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Method to collect ground truth data for walking speed in real-world environments: description and validation

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Background. Physical activity (PA) is increasingly being recognized as a major factor related to the development or prevention of many diseases, as an intervention to cure or delay disease and for patient assessment in diagnostics, as a clinical outcome measure or clinical trial endpoint. Thus, wearable sensors and signal algorithms to monitor PA in the free-living environment (real-world) are becoming popular in medicine and clinical research. This is especially true for walking speed, a parameter of PA behaviour with increasing evidence to serve as a patient outcome and clinical trial endpoint in many diseases. The development and validation of sensor signal algorithms for PA classification, in particular walking, and deriving specific PA parameters, such as real world walking speed depends on the availability of large reference data sets with ground truth values. In this study a novel, reliable, scalable (high throughput), user-friendly device and method to generate such ground truth data for real world walking speed, other physical activity types and further gait-related parameters in a real-world environment is described and validated.

Methods. A surveyor’s wheel was instrumented with a rotating 3D accelerometer (actibelt). A signal processing algorithm is described to derive distance and speed values. In addition, a high-resolution camera was attached via an active gimbal to video record context and detail. Validation was performed in the following main parts: 1) walking distance measurement is compared to the wheel’s built-in mechanical counter, 2) walking speed measurement is analysed on a treadmill at various speed settings, 3) speed measurement accuracy is analysed by an independent certified calibration laboratory - accreditation by DAkkS applying standardised test procedures.

Results: The mean relative error for distance measurements between our method and the built-in counter was 0.12%. Comparison of the speed values algorithmically extracted from accelerometry data and true treadmill speed revealed a mean adjusted absolute error of 0.01 m/s (relative error: 0.71 %). The calibration laboratory found a mean relative error between values algorithmically extracted from accelerometry data and laboratory gold standard of 0.36% (0.17-0.64 min/max), which is below the resolution of the laboratory. An official certificate was issued.

Discussion. Error values were a magnitude smaller than the any clinically important difference for walking speed.

Conclusion. Besides the high accuracy, the presented method can be deployed in a real world setting and allows to be integrated into the digital data flow.

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Abstract

Background. Physical activity (PA) is increasingly being recognized as a major factor related to the development or prevention of many diseases, as an intervention to cure or delay disease and for patient assessment in diagnostics, as a clinical outcome measure or clinical trial endpoint. Thus, wearable sensors and signal algorithms to monitor PA in the free-living environment (real-world) are becoming popular in medicine and clinical research. This is especially true for walking speed, a parameter of PA behaviour with increasing evidence to serve as a patient outcome and clinical trial endpoint in many diseases. The development and validation of sensor signal algorithms for PA classification, in particular walking, and deriving specific PA parameters, such as real world walking speed depends on the availability of large reference data sets with ground truth values. In this study a novel, reliable, scalable (high throughput), user-friendly device and method to generate such ground truth data for real world walking speed, other physical activity types and further gait-related parameters in a real-world environment is described and validated.

Methods. A surveyor's wheel was instrumented with a rotating 3D accelerometer (actibelt). A signal processing algorithm is described to derive distance and speed values. In addition, a high-resolution camera was attached via an active gimbal to video record context and detail. Validation was performed in the following main parts: 1) walking distance measurement is compared to the wheel's built-in mechanical counter, 2) walking speed measurement is analysed on a treadmill at various speed settings, 3) speed measurement accuracy is analysed by an independent certified calibration laboratory - accreditation by DAkkS applying standardised test procedures.

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Discussion. Error values were a magnitude smaller than the any clinically important difference for walking speed.

Conclusion. Besides the high accuracy, the presented method can be deployed in a real world setting and allows to be integrated into the digital data flow.

Introduction

Physical activity (PA) is increasingly being recognized as a major factor related to the development or prevention of many diseases (Warburton, Nicol & Bredin, 2006; Reiner et al. 2014), as an intervention to cure or delay disease and for patient assessment in diagnostics, as a clinical outcome measure or clinical trial endpoint (Byrom & Rowe, 2016; Zijlstra et al. 2017). Thus, wearable sensors and signal algorithms to monitor physical activity in the free-living environment (real-world) are becoming popular in medicine and clinical research (Robson & Janssen, 2015; Grimm & Bolink 2016).

