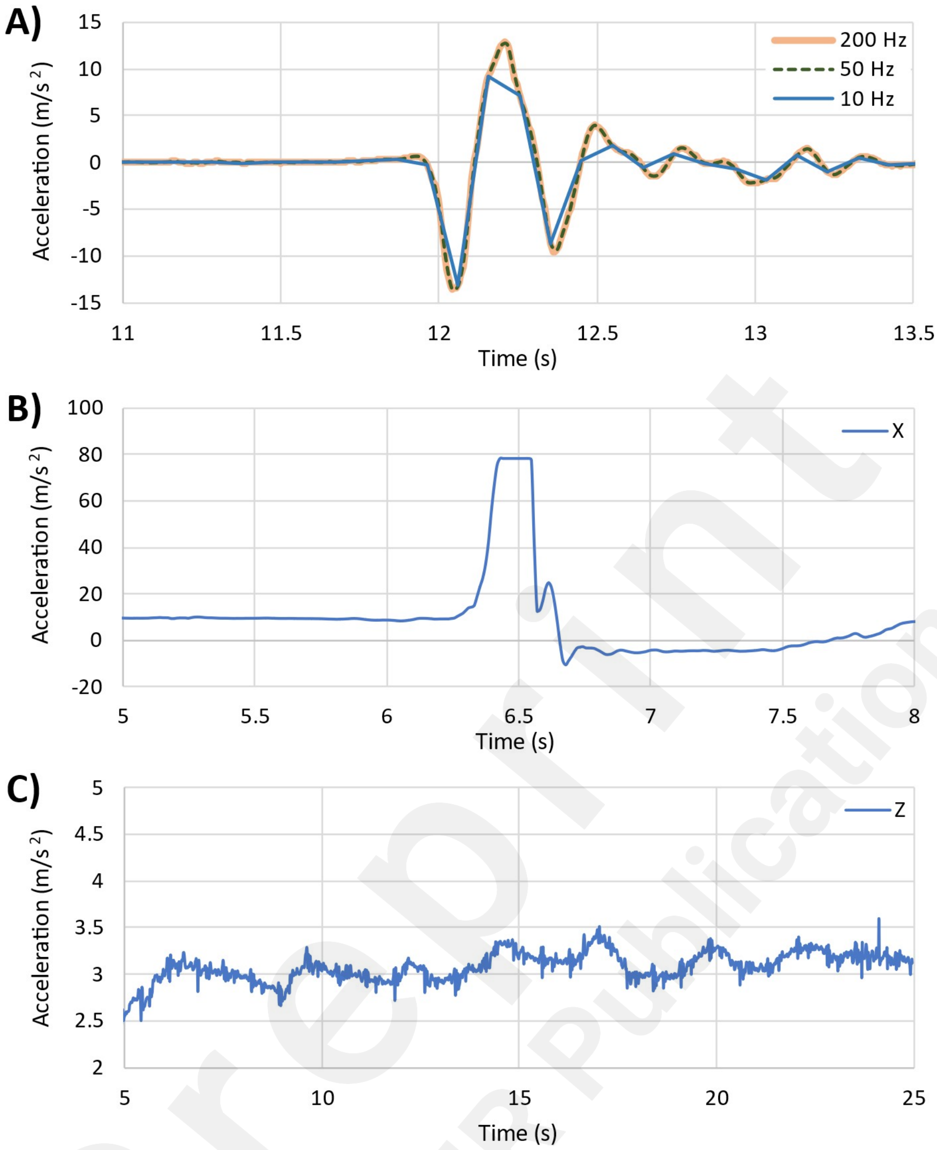


Figure 5: Common issues during data collection with smartphones. A) Effect of sampling rate on peak acceleration. The peak vertical acceleration during a ballistic heel raise collected at 200 Hz was approximately 12.5 m/s^2. When the acceleration signal is down-sampled to 50 Hz, the peak acceleration is similar. When the signal is down-sampled to 10 Hz, however, the peak acceleration is only 9 m/s^2. B) Saturation of acceleration signal during a ballistic shoulder flexion; note that the signal is 'clipped' at 80 m/s^2, which is the upper extreme of the accelerometer range. C) Artifact due to heartbeats. Acceleration was collected during quiet standing with a smartphone placed on the chest. High-frequency disturbance ('spikes') due to heartbeats are superimposed to low-frequency fluctuations of acceleration associated with antero-posterior postural sways. If the aim of the

assessment was to characterize body sways, the high-frequency component can be considered an artefact.

Orientation

Smartphone sensors can characterize the orientation of the device in space. Smartphones have been used to estimate human motion in several studies, including range of motion in static and dynamic tasks [28–30], proprioception estimated as joint position error [31,32], and dynamic balance [33]. Research shows that smartphones usually have good validity compared to laboratory equipment and good reliability between days [28–30].

Technical considerations when working with smartphone orientation

Orientation data is obtained by ‘sensor fusion’, which is a technique that combines readings from different sensors to obtain a more precise estimate of the smartphone orientation. In the case of orientation, gyroscopes can be used to measure angular velocity (how fast angular position changes with time), which can then be integrated to estimate the device angular position. Gyroscopes are however unable to determine the absolute inclination of the sensors in static position, and angular position estimation is vulnerable to drifts associated with measurement error. By contrast, accelerometers and magnetometers can estimate absolute orientation of the device in static positions, but are inaccurate in dynamic conditions. Sensor fusion techniques combine the information collected from these three sensors, thus providing accurate orientation estimates even in dynamic conditions. Note that in some apps the smartphone orientation is estimated using trigonometry on the acceleration signals alone (e.g.: Phyphox Inclination experiment, designed for measuring static orientation); this is appropriate for static orientation, and possibly for very slow movements, but the estimate is inaccurate in dynamic movements because the accelerometer signals are affected by both gravity acceleration (needed to determine orientation) and acceleration due to user motion (which introduces a bias when determining orientation).

Orientation is usually defined using Euler angles. As position in space can be represented using different coordinates, from Cartesian to polar coordinates, rotations of a mobile frame of reference or between two frames of reference, associated with two body segments, can be described using different parameterizations as well. Euler angles are the most commonly used set of parameters, describing orientation as a set of three, consecutive rotations. For instance, different combinations of rotations could explain moving the shoulder from the reference anatomical position to 90° of abduction: from pure, 90° abduction with 0° flexion-extension and 0° internal-external rotation, to 90° flexion, followed by 90° abduction and then 90° internal rotation. Which sequence to consider for computing Euler angles is strictly dependent on the joint we wish to assess [34,35], with recommendations being provided by the International Society of Biomechanics [36,37]. When using smartphone sensors to assess orientation, it is crucial to understand the convention used by the app providing the orientation data. Considering Matlab Mobile, Euler angles are provided as follows:

- *Azimuth* corresponds to angular deviation of the device Y axis from the Earth magnetic north
- *Pitch* corresponds to angular deviation of the device Z axis towards the Y axis when lying flat
- *Roll* corresponds to angular deviation of the device Z axis axis towards the X axis when lying flat

When collecting orientation, Euler angle readings are defined between specific limits. For the first and third rotations these limits are defined by −¿180 and +¿180 degrees (or 0 and 360 degrees), whereas for the second rotation angle reading is limited within ±90 degrees (or from 0 to 180 degrees). For instance, when collecting orientation data while spinning the smartphone undefinedly counterclockwise around its Z axis, the Azimuth value will not increase continuously—it will rather jump to −¿180 degree from +¿180 degrees. The 360-degree or 180-degree ‘jump’ is respectively associated with the use of the inverse tangent or inverse sine (or cosine) function for computing the angles. Also, it should be noted that any given angle (e.g. φ) in a circle is defined over 2π radians: that is, $\forall k \in Z : \varphi \equiv \varphi + 2\pi k$. This discontinuity can be avoided during data collection by avoiding smartphone orientations that result in starting values close to the point of discontinuity.