The development and validation of sensor signal algorithms for PA classification (e.g. walking) or deriving specific PA parameters (e.g. walking speed) at clinical grade quality depends on the availability of large reference data sets with ground truth values for the activities and parameters to be derived. This is especially true when the machine learning methods are employed in algorithm development requiring large and patient-specific datasets for algorithm training and validation. Thus, reliable, scalable (high throughput), practical and itself valid methods to generate such datasets at reasonable effort and cost are required but no gold-standard methods have yet been established (Awais, Mellone & Chiari, 2015).

This is especially true for walking speed, a parameter of physical activity behaviour increasingly gaining recognition as a powerful dimension of patient outcome in many disease areas (Hardy et al., 2007; Abellan van Kan, 2009; Grcic et al., 2011; Studenski et al., 2011; Schimpl et al., 2011; Bohannon & Glenney, 2014; Hass et al., 2014) and as endpoint candidate in clinical trials. The generation of ground truth data for algorithm development to derive walking speed a real-world setting (Schimpl, Lederer & Daumer, 2011) is particularly challenging. Video-observation and manual annotation as common for the classification of basic physical activities such as sitting, standing, walking and transfers are not able to produce a true value for walking speed. Thus, a new method needs to be developed and validated to generate ground truth data for walking speed.

The definition of walking speed in the real world is not yet standardised and may affect the design of a suitable method to generate ground truth measurements. In a laboratory setting walking continuously and straight on an even surface for a measured distance, the definition of walking speed seems straightforward. Walking in the real-world however usually involves a curved trajectory and may take place on inclined or uneven surfaces. Possible definitions of walking speed may e.g. account for a straight-line distance between the beginning and end of a walking episode, or the distance described e.g. by the polygon created by the lines connecting individual steps or by the curved projection of the body centre-of-mass on to the ground. Instead of following a body-centre-of-mass trajectory which is influenced by shifting mass of the upper body alone and when stationary, we define real-world walking speed based on the distance described by the trajectory of the geometric centre between the left and right hip joint centre. Reference to this point of skeletal anatomy seems most related to the walking motion, reproducible to identify and by being geometric, most practical to follow by any tracking method.

It is the aim of this study to describe and validate a novel, reliable, user-friendly and affordable device and method to generate ground truth data for real world walking speed as defined above, other physical activity types and gait-related parameters in a real-world environment using a surveyor's wheel instrumented with a 3D accelerometer and carrying a video-camera.

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Materials & Methods

Method to measure walking speed:

The method to generate ground truth data for walking speed in a real-world environment comprises two devices, a wheel and a spoke-mounted accelerometer, together with a signal processing algorithm to derive distance and speed data. In addition, a camera is attached to video-record context and detail known to aid and expand algorithm development possibilities.

a) Wheel

With (walking) speed being the derivative of (walking) distance, the use of an established distance measurement tool such as a surveyor's wheel as e.g. applied in civil engineering made the appropriate basis for a device to collect walking speed from a human ambulating in the natural environment. Such a surveyor's wheel, also called click wheel, odometer or perambulator mechanically counts partial (equidistant segments) and full revolutions (common wheel circumference= 1m) to derive the distance the wheel has travelled. The successful use of such a mechanical wheel for measuring walking distance and speed for reference and algorithm development has already been described before (Schimpl, Lederer & Daumer, 2011) albeit here in combination with a bicycle computer to electronically register the distance.

In this study, the surveyor's wheel model used was the calibratable geoFennel M 10 (Baunatal, Germany) comprising a built-in mechanical precision counter with a tolerance <0.02%. When distance (and speed) are to be collected from a walking human in a real-world environment, an observer is instructed follows the free roaming subject with the surveyor's wheel from slightly behind and lateral (ca. 1m)) allowing free and natural ambulation of the test subject while closely following the route in in direction and speed.

b) Acceleromter

In order to digitally record wheel travel distance and speed, a 3D accelerometer, in particular the recording box of the actibelt RCT2 (trium, Munich, Germany), a belt-buckle integrated activity monitor was mounted onto the wheel's spoke near the hub (50mm distance to rotational axis) in a position so that two axes were aligned with the wheel plane (Figure 1, here in final design with hub-mounted actibelt). The actibelt recording box (Figure 2) measures ca. 50x40x10mm and records accelerations in three axes at 100Hz sample frequency with data storage (4GB) and battery capacity enabling for up to 8 weeks of continuous recording.

This approach towards recording distance was chosen over using the wheel's built-in mechanical counter or the electronic bicycle computer because of the cumbersome data readout, documentation and necessary laborious and error prone data transcription and transformation for both the built-in counter or bike computer. For an accelerometer and the actibelt in particular, the same sensor device is used to monitor patient activity (Soaz et al. 2011, Motl et al. 2012, Stellmann et al. 2015) and to generate the ground truth values for distance and speed. Thus, data collection from the walking subject and the turning wheel are conveniently synchronized and of identical format for efficient handling. Such usability aspects are important to allow the generation of consistently documented large amounts of synchronized data required for activity classification and gait parameter algorithm development and validation, especially when machine learning methods are employed demanding large training data sets.

c) Algorithm:

The algorithm to derive distance and speed values from the spoke-mounted accelerometer signal uses the sinusoidal waveform produced by the two accelerometer axes aligned with the plane of the rotating wheel and thus measuring the momentary static gravity component. Each full rotation of the wheel generates one period of a sinusoidal in both axes with a 90-degree phase-shift between them. Thus, automated peak-detection of the maxima and minima in both curves using the "findpeaks" function of the "pracma" package (v1.9.9) in R (version 3.3.2) distinctly marks 4 subsequent quarter rotations. These translate into 4 equidistant units of wheel travel, in the case of a wheel with a 1m circumference as used in this study, marking distances in multiples of 25cm. Speed is then calculated by dividing distance by the know time between two peaks or the peaks marking the start and end of a walking bout episode. Prior to acceleration peak detection, the signal is filtered (Chebyshev, Type 1) to exclude frequencies (e.g. bumps from surface, general noise) outside what a human would produce walking at speeds ranging between 0.35 m/s to 1.75 m/s. In a self-written post-processing script, the algorithm only documented a distance and speed value for a walking bout when a minimum number of subsequent quarter rotations of the wheel were recorded and the individual subsequent values showed a certain coherence as expected for human walking characterized by smooth and not abrupt accelerations or decelerations. This feature is used to avoid the output of false distance and speed values from confounding acceleration peaks stemming from e.g. hitting the wheel or moving it slightly back and forth at a moment of stand-still with the accelerometer axes accidentally aligned with gravity. In this set-up validated here, any possible wheel travel distance from rest until recording the first acceleration peak count of a walking bout is missed (<25cm) as well as any possible wheel travel distance at the end of a walking bout after the final peak and before wheel stop. This systematic source of error was neglected as it is also inherent with the mechanical counter (or a wheel magnet driven bike computer) and because for the walking distances studied, even the theoretical maximum error would be relatively small (<1%). In addition, the wheel starting position can be chosen to minimize this effect, Furthermore, if required e.g. to reduce relative error for very short walking distances, missed distances before the first and after the last acceleration peak could be algorithmically estimated from the sinusoidal curves.

d) Camera

In order to document additional context, detail and ground truth data beyond distance and speed, a smartphone (Huawei, Mate 9, Shenzhen, China) with a high-resolution video-camera and an active gimbal for image stabilisation was mounted onto the surveyor's wheel. The camera was augmented with a frog eye lens and the field of view focused onto the lower legs and feet of the subject being followed (Figure 3). This way, each step is visually recorded in detail simultaneously with the wheel speed and the subject-worn actibelt accelerations. For time synchronization between both actibelts and the camera, both sensing units (recording boxes) are coupled and vigorously tapped in front of the running camera before being fit back the test subject's belt and surveyor's wheel.