Assessing orientation of body segments using smartphone sensors

If a smartphone is secured to a body segment, changes in smartphone orientation may serve as a proxy for changes in body segment orientation. For instance, if someone is sitting while holding a smartphone on the chest in landscape orientation, the Matlab Mobile app will mainly record a change in Roll when the individual performs trunk flexion-extension, a change in Pitch when performing side flexion, and a change in Azimuth when performing rotation (Figure 6). When in doubt about how the orientation signals are associated with the body motion, a simple solution is to perform an 'axis recognition' task where the individual performs isolated, known movements in the three planes to identify which axis detects motion in each plane of movement. For instance, if a smartphone is fixed to the outside of the arm to estimate arm orientation, performing a simple axis recognition task consisting of: 1) shoulder flexion; 2) shoulder abduction; 3) shoulder external rotation; would illustrate how movements in different anatomical planes are detected by the smartphone, and whether positive/negative changes in orientation correspond to shoulder flexion/extension or vice versa. Note that to be able to easily represent changes in orientation along the anatomical planes, the smartphone must be aligned to the body segment so that any two axes of the smartphone are as parallel as possible to any of the two axes defining the segment for which orientation is to be estimated. Otherwise the motion will be recorded on multiple axes, and this will complicate the interpretation of the motion data collected.

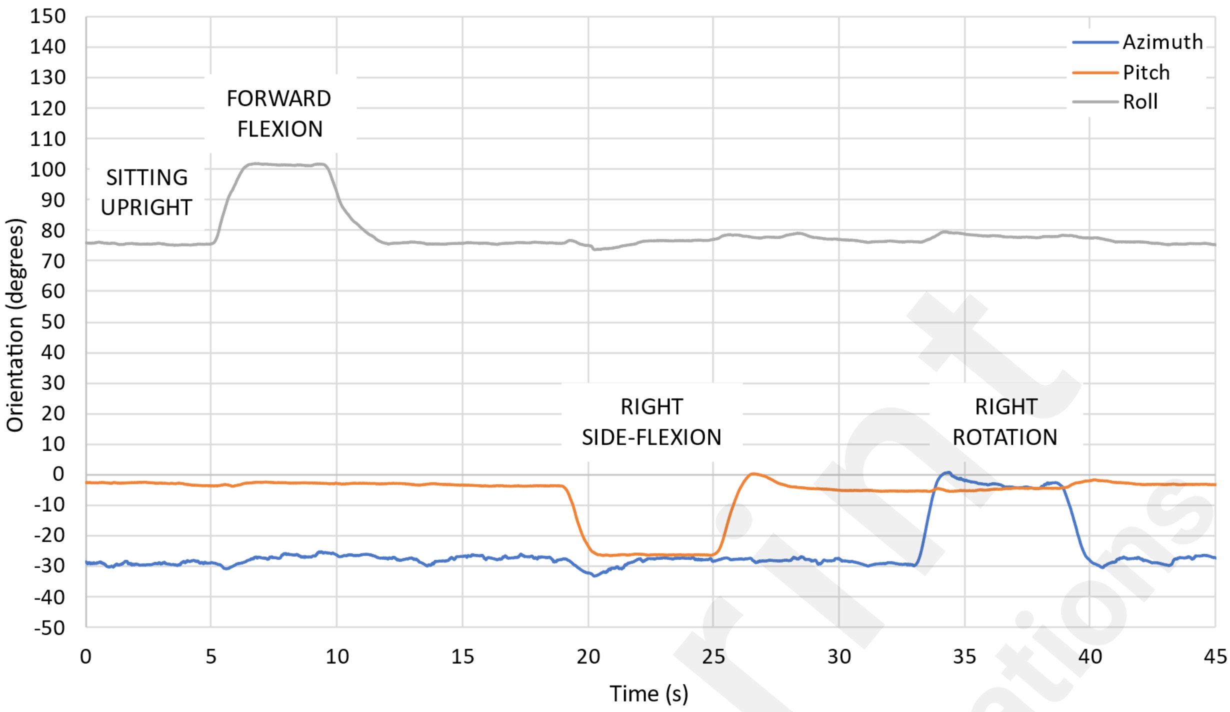


Figure 6: Trunk orientation estimated using smartphone. The participant held a smartphone on their chest in landscape orientation, camera to the left and screen facing outwards. While sitting upright, Roll was about 75 degrees (slight backward tilt from the vertical), Pitch was about 0 degrees (y axis close to horizontal), and Azimuth was -30 degrees (depending on where the magnetic North location with respect to the participant). Trunk flexion, side flexion to the right, and rotation to the right resulted in mainly isolated changes in Roll, Pitch and Azimuth respectively. Trunk extension, side flexion to the left, and rotation to the left would have resulted in changes in the same axis, but in the opposite direction.

Potential issues when collecting orientation data

A key issue to consider when placing the smartphone to collect orientation data is to avoid smartphone orientations that result in 'gimbal lock'. In short, gimbal lock is a phenomenon where, for a specific smartphone orientation, the Euler angles cannot be univocally identified. This can be easily verified when collecting data using the Matlab Mobile app. When holding the smartphone in portrait orientation so that the Pitch angle is as close as possible to 90 degrees, the Roll and Azimuth estimates become inaccurate, recording large variations in angles that do not correspond to the actual changes in smartphone orientation (Figure 7A). Since this issue is associated with the sequence of rotations considered to compute the Euler angles, it should be noted that the smartphone orientation resulting in gimbal lock may differ between apps; for instance, the same smartphone may result in gimbal lock in portrait orientation when using Matlab Mobile, and in landscape orientation when using Phyphox. The easiest solution to this issue is to identify the smartphone orientation that results in gimbal lock for the app of choice and avoid such orientation during data collection.

Discontinuities are often observed in orientation data collected with smartphones. Since the orientation range is defined between ± 90 degrees or ± 180 degrees, if the orientation data crosses the limits of these ranges, the data will ‘jump’ from an extreme of the range to the other. For instance, in Figure 7B Azimuth starts at 150 degrees, but during the motion the data crosses the 180-degree limit and ‘jumps’ to −¿180 degrees. To avoid these discontinuities, users can ensure that the reading throughout the movement doesn’t cross the +¿180 degrees or −¿180 degrees; alternatively, discontinuities can be solved while analyzing the data, for instance by adding 360 degrees when the estimate is below −¿180 degrees.

Another potential issue during collection of orientation data is that readings of magnetic field provided by magnetometers may be affected by the environment. In the absence of nearby material emitting strong magnetic field (magnets, speakers, etc) or with high magnetic permeability (iron, nickel), the readings provided by the magnetometer sensor present in the smartphone will be mainly affected by the Earth magnetic field. The components of the readings along the X, Y and Z axis will thus be directed according to the direction of the Earth magnetic field, providing therefore a global reference for orientation on the Earth surface. In the presence of large metallic objects in proximity to the smartphone, however, magnetometers provide inaccurate readings of the Earth magnetic field, affecting the orientation data. This issue can be limited by ensuring that no metallic materials are present nearby when collecting data.

A critical consideration when interpreting orientation data is the difference between segment orientation (e.g.: angle between a body segment and the Earth reference) and joint angle (angle between two body segments). For instance, a smartphone strapped around the forearm can be used to estimate the orientation of the forearm in space. If the person performs a 90 degrees elbow flexion, the orientation of the smartphone will change by 90 degrees, and therefore the smartphone orientation sensor effectively represents elbow flexion. However, if the person instead performs a 90-degree shoulder flexion, the orientation of the smartphone will also change by 90 degrees. Therefore the orientation signal alone cannot be used to differentiate if the motion occurs at the elbow or at the shoulder. In this case, the smartphone orientation only represents elbow motion if the proximal segment (the arm) does not move. Another example could be head orientation vs cervical motion: a smartphone placed on the head estimates head orientation, and these estimates approximate cervical motion only if the trunk does not move. As a general rule, smartphone orientation sensors can be used to assess joint angles only if one of the two segments defining the joint of interest is fixed.