Video-recordings were made using the OpenCamera App which allows high-definition videos (1080p) to be captured at 120fps and stored in mp4 format. The video-recording is later manually annotated by a human observer to mark detailed gait events such as individual steps, heel strike and toe-off to generate ground truth for developing and validating algorithms for real-world activity parameters such as step counts, stance or swing time. The feet-focused camera position guarantees the anonymity of the recordings required for collecting data also in public spaces which are well suited for generating real-world data. The camera also records context such as properties of the surface walked on, perturbations from the real-world environment or the subject's footwear which can be useful information for deeper understanding during algorithm validation. Another reason to integrate a camera for video-recording the steps of walking is that computerized image analysis methods under development to detect gait phases and annotate them promises to automate and accelerate the generation of ground truth data for real-world gait monitoring algorithms. This is useful to generate large datasets required especially for machine learning approaches which are popular now.

e) Real-World parkour

Finally, besides the device and algorithm described in this study, the full method to generate ground truth for real-world walking speed also requires a) information about the real-world environments recommended for application and b) instructions for the measured subject and the observer (Figure 4). While the system presented in this study is explicitly designed to be used outside the lab in any natural setting, the efficient generation of ground truth datasets for algorithm development benefits from defining and then finding or creating an environment in the real-world and some instructions to the measured subject on where and how to walk. This way it is possible to combine and assess many typical types and conditions of human walking in a small space and short time frame reducing the burden to test subject and observer. The set-up of such an environment in the real-world and the instructions to the test subject is called Parkour and its detailed description and validation requires a separate study.

Validation:

The validation of this method was performed in four parts, 1) validating the distance measurement derived from the wheel-mounted accelerometer versus the built-in mechanical counter, 2) validating the speed measurement derived from wheel-mounted accelerometer versus speeds set on a treadmill, 3) an external validation by a certified calibration service, 4) investigating the influence of centrifugal forces and off-centre position of the wheel mounted accelerometer on signal quality and thus distance and speed measurement. For part 2) the systematic error for speed settings on the treadmill was established first using the mechanical counter built-into the wheel. The Ethics Committee of the Ludwig-Maximilians-University München) granted ethical approval to carry out this study (Ref: 627-16) and written consent was collected from subjects involved.

Validation protocol 1: Distance

Three walking bouts of various length and with breaks of variable duration before, in-between and after were performed by one subject walking at self-selected speed with the wheel set-up described above. The three distance measurements derived from the built-in mechanical counter were compared to the distance values derived from the accelerometer and algorithm described above and the mean absolute and relative error were calculated.

Validation protocol 2: Walking Speed

A direct comparison between the walking speed derived from the wheel-mounted accelerometer and algorithm and a reference value for speed was performed using a treadmill (Kettler, Boston XL, Germany). It was set to various speed readings with the wheel mounted to the treadmill excluding any potential error of an observer guiding the wheel. Treadmill speeds were run for 30s duration per setting with speeds rising from 0.5 m/s to 1.75 m/s in increments of 0.25 m/s.

As a consumer device, the treadmill satisfies different requirements and thus was expected to be less accurate than a dedicated measurement tool. To enable its usage as a reference device the systematic error of the treadmill was estimated beforehand as follows: The treadmill was operated at two set speeds, 6 km/h and 3 km/h respectively for a time period of 300s each as measured by a stopwatch. The distance as calculated from the set speed and time ("expected distance") was than compared to the distance as measured by the treadmill mounted wheel and its mechanical counter to derive the errors. The mean relative error was then used to correct speed values from the treadmill for the comparison with the accelerometer derived speed.

Validation protocol 3: External validation

The measurement wheel with the hub-mounted actibelt accelerometer was provided to a calibration laboratory (SBS Kalibrierungsservice GmbH, Unterweilerbach, Germany) accredited by the national accreditation body for the Federal Republic of Germany (DAkkS) for official certification. The certificate issued under the number D-K-18447-01-00 can be found in the supplementary material.

For calibration of the measurement method described here, the calibration laboratory followed the standardised test procedures for measurement instruments measuring revolutions and frequencies (DAkkS, 6.4.05 and 6.4.06). According to these normed procedures, the actibelt was mounted onto a speed-regulated electric screwdriver and the true values for revolutions [1/min] and frequency [1/s] were measured employing a waveform generator (Model 33250A, Agilent Technologies, Santa Clara, Ca, USA) and a Laser tachometer (DT-207 B, Nidec-Shimpo Instruments, Glendale Heights, IL, USA). Nine settings for speed (rotational frequencies) were measured covering a range equivalent to walking speeds ranging from 0.78m/s to 1.94m/s which represents a broad interval of human real-world walking speeds. For each setting, 5 measurements were performed to derive a mean value and the relative difference between the true (calibration reference) and measured (actibelt and algorithm) value was calculated.

Validation protocol 4: Influence of sensor position

Two positions for the wheel-mounted accelerometer were compared to study the influence of centrifugal forces during rotation on the sensor signal used for the speed calculation algorithm. Based The experiment was meant to identify possible walking speed thresholds up to which values can be considered reliable and when signal drift would critically affect them. For this, the treadmill mounted wheel recorded raw accelerations from two sensor positions, the spoke-mounted actibelt and from an actibelt attached close to the rotational axis (hub). Treadmill speeds were increased step-wise (0.25km/h) from standstill to 10 km/h. The speed where the sinusoidal maxima significantly exceeded the 1g static gravity was considered a threshold.

Results

Validation protocol 1: Distance

The raw acceleration trace from spoke-mounted accelerometer recorded during distance measurement validation clearly reflected the experimental set-up with three walking bouts of different length interrupted by two breaks (Figure 1). The accelerometer signals from the axes aligned with the wheel plane followed a sinusoidal waveform during rotation (Figure 1). Numerical analysis of comparing the reference distance from the mechanical counter to the accelerometer and algorithm output gave a mean relative error of 0.12% (max: 0.22%, Table 1).

Validation protocol 2: Walking Speed

The experiment to establish the error of the treadmill's speed settings revealed a mean relative error for both speed settings of +3.63% (Table 2), indicating that true treadmill speed is slightly higher than the set speed. The mean relative error was used to adjust the subsequent relative error calculations when comparing treadmill speed to speed output from the accelerometer.
The speed validation experiment with its stepped treadmill speed increments showed how the accelerometer and algorithm output closely followed these increments with values slightly above the set speeds (Figure 3). Numerical analysis of the 11 paired treadmill and algorithm speed values revealed a mean unadjusted absolute error of 0.03 m/s (adjusted: 0.01 m/s) and an unadjusted mean relative error of 2.89 % (adjusted: 0.71 %).

Validation protocol 3: External validation

Performing a standardised calibration protocol for instruments measuring revolutions and frequencies by an independent laboratory accredited by the German authority revealed a mean relative error between the true and measured value for revolutions and frequencies of 0.36% (0.17-0.64 min/max, see Table 4). These values were within the accuracy range of the calibration equipment and an official certificate was issued.

Validation protocol 4: Influence of sensor position

For the spoke-mounted accelerometer outside the rotational axis it was seen that the theoretical maximum/minimum acceleration value per axis, gravity at ±1g, visibly exceeded this threshold at (walking) speeds beyond 5 km/h (Figure 3). At speeds above 10 km/h it exceeded the measurement range of the sensor (6g, Figure 3) due to the added centrifugal forces. When the actibelt was mounted at the hub near the rotational axis, no such effect was visibly throughout the entire speed range up to 10 km/h.

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Discussion

The development and validation of algorithms for wearable sensor derived measures of physical activity in the real-world and for accelerometers and walking speed in particular requires large data-sets with reliable ground truth values as reference. This is especially true when machine learning techniques are employed depending on large training and validation data sets for algorithm development. Thus, reliable, user-friendly and proven (i.e. itself validated) methods with high throughput capacity are needed to generate such ground truth reference data. This study describes and validated a method to collect ground truth data for walking speed in real-world environments, a gait parameter of increasingly recognized clinical relevance and until now difficult to generate ground truth for in a simple and valid manner.

The solution developed comprises a standard surveyor's wheel with an accelerometer mounted close to the hub and an algorithm which detects the peaks of the phase-shifted sinusoidal signals from two accelerometer axes to count wheel revolutions and derive speed from it. As a recommended optional addition, a mounted (smartphone) camera can provide additional context and detail for algorithm development.