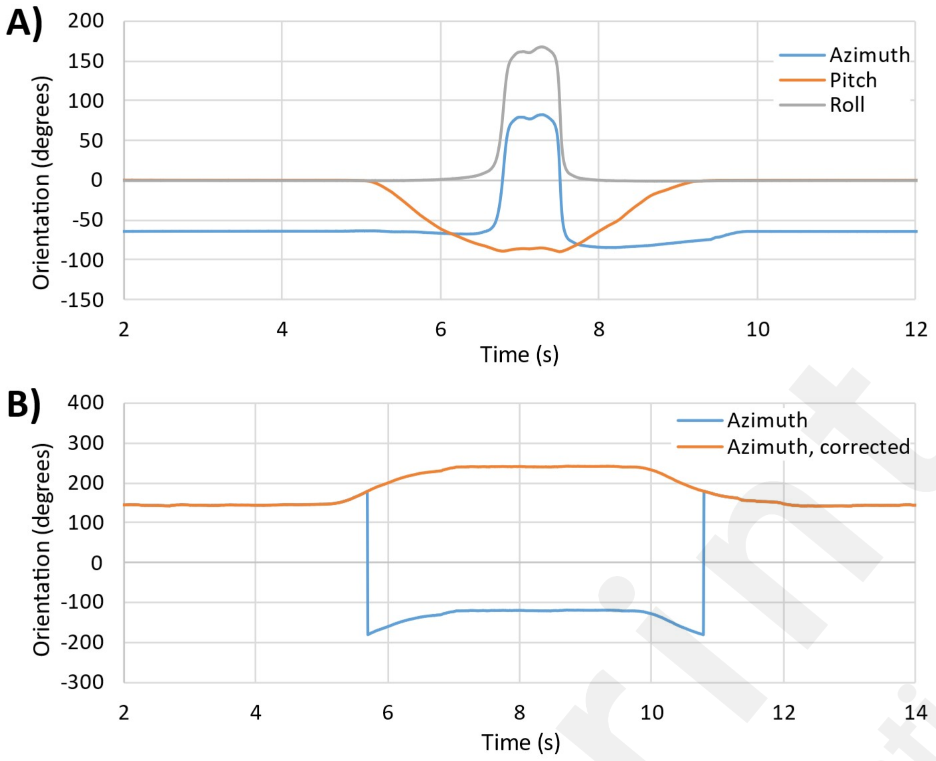


Figure 7: A) Gimbal lock. The smartphone orientation was tilted from flat orientation, to just over portrait, to flat again. Ideally, the graph should show the Pitch angle changing from zero degrees, to just over 90 degrees, and back to zero degrees; Roll and Azimuth should show negligible changes. Instead, Pitch plateaus at −¿90 degrees, returning toward zero instead of exceeding −¿90 when the smartphone tilts past portrait orientation (6.8-7.5 s). Azimuth and Roll show 180-degree changes that do not represent the smartphone motion. B) Discontinuity observed during trunk rotation (blue line). When the signal reaches 180 degrees, it 'jumps' to -180. The discontinuity was corrected numerically (orange line, see 'Examples of applications: Knee extension range of motion').

Other sensors

Smartphones have other built-in sensors that could be useful to assess human motion. Some of these sensors are listed below, but an in-depth review is outside the scope of this tutorial.

Gyroscopes measure the angular velocity (how fast the device rotates in space) around the smartphone axes illustrated in Figure 2. This is useful when one is interested in angular rates measured with respect to the smartphone, as opposed to angular rates measured with respect to the Earth reference (which can be derived from the orientation sensor).

Global Positioning System (GPS) sensor data is widely used in practice to study player position and monitor workload [38,39]. The key limitation of smartphones is that the GPS sampling rate is usually 1Hz, which lower than most dedicated GPS units [40], and may provide biased estimates when characterizing sport activities that include sprinting [41].

Both cameras [42,43] and microphones [44] have been used to characterize time of flight, which can be used to estimate jump height, similar to one of the applications described in this tutorial.

It should be noted that some of the sensors record geographical location, speech and videos, all of which may contain personal and potentially sensitive information.

Common features of smartphone sensors

A main advantage of the use of smartphone sensors to assess movement is their wide availability to the general population. However, smartphones of different brands have different size, weight, sensors and processing capabilities, and this may be reflected in the quality of the signals collected. Depending on the task and the required fixation, larger smartphones may result in lower quality signals due to the difficulty in securing them to the person’s body segment of interest. Heavier smartphones may slide during data collection or influence how the task is performed. Differences in both orientation [45] and acceleration [46] estimates were also identified across devices; the potential error that this variability can introduce in the measure of interest should be considered. Some studies have also identified inconsistencies in the smartphone sensor sampling rate [46,47]. This was confirmed in the data collected for this tutorial; despite setting a sampling rate of 100 Hz in five of the six examples below, the actual sampling rate based on the timestamps of the recording ranged between 91 and 111 Hz in different experiment; however, the sampling rate was always constant throughout the data collection, with minimal inter-sample variability (well below 1 ms). These inaccuracies, if not accounted for by processing techniques based on the timestamps provided along with the readings, may introduce errors, especially when analyzing peak amplitude of a signal or specific time points. Most of the limitations listed above are unlikely to occur when using dedicated research IMUs; advantages and disadvantages of using smartphones compared to dedicated IMUs should be carefully assessed, especially for research applications.

Privacy and data security

Over the last years, there have been growing concerns over the potential use of smartphone motion sensors to obtain sensitive information from the smartphone user [48]. Examples include inferring an individual's lifestyle and personal characteristics based on collecting motion data continuously in the background [49], reconstructing speech from data collected when the smartphone is on the same surface as a loudspeaker [50] or when sound is played through the smartphone speaker [51,52], and recognizing text typed on the smartphone touchscreen [53]. A critical issue is that, differently from camera, microphone and location, users are currently not required to explicitly allow applications to collect data using motion sensors on the smartphone. It should be noted that these privacy threats are mainly relevant when smartphones collect motion data continuously in the background. In the approach proposed in this tutorial, the users manually start the recording, perform the motor task, stop the recording, and then share the data. Risks can be further minimized by using applications that don't record motion data in the background (for instance, when the screen is locked or when the user switches to a different application). With respect to the potential of accidentally collecting personal information during the short data collections proposed in this tutorial, early work suggests that speech cannot be reconstructed from accelerometer recordings of live human speech transmitted through aerial vibrations [54]. Accelerometers placed on the sternum have been used to detect whether someone is speaking or not [55], but the potential of these recordings to reveal the actual word spoken is currently unknown. Since the human voice is mainly represented in frequencies above 80 Hz, which require sampling rates higher than 160 Hz, reducing the sampling rate of the recording may help decrease the risk of accidentally recording data that may contain personal information [51,52]. A further, simple solution is to ask the users to pause or stop the recording during the pauses between repetitions of the motor task, when the user is more likely to speak. While further studies are needed to better understand the actual threat risk of the uses of motion sensors as described in this tutorial, users should consider the potential risks mentioned above and put in place mitigations. When relevant, users should be warned about possible risks, for instance on consent forms in research studies and when opening the application in custom-made applications. Especially when recording data for long time, it may be appropriate to tell users to avoid saying personal information, typing personal information, taking calls or playing sounds through the smartphone loudspeaker while recording data.

Data analysis

The data collected using smartphone sensors can be analyzed in different ways, depending on the task, outcome of interest, and technical skills. Data can be analyzed directly on the smartphone screen, or on a separate computer if streaming the data. A simple data analysis could be, for instance, to estimate body segment orientation during a static task. This can be achieved simply by placing the smartphone over the segment of interest, and by reading the angle values displayed on the screen. When analyzing data that changes over time, for instance the peak trunk orientation on the frontal plane during sit-to-stand, or the number of acceleration peaks representing landing impacts during a run, it is necessary to plot the data in a graph to extract the information of interest. Apps such as

Phyphox create plots automatically (e.g.: time vs acceleration), while also providing a simple interface to manually select data points on the smartphone screen to extract the X and Y coordinates of data points of interest. This information can then be saved as a screenshot and shared as a figure. Matlab Mobile allows to load and plot the data, although this currently needs to be manually coded. Examples of in-app data analysis are shown in Figure 8.

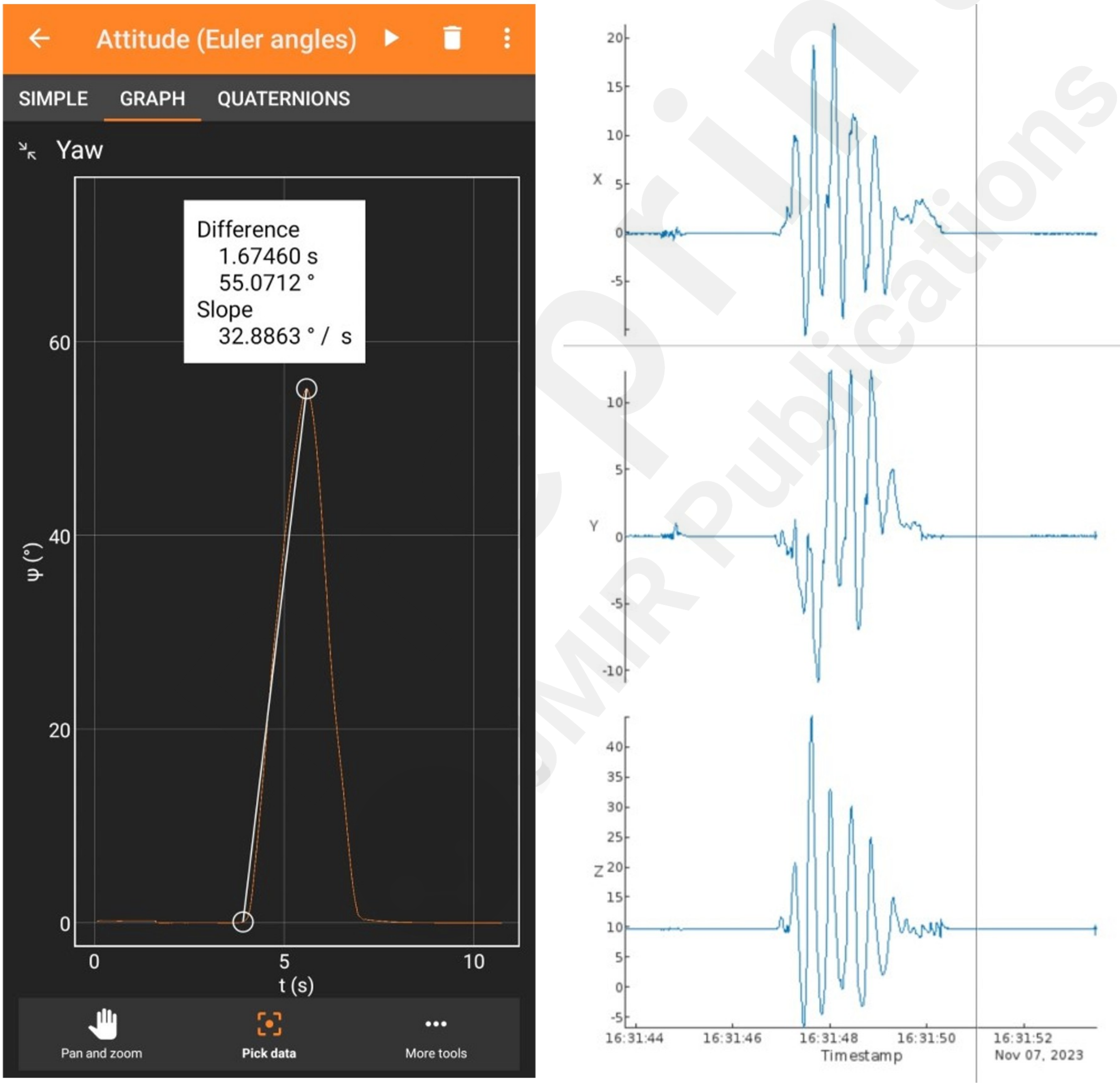


Figure 8: Examples of in-app data analysis. Left: Smartphone screenshot illustrating the use of the Phyphox 'attitude sensor' to visualize and analyze orientation data (experiment available here:

[56]*). The app automatically creates data plots. Users can select two data points to estimate time interval duration, magnitude difference, and slope. Right: Smartphone screenshot illustrating the use of Matlab Mobile to visualize acceleration data. The data was loaded in the command line and plotted using 'stackedplot(Acceleration)'.*

A simple, graphical way to approach data analysis is to open smartphone sensor data as spreadsheets in software or browser interfaces such as Google Sheets and Microsoft Excel, similar to what has been previously described for force platform data [57,58]. Spreadsheet editors offer a simple solution to visualize the data and to extract outcomes of interest, while minimizing the necessity of custom-written code. Phyphox allows to share the data in '.csv' or '.xls' format, whereas the current version of Matlab Mobile saves the data in '.mat' in the Mathworks cloud-based storage service, Matlab Drive; custom-made scripts are necessary to export the data to '.csv' (see Multimedia appendix 1). Spreadsheet data are usually organized in columns (time and different axes of each sensor from which data was collected) and rows (samples). Numerical values in the spreadsheet can be processed using basic functions (e.g.: rectified, squared, differentiated). The data can then be plotted, for instance in a time (X axis) vs sensor data (Y axis) plot, and the data visualization can then be improved by adding legends, axes labels, and setting specific limits to the X and Y axes. Specific information can be extracted from the data either by manually selecting points from the graph, or by using formulas to calculate maximum, minimum, standard deviation or root mean square over a specific interval. Some of these procedures are illustrated in the examples below.

Examples of applications

Here we illustrate examples of how to collect and analyze smartphone sensor data to assess the motor performance of six tasks: jump height, balance, jogging cadence and heart rate, knee extension range of motion, pelvic orientation during single-leg squat, and performance of the timed up-and-go test. The first three tasks use the acceleration sensor, and the others use orientation data. ‘Jumping’ and ‘Knee extension range of motion’ are simpler because they only use a single axis of the smartphone sensor, whereas the other tasks require integration of the information from multiple axes. We collected the data using a Samsung Galaxy A5 and two different apps (Phyphox or Matlab Mobile; raw data provided in Multimedia appendices) and analyzed it using two different software (Microsoft Excel or Google Sheets; links to video tutorials: [59–64]). Since the standard Phyphox experiments pre-installed in the app do not include a way to estimate orientation, we have used Phyphox to collect acceleration data, and Matlab Mobile to collect orientation data. These tasks could be used in teaching as self-directed activities or in practical sessions.

Jump height

If a person jumps with the smartphone secured to their body, the built-in accelerometer will measure no acceleration due to gravity while in the air; this can be used to estimate for how long the person was in the air, that is, the flight time. By identifying the instants when the magnitude of acceleration first approaches and last departs from 0 m/s^2, it is possible to identify instants that approximate take off and landing; there is preliminary evidence that estimates of time of flight from accelerometers [65] and from smartphone accelerometers [66] are comparable to those obtained using contact mats and force platforms. Jump height, in centimeters, can then be estimated using the formula $122.6\,T_{FT}^2$, where T_{FT} is the duration of the flight time estimated from the take-off and landing instants and the 122.6 coefficient accounts for the magnitude of gravity acceleration and for the conversion to centimeters from meters (equivalent to equation 1 in [67], but with jump height in centimeters instead of meters).

The data in Figure 9 was collected using Phyphox (‘Acceleration with g’ experiment, sampling rate set at 100 Hz), holding the smartphone on the chest in landscape orientation with the X axis pointing down (screen facing outwards, camera on the left). The participant performed three hops of increasing height. After the recording, the data (Multimedia appendix 2) was transferred to a laptop and analyzed using Microsoft Excel (video tutorial: [59]). The acceleration on the X axis is −¿9.8 m/s^2 when standing; note that if the smartphone was in landscape orientation with the X axis pointing up (e.g.: screen facing outwards but camera on the right), the acceleration on the X axis would have been +¿9.8 m/s^2. What is reported below applies regardless of whether the acceleration measured during quiet standing is −¿9.8 m/s^2 or +¿9.8 m/s^2, but the indication of ‘positive’ and ‘negative’ needs to be adapted based on the axis direction. For each jump, readings on the X axis show first a small positive peak (unweighting phase; see [58] for graphical depiction of the phases of the jump) followed by a decrease in acceleration (propulsive phase) and then a sudden increase toward 0 m/s^2 (start of the flight phase). Upon landing, the X acceleration decreases abruptly to reach a peak (landing impact) and then increases toward baseline reading (−¿9.8 m/s^2). To identify the flight phase, we used a conservative threshold of -2 m/s^2 since acceleration during the flight phase may not be exactly 0 m/s^2 due to changes in trunk orientation, user motion and noise; therefore, a the first value lower than -2 m/s^2 was selected for the ascending (take-off) and descending (landing) phase of the jump; future research should identify the optimal threshold to estimate time of flight. Using the current threshold, the estimated flight times are: 0.38 s, 0.44 s and 0.54 s, which correspond to 18.0 cm, 23.5 cm and 35.4 cm. The estimates match with the task performed.