In a 4-part validation, various aspects of the method's validity were established. It was shown that the described solution can measure distance with a mean relative error of 0.22% giving an accuracy much higher than what is currently achieved or would be expected or required for a wearable device and algorithm combination estimating walking distance (or speed) in a real-world environment. Also, the direct speed output showed to be very precise against a reference (treadmill) with both absolute (0.01 m/s) and relative error (0.71%) being negligibly small for real-world practice where e.g. the clinically important differences for walking speed, e.g. ±0.1m/s (Bohannon & Glenney, 2014) are one order of magnitude higher. Independent external validation by a certified calibration agency confirmed these results and further supports the method's application in an environment where regulatory requirements may demand such formal approval. Finally, it was also shown that the method can be affected by centrifugal forces when speeds exceed ca. 5 km/h and the accelerometer is mounted off-centre in the spokes. However, this effect can be removed when the accelerometer is mounted at the hub near the centre of rotation. Then the method works reliably at speeds up to and beyond 10 km/h. Thus, the accelerometer position near the rotational axis is recommended and now routinely implemented in our set-up. As walking speeds, especially those of patients or elderly, are usually below 2 m/s (Studenski et al., 2014) and thus well below where centrifugal forces showed signal drift for a spoke-mounted accelerometer, past or future data collected in such an environment are still reliably accurate.

The method described and the validation performed have some limitations. As stated in the introduction, already conceptually, any attempt to record true human walking speed in the real-world is challenged by the precise definition of it. From various imaginable alternatives, we pragmatically defined real-world walking speed based on the distance described by the trajectory to the ground of a point from skeletal anatomy, the geometric centre between the left and right hip joint centre. This highly reproducible point can easily be generated in computer simulations of gait kinematics, can be closely estimated using video-capture of related anatomical landmarks (reflective markers) and can be aimed at and followed by a human observer. Differences between this definition and alternatives seem small but in certain conditions, definitions based on mass (e.g. upper body motion) or the polygon connecting steps (e.g. uneven, inclined surfaces) seem less appropriate and accessible for a ground truth generating method.
The method described is designed to generate ground truth for walking speed. Stepping motions like side-stepping, shuffling or bouts of a very few steps like common e.g. in the home environment (e.g. household chores) would not be accessible for generating a walking speed value by this method. However, it also does not seem appropriate to label the velocity of such stepping movements as walking speed, nor has the velocity of such events yet been reported as parameter with clinical meaning.

Besides these definitional aspects, generating ground truth for walking speed by a having a human observer follow a subject with a measurement wheel adds extra effort and some observer subjectivity. The observer's wheel speed and the walker's true speed will differ to some degree especially when sudden starts and stops or changes in speed or direction (corners) happen in a real-world environment causing some delays, false reactions or corrections of the observer. However, in practice, when such reference datasets are created, measurements are often performed in a real-world like gait course ("parkours") to generate many different events of walking in a small space and short period of time. This way walking paths are more predictable, and in addition observers are well experienced. Also, the theoretical effect of influencing the behaviour and gait pattern of the person being followed is avoided or minimised by the observer following from behind and the parkours set-up providing a natural environment and real-world distraction.

The elaborate 4-part validation protocol described involved level, smooth and non-slippery surfaces and longer walking bouts (>30 steps). Thus, from the data presented, the validity on uneven surfaces with bumps potentially causing "false" acceleration peaks, slippery surfaces potentially causing wheel slip or short bouts with many stops and turns like e.g. encountered roaming indoors at home can only be commented on. The chance for peaks from bumps being of a nature to offset the algorithm seems unlikely and if so, could be removed with a low-pass filter.

Wheel slip for a professional surveyor's wheel may only be encountered in theory and on surfaces which would need to be so slippery (e.g. ice) that in the practice of generating patient reference data for algorithm development such situations would not be encountered unless specifically wanted. The performance of the method on shorter walking bouts should be maintained and may only degrade for very short bouts of walking (e.g. <5 or <3 steps). Such short bouts would be encountered e.g. indoors during housework and thus possibly may be better classified as roaming or shuffling instead of walking. In addition, for a "mean real-world walking speed" calculated over a day or week such very short bouts add too few steps to be relevant overall. Thus, their inclusion into a parkours for generating reference data is not typical.

Conclusions

A surveyor's wheel equipped with a hub-mounted 3D-accelerometer aligned with the wheel plane and an algorithm counting the peaks of two signal axes has proven to be a highly accurate method to generate ground truth data for walking distance and speed in a real-world environment. Besides its high accuracy, this method can be deployed in a real world setting and allows to be integrated into the digital data flow so that it may serve as a gold standard method for the development and validation of wearable sensor algorithms estimating real work walking speed. Future research will investigate the observer reliability of using this method in various real-world environments and with different subjects or patients, will describe the real-world environments and subject instructions (Parkour) most effective to generate large algorithm training and validation data sets and will develop computerized image analysis methods to automatically annotate video-recordings for additional context and detail.

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Table 1(on next page)

Distance measurement validation: Comparing built-in mechanical counter (reference) to spoke-mounted accelerometer values (algorithm) for three walking bouts.

	Distance Measurement			
	Reference value [m]	Algorithm output [m]	Reference value [m]	**Relative error [%]**
Bout 1	34.48	34.50	0.02	**0.06**
Bout 2	27.81	27.75	0.06	**0.22**
Bout 3	36.03	36.00	0.03	**0.08**

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Table 2(on next page)

Establishing the treadmills systematic error for speed: Comparing distance calculated by set speed and measurement duration (expected) versus distance from the wheel's mechanical counter (measured).

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	Treadmill set-up [km/h]	Measurement duration [s]	Expected distance [m]	Measured distance [m]	Absolute error [m]	Relative error [%]
Test 1	3	300	250	260.05	10.05	4.02
Test 2	6	300	250	516.15	16.15	3.23

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Table 3(on next page)

Speed measurement validation: Comparing treadmill speed versus output from the spoke-mounted accelerometer and speed algorithm.

The adjusted relative error takes the treadmill's estimated mean error of +3.63 % into account.

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Treadmill setting [m/s]	Algorithm output [m/s]	Absolute error [m/s]	Relative error [%]	Adj. relative error [%]
0.50	0.51	0.01	2.58	1.01
0.75	0.77	0.02	2.99	0.62
1.00	1.03	0.03	2.99	0.62
1.25	1.29	0.04	2.94	0.66
1.50	1.54	0.04	2.83	0.77
0.50	0.51	0.01	2.97	0.64
0.75	0.77	0.02	3.14	0.47
1.00	1.03	0.03	3.02	0.59
1.25	1.29	0.04	2.94	0.67

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Table 4 (on next page)

Values from following a prescribed standardised test protocol for instrument calibration comparing the true value from the reference measurement device and the actibelt (measured value).

True value		Measured value			
Revolutions [1/min]	f [1/s]	Revolutions [1/min]	f [1/s]	Abs. diff f [1/s]	Rel. Diff [%]
46.6	0.7767	46.3	0.7717	-0.0050	0.64
48.1	0.8017	48.0	0.8000	-0.0017	0.21
81.0	1.3500	81.2	1.3533	0.0033	0.25
81.5	1.3583	81.4	1.3567	-0.0017	0.12
82.2	1.3700	82.3	1.3717	0.0017	0.12
83.0	1.3833	83.1	1.3850	0.0017	0.12
84.5	1.4083	85.5	1.4250	0.0167	1.18
90.3	1.5050	90.7	1.5117	0.0067	0.44
116.2	1.9367	116.0	1.9333	-0.0033	0.17
			Avg.	**0.0020**	**0.36**

1

Figure 1

Measurement device to generate ground truth data for walking speed in real-world environments. Surveyor’s wheel with hub-mounted actibelt and smartphone video-camera attached via an active gimbal.

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Figure 2

Detailed view of the accelerometer (open actibelt recording box) positioned at hub near the rotational wheel axis.