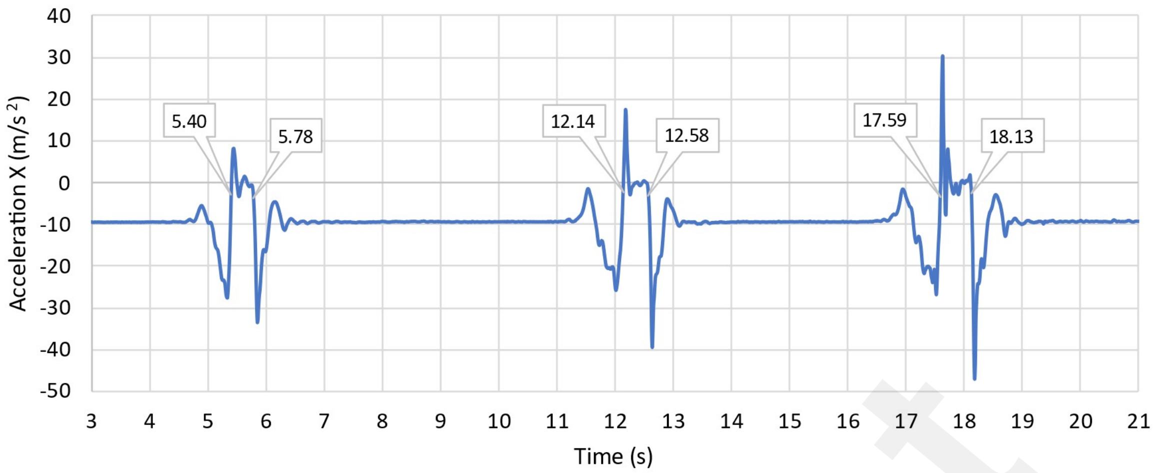


Figure 9: Jump height estimated using smartphone acceleration sensors. The duration of the time of flight increases from the first jump (small hop) to the last (large jump).

Balance

Body accelerations due to postural sways can be characterized using smartphone accelerometers [15,17]. Here we used the smartphone acceleration sensor to identify changes in body acceleration for increasingly difficult balance conditions: standing quietly with both feet on the ground, standing on one leg with eyes open, and standing on one leg with eyes closed. The smartphone was placed in landscape orientation on the sacrum, kept in place using the elastic band of the participant's clothing. Since the acceleration sensor axes were approximately aligned with the body anatomical axes, the acceleration due to sways in vertical, mediolateral, and anteroposterior directions was recorded from the acceleration readings mainly in the smartphone X, Y, and Z axes respectively. The data in Figure 10 was collected using Phyphox ('Acceleration without g' experiment, sampling frequency set at 100 Hz). We used 'Acceleration without g' to reduce the effect of gravity on the linear acceleration estimates: i.e., acceleration profiles in Figure 10 approximate the horizontal ground reactions forces on the feet for standing experiments [68] and are minimally affected by changes of pelvic orientation (see Figure 4). After data collection, the data (Multimedia appendix 3) was transferred to a laptop and analyzed using Google Sheets (video tutorial: [60]). The plots show increasing mediolateral and anteroposterior accelerations between double- and single-leg stance, and between eyes closed and open. When quantified using standard deviation, double-leg stance resulted in comparable mediolateral (0.019 m/s^2) and anteroposterior acceleration (0.016 m/s^2). As expected, body accelerations estimated indirectly from pelvic acceleration increased with more challenging balance conditions, with mediolateral readings being larger than anteroposterior values in single-leg stance both with eyes open (0.076 vs 0.032 m/s^2) and eyes closed (0.260 vs 0.100 m/s^2).

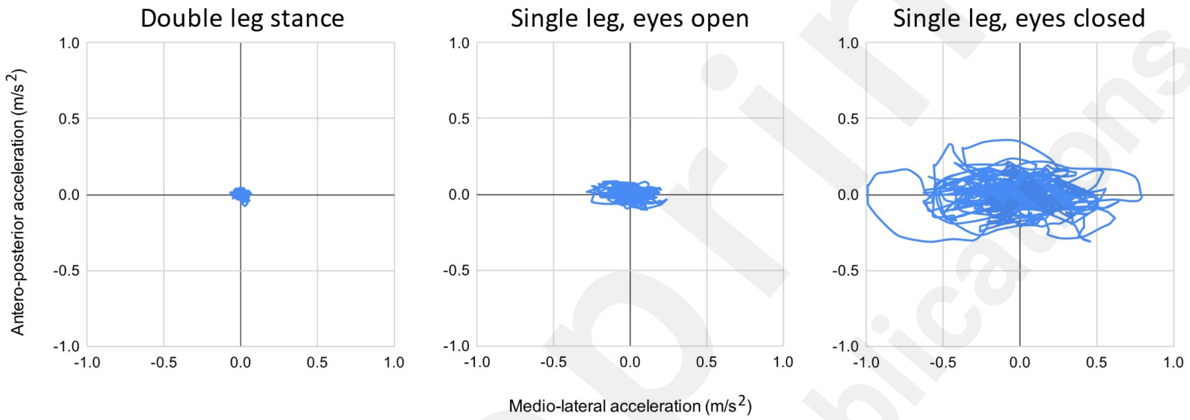


Figure 10: Acceleration due to postural sways estimated using smartphone acceleration sensors. Progression from double-leg stance, to single leg stance with eyes open, to single leg stance with eyes closed increased body acceleration, especially in the medio-lateral direction.

Jogging cadence and heart rate

Accelerometers record changes in acceleration in response to internal forces (produced by the human body) and external forces (impacts). These signals can be used to estimate frequencies, intended as events per minute. For instance, since landing impacts due to contact of the foot with the ground can be recorded using accelerometers [69], smartphones may be used to determine cadence estimated as steps per minute during walking [47]. Similarly, the contraction of the heart generates accelerations that can be recorded using smartphones placed on the chest [21]. By counting the number of peaks per minute, smartphone accelerometers may be used to estimate heart rate. In Figure 11 we estimated acceleration to determine cadence while jogging on the spot for 30 s and the heart rate after the exercise. Acceleration was recorded using Phyphox (‘Acceleration with g’ with sampling rate set at 100 Hz, Multimedia appendix 4) and analyzed using Google Sheets (video tutorial: [61]). The running cadence was determined by plotting a 10 s interval at the beginning of the jogging exercise. Starting from the first negative peak, we counted one cycle every two peaks (peaks represent left foot and right foot; usually cadence is reported unilaterally). We counted 14 cycles in 9.9 s (time interval between the first and last peak), which results in a cadence of 84.8 steps/min. Heart rate was calculated by visually identifying how many times the peaks highlighted in the bottom panel of figure 11 repeated in 10 s. This analysis resulted in 132 beats/min after the jogging exercise. This example demonstrates how smartphone acceleration can be used to characterize the number of events per minute, such as jogging cadence and heart rate.

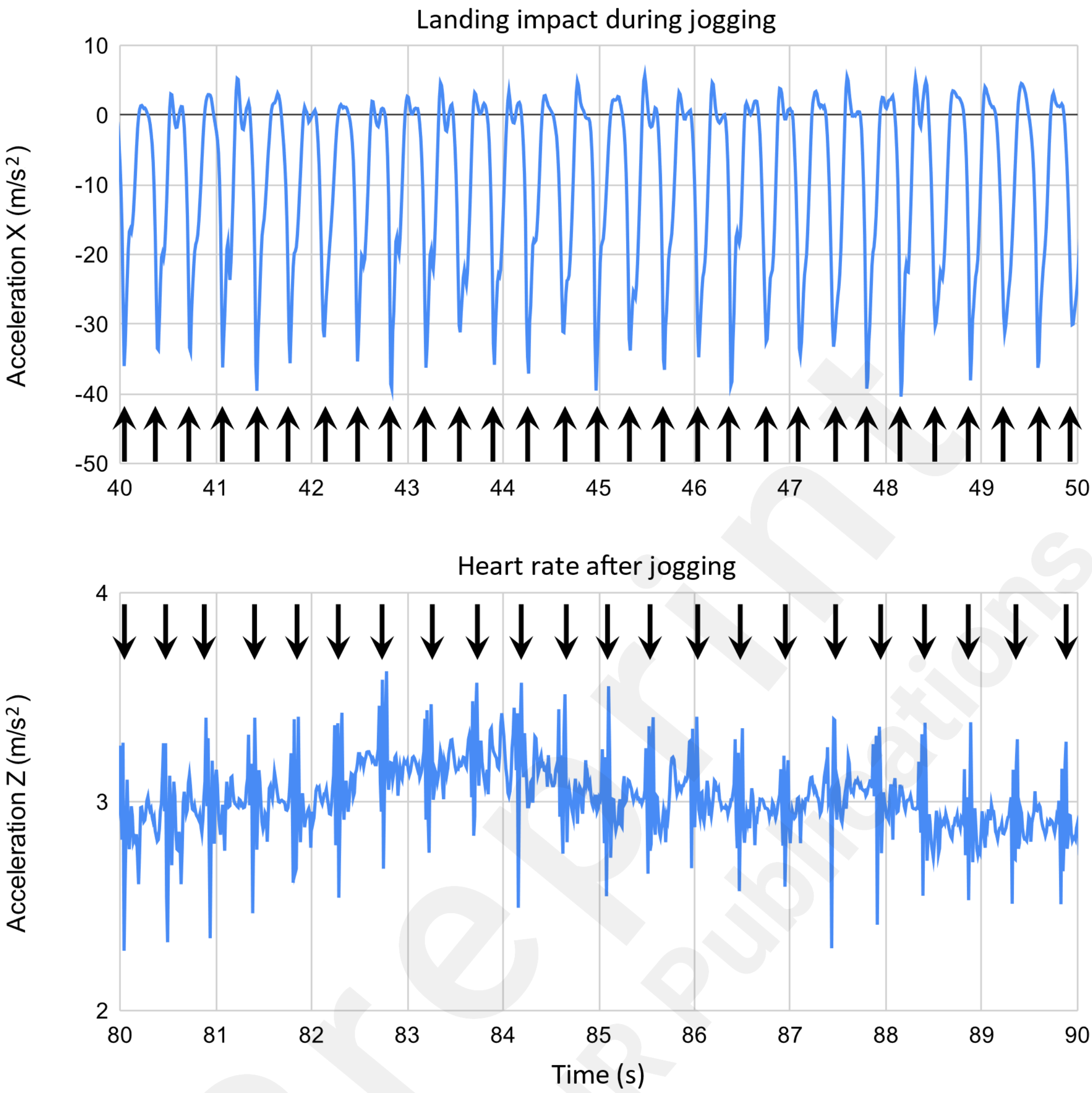


Figure 11: Top: Vertical acceleration while jogging on the spot; the black arrows identify the landing impacts used to estimate jogging cadence. Bottom: Anteroposterior acceleration after the jogging exercise; the black arrows identify the time instants used to estimate heart rate.

Knee extension range of motion

Smartphone sensors may be used to assess joint range of motion [28–30]. Here we used smartphone orientation data to estimate the knee extension range of motion during an active knee extension task. The smartphone was placed in landscape orientation over the calf, held in place inside the participant's sock. Matlab Mobile was used to record orientation data at 100 Hz (Multimedia appendix 5), which was analyzed using Google Sheets (video tutorial: [62]). The participant sat quietly with the leg in a vertical position and the knee at a 90-degree angle (reference task, 16-21 s), then performed one complete knee extension movement (22-28 s) and a knee extension movement without reaching full extension (27-44 s). The thigh was manually stabilized to ensure that changes in leg orientation were due to knee extension, and not hip flexion. Motion on the sagittal plane was recorded as changes in Roll. After solving a discontinuity, the data was adjusted so that sitting with the knee at a 90-degree angle (reference task: horizontal thigh, vertical tibia) resulted in a value of 90 degrees, and lower values would identify knee extension (Figure 12). When the knee was fully extended, the smartphone orientation value was close to 0 degrees; when the task was repeated simulating a knee extension range of motion deficit, the smartphone orientation data approached 10 degrees, therefore indicating a 10-degree deficit of knee extension. This example shows how smartphone orientation data can be used to assess joint range of motion.

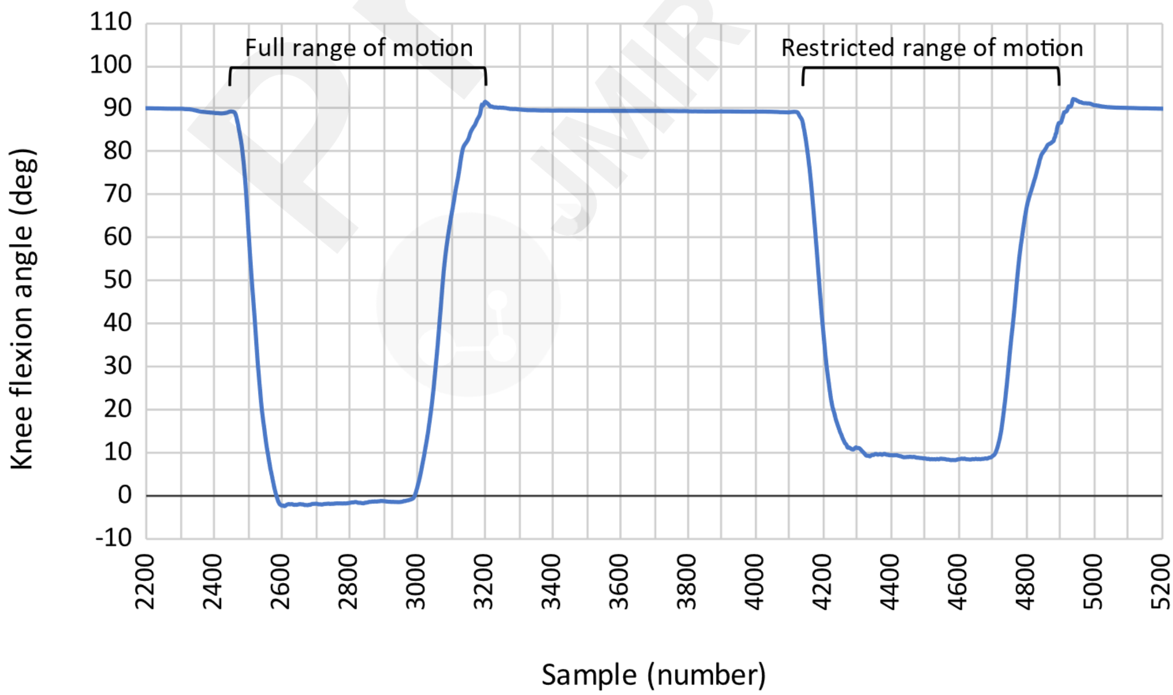


Figure 12: Knee flexion angle estimated from leg orientation during seated knee extension. The knee

reached full extension in the first repetition, whereas a 10-degree deficit of range of motion can be observed in the second repetition.

Pelvic orientation during single-leg squat

Smartphone orientation data can be used to describe changes in orientation during dynamic tasks. For instance, three-dimensional pelvic kinematics during single leg squats has been shown to be reliable between days when assessed remotely using smartphone sensors [70]. Orientation data was recorded using Matlab Mobile (sampling frequency set at 10 Hz, Multimedia appendix 6) with a smartphone placed on the skin over a participant's sacrum, held in place using the elastic band of the participant's clothing. Data was analyze using Microsoft Excel (video tutorial: [63]). The smartphone was placed in landscape orientation, with the screen facing outwards and the camera to the left (X axis pointing down and Y axis pointing left). To understand which signals represented movements in the different planes, and what a positive change represented, the participant performed an axis recognition task consisting in isolated movements in the sagittal (bend forward) and frontal (pelvic drop) planes. This indicated that more positive Roll meant anterior pelvic tilt, and more positive Pitch meant contralateral pelvic drop. The participant stood quietly for 5 s, then performed 5 single leg squats with their usual pelvic alignment and 5 with increased contralateral pelvic drop. In Figure 13, we identified the pelvic orientation in the frontal plane at peak anterior pelvic tilt; this was done by identifying the peak anterior pelvic tilt in the Roll data for each repetition, and using the same time point to identify the orientation in the frontal plane. Orientation estimates are reported as a change from baseline, estimated during a 5 s quiet stance period (27-32 s). Despite similar anterior pelvic tilt (15.5-17.1 degrees), pelvic orientation in the frontal plane clearly differed between trials with usual pelvic orientation (-0.7$\pm$0.3 degrees) and increased pelvic drop (8.7$\pm$1.1 degrees).

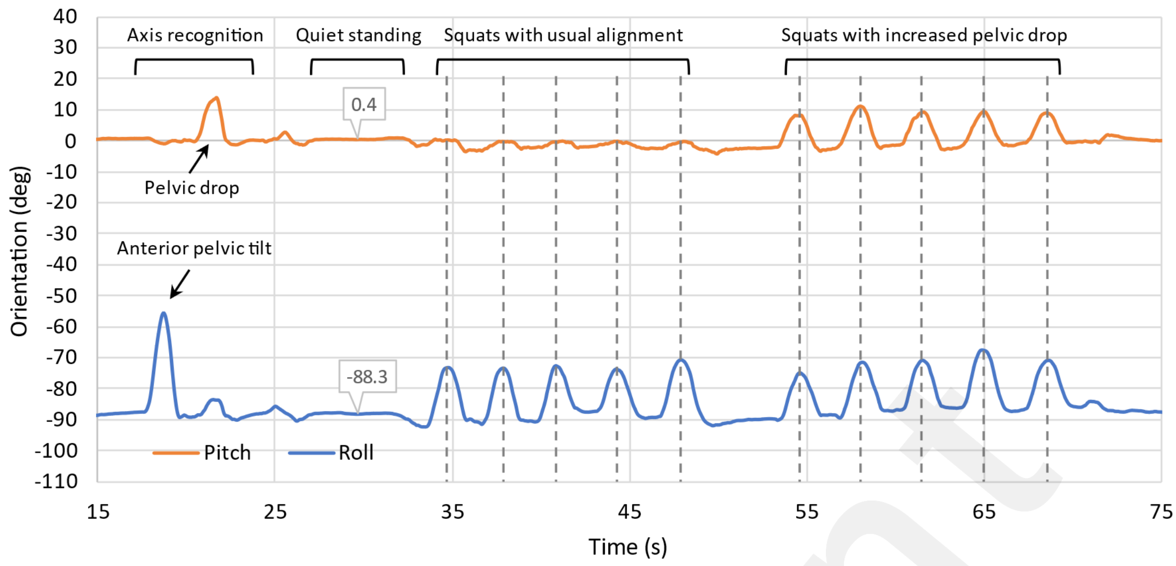


Figure 13: Sagittal and frontal plane pelvic orientation during single-leg squat. Despite a similar anterior pelvic tilt, performance of single leg squats with increased pelvic drop resulted in clear changes in frontal plane kinematics.

Timed up-and-go test

Smartphone orientation data can be used to assess postural transitions and gait direction. The timed up-and-go is a test used to assess mobility [71]. To perform this test, participants stand up from a chair, walk 3 meters, turn around, walk back 3 meters, and sit down on the chair. Although the total test time estimated using a stopwatch provides useful information from a clinical point of view, the duration of the specific phases and the kinematic characteristics of the individual phases of the test has been suggested to provide additional information relevant for practice [72,73]. In this example, a participant performed the test while holding a smartphone on their chest (landscape orientation, screen facing outwards, camera on the left). This smartphone location was preferred to be able to better quantify start and end of the task (when the participant touches the backseat of the chair) and the trunk orientation during sit-to-stand; a smartphone placed on the sacrum would allow the participant to use the upper limbs to stand up and sit down, and would leave the upper limbs free to swing during the gait. Orientation data was collected using the Matlab Mobile app (Multimedia appendix 7) and analyzed using Microsoft Excel (video tutorial: [64]). Figure 14 shows the orientation data after correction of a discontinuity on Azimuth; Pitch was not included since frontal plane kinematics did not provide useful information for the test in this participant. Start and end of the different phases were identified visually; the use of objective criteria or automatized processes [74] may result in more valid and reliable estimates. Roll increases with anterior trunk flexion, therefore the two peaks identify stand up and sit down. Azimuth describes the orientation of the trunk in the transverse plane. Starting from when the participant stands up, Azimuth shows an initial plateau (walking forward), a decrease (first turning phase), a second plateau approximately 180 degrees lower than the first one (walking back), a second decrease (second turning phase), and finally another plateau approximately 360 degrees lower than the first one (sitting down and sitting). This difference is due to a 360-degree turn of the smartphone, and resolving the discontinuity resulted in a difference in the starting and final orientation (note that 0 and 360 degrees identify the same angle). Depending on how the person sits down (pivoting on their left or right foot), the Azimuth signal may be similar to that presented in figure 14, or the second turn may show as an increase and the data may return close to the starting value in the third plateau. The total duration (start of stand up to end of sit down) was 8.66 s. The individual phases were: 1.46 s for sit-to-stand; 1.60 s for stand-to-sit; 1.81 s for the first turn, 1.45 s for second turn. Besides the information provided in this example, further information may be extracted from this data, for instance the range of motion of the trunk on the sagittal plane during sit to stand which was shown to be repeatable between days when tested remotely using smartphone sensors [75]. This example demonstrated how to use the orientation data to characterize the performance of the timed up-and-go test.

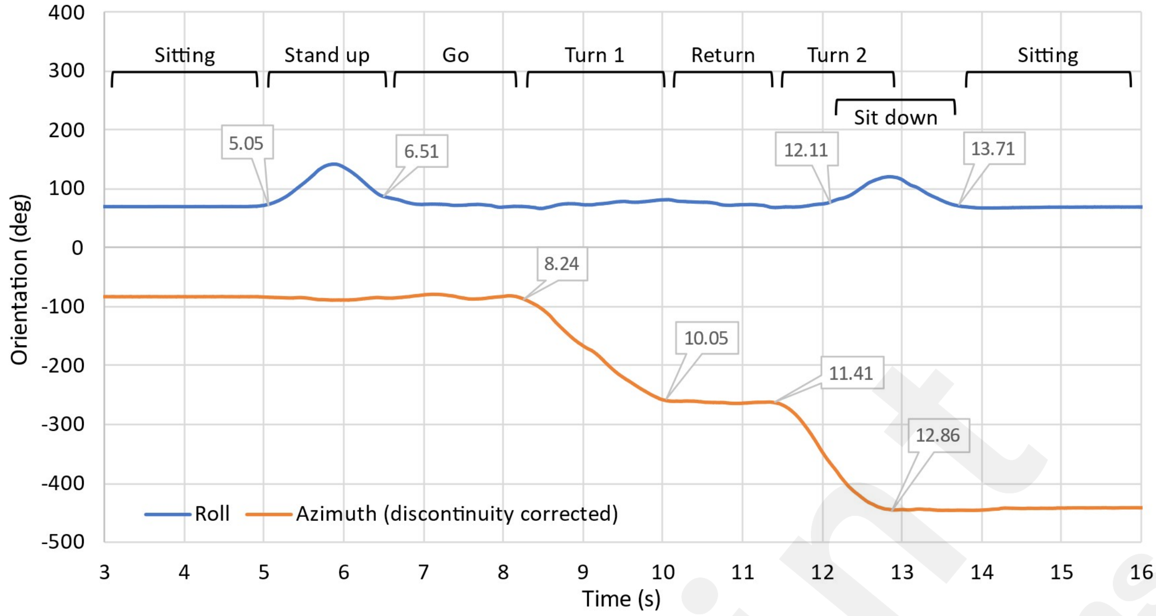


Figure 14: Sagittal and transversal trunk orientation during the timed up-and-go test. Duration of stand up and sit down, and of the two turn phases, were identified on Roll and Azimuth respectively.

Implementation in Education

When faculty members teaching biomechanics in the United States [76] were asked about how they would change their courses, the two most common answers were to ‘Obtain equipment’ (40.0%) and to ‘Incorporate technology’ (31.4%). As previously shown in physics education [3–5,8], the approach described in this tutorial may be easily implemented in education to provide students with hands-on experience in objective motion analysis. A key advantage of the proposed approach in education is that every student who owns a smartphone has access to their own sensors, allowing them to gain first-hand experience with the data collection procedure. This can take place in a classroom, where students can work in small groups to discuss the best approach for the chosen assessment and give peer feedback; or remotely, which gives the students the freedom to collect data on their own, for instance to repeat something that was not clear in class, to perform a practical exercitation they had to miss, to spend some time trying the sensor to understand what it measures, or to explore the use of the sensors to assess other tasks of interest. Similarly, data analysis with spreadsheet editors that are free or widely available, without the need of specialized software, further allows students to analyze their own dataset, even remotely if needed. When considering the different cognitive skills in education, students may be challenged to apply what they have learnt in the module to ‘create’ [77]. For instance, a potential assessment could consist in identifying a motor test commonly performed in practice where adding smartphone sensors could allow to collect objective motion data, collect data, analyze data, and write up a report reflecting on whether the approach is effective and what its limitations are.

Another key aspect of using smartphones for movement analysis education is that students will still be able to collect and analyze data after they graduate, therefore providing a direct link between what students learn in their degree and what they use in practice after graduation. Should smartphone sensor not be used in practice in the future, the first-hand experience with data collection and analysis will still prove useful for any motion analysis technique used, likely more so than what is taught in traditional motion analysis courses that focus on theory and demonstrations where the students only watch staff members collect and analyze data. It should be noted that smartphone sensors and free spreadsheet editors allow to collect and analyze human motion data completely for free, which facilitates the implementation of this approach in institutions that have a restricted budget, potentially fostering inclusivity and equality in biomechanics education.

Implementation in Research

Smartphone sensors that have been proven to have acceptable validity and reliability when used to estimate human motion in the task of interest may be used for research. The unique opportunities that wearable smart devices offer for research have prompted international collaborative efforts to standardize their use, such as those brought forward by the Interlive Network [78–81]. As for education, the key advantage is the wide availability of smartphones. To start, this low-cost approach (often no-cost, since most people already own a smartphone) may enable even research institutions with limited funding to meaningfully contribute to quantitative human motion research. The possibility to record movement data remotely at any time during the day, as opposed to collecting data in a session in laboratories that may have to be booked weeks in advance, may enable researchers to obtain larger amounts of data, and data that better represent what people experience in their daily lives. Flexible data collection may for instance provide more representative data in people with musculoskeletal disorders where their pain fluctuates daily, or to assess physical performance in athletes who train multiple sessions a week. For data collections that can be performed entirely online, smartphone sensors may allow to collect biomechanical data from people in different countries all over the world [82], increasing the diversity and representativity of the sample size and the generalizability of the results. It should be noted that, compared to laboratory equipment, smartphones have limitations with respect to the type of data they can collect. For instance, the 1 Hz sampling rate of smartphone GPS units may be too low to appropriately characterize sprinting motion; segment orientation can be considered equivalent to joint angle only in specific cases; or the smartphone may be too large and heavy to be secured appropriately to detect acceleration during highly dynamic tasks. In these cases, specialized research equipment (e.g.: dedicated GPS units; IMU systems with multiple sensors; small and light IMU) are necessary to collect data. Another factor to consider is that even if smartphone sensors show acceptable validity and reliability in the laboratory, it does not necessarily mean that the same applies when people collect data from themselves at home without supervision. This issue may potentially be limited by having a researcher supervise the data collection remotely, for instance over video-conferencing, but some of these factors should be considered in future validity and reliability studies when the procedure is meant to be implemented by individuals alone (e.g.: does the researcher or the individual secure the smartphone? Is the study performed in a laboratory or in the setting where data will be collected? Is the procedure validated using a single smartphone brand and model? If a strap is used to hold the smartphone in place, do all participants have access to the same strap?). While validity and reliability of smartphone sensors appears to be good in specific conditions (mainly static tasks, assessed in the laboratory using a single smartphone placed by researchers), further studies assessing the measurement properties of smartphone sensors in research in other conditions are needed.

Implementation in Practice

A recent survey [83] showed that about 60% of sport and exercise practitioners use apps to collect data, most frequently of biomechanical nature, although more than half used apps with unknown validity and reliability. This data demonstrates an interest in the use of smartphone apps for quantitative motion analysis, although this needs to be supported by education (understand the data) and research (validate the app and demonstrate if they make a difference in practice). Although the procedure presented in this tutorial may be used in sports and rehabilitation practice, dedicated apps may be better suited for the task. If athletes or patients were to collect data by themselves, a custom app that automatically selects the appropriate sensors, with the appropriate sampling rate, and clearly explains how to place and orient the smartphone, is likely going to be simpler to use than the procedure described in this tutorial. Similarly, a semi-automated analysis built in the app would help the practitioner visually check the data collected and ensure that the information extracted is accurate, without the amount of time required to download the data and analyze it on a spreadsheet. Implementation in practice should be based on research development (for instance, to ensure that the sensors have appropriate validity and reliability, and that their use effectively improves performance or clinical outcome; see [84] for a recent review) and appropriate education (for instance, to ensure that practitioners are aware of the possibility to use smartphone sensors to objectively quantify human motion, and that they can identify issues with data collection and analysis).

Conclusions

Smartphone sensors can provide objective motion analysis data. Since smartphones are widely available to the general population, smartphone sensors have the potential to help students learn how to collect and analyze biomechanical data, to help researchers gather biomechanical data, and to guide practitioners who routinely assess how people move. In this tutorial, we introduced some basic concepts about how to collect acceleration and orientation data, demonstrated how to collect data in six tasks commonly used in practice, analyzed the data using spreadsheet editors, and discussed this approach in the context of education, research and practice. We hope that this tutorial will contribute to promoting data-driven education and practice in fields that may benefit from objective analysis of human motion, such as sport science and rehabilitation.

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Conflicts of interest

The authors declare no conflicts of interest. No funding was received for this work.

Abbreviations

GPS: global positioning system.

IMU: inertial measurement unit.

Multimedia appendices

Multimedia appendix 1: Example of Matlab code to convert ‘.mat’ files to ‘.csv’.

Multimedia appendix 2: Spreadsheet with data and formulas used to analyze Jump height (Figure 9).

Multimedia appendix 3: Spreadsheet with data and formulas used to analyze Balance (Figure 10).

Multimedia appendix 4: Spreadsheet with data and formulas used to analyze Jogging cadence and heart rate (Figure 11).

Multimedia appendix 5: Spreadsheet with data and formulas used to analyze Knee extension range of motion (Figure 12).

Multimedia appendix 6: Spreadsheet with data and formulas used to analyze Pelvic orientation during single leg squat (Figure 13).

Multimedia appendix 7: Spreadsheet with data and formulas used to analyze Timed up-and-go test (Figure 14).

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Supplementary Files

Multimedia Appendixes

Example of Matlab code to convert '.mat' files to '.csv'.
URL: http://asset.jmir.pub/assets/c08cc4b4090cd7c6851c0ae4815c5f01.txt

Spreadsheet with data and formulas used to analyze Jump height (Figure 9).
URL: http://asset.jmir.pub/assets/0491cf4a05f3d2dde3f247cda441bece.xlsx

Spreadsheet with data and formulas used to analyze Balance (Figure 10).
URL: http://asset.jmir.pub/assets/e1a8bf92a64a9e6738fa636962293885.xlsx

Spreadsheet with data and formulas used to analyze Jogging cadence and heart rate (Figure 11).
URL: http://asset.jmir.pub/assets/189e1bfc8c79254059bcc93f201be819.xlsx

Spreadsheet with data and formulas used to analyze Knee extension range of motion (Figure 12).
URL: http://asset.jmir.pub/assets/c46602f6ff519e8740719e68a30a89a8.xlsx

Spreadsheet with data and formulas used to analyze Pelvic orientation during single leg squat (Figure 13).
URL: http://asset.jmir.pub/assets/e86956a47dcc29a5f29ae7b32693365f.xlsx

Spreadsheet with data and formulas used to analyze Timed up-and-go test (Figure 14).
URL: http://asset.jmir.pub/assets/10ab1f421a316d1aaec46a96100d1070.xlsx