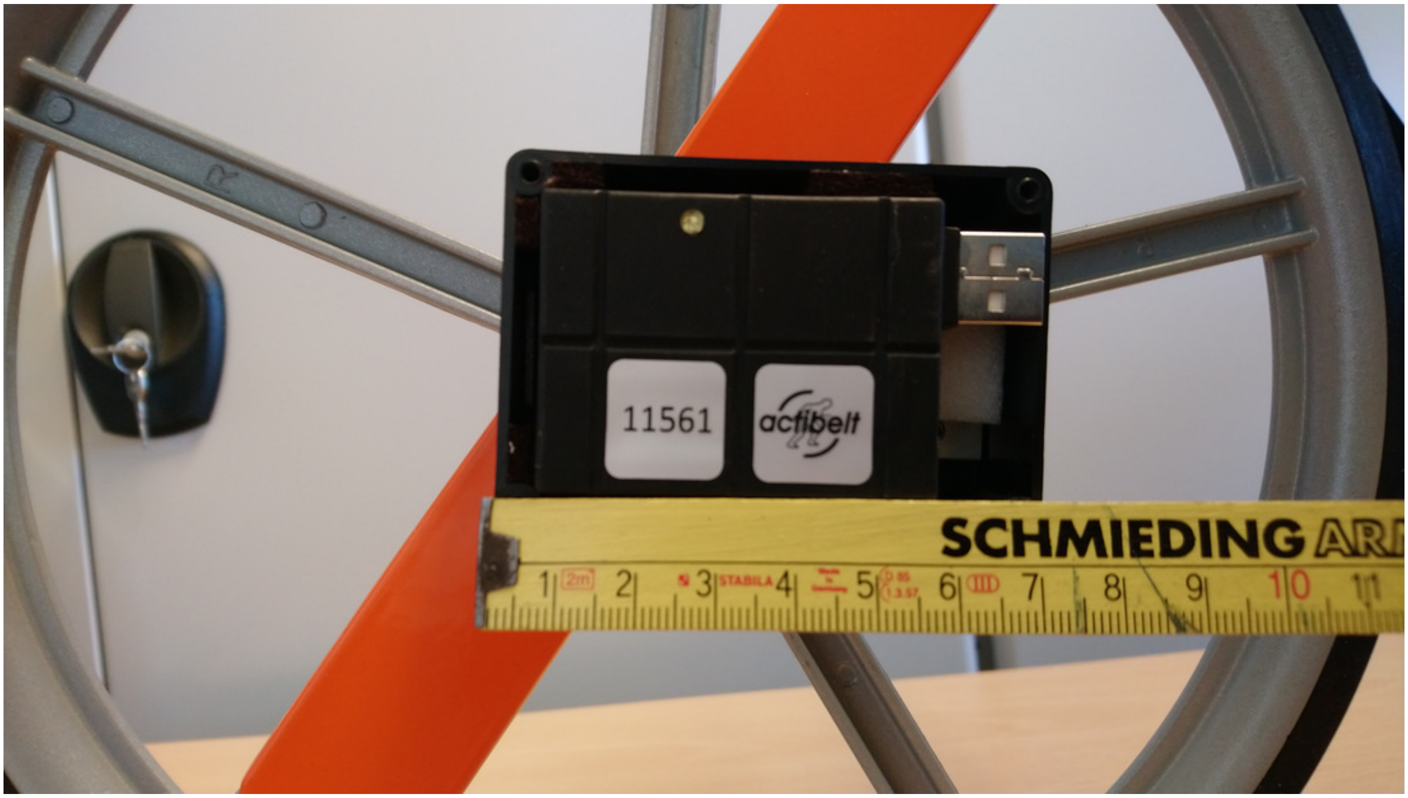

Figure 3

Detailed view of the smartphone screen during operation.

Screen shows the camera plus fish-eye lens recording the ground, feet and lower legs during walking to add visual context and additional detail for algorithm development and validation.

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Figure 4

Measurement wheel in use by observer following walking subject.

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Figure 5

Raw acceleration from spoke-mounted actibelt accelerometer recorded during distance measurement validation. Red, green: axes in wheel plane, blue: axis perpendicular to wheel plane.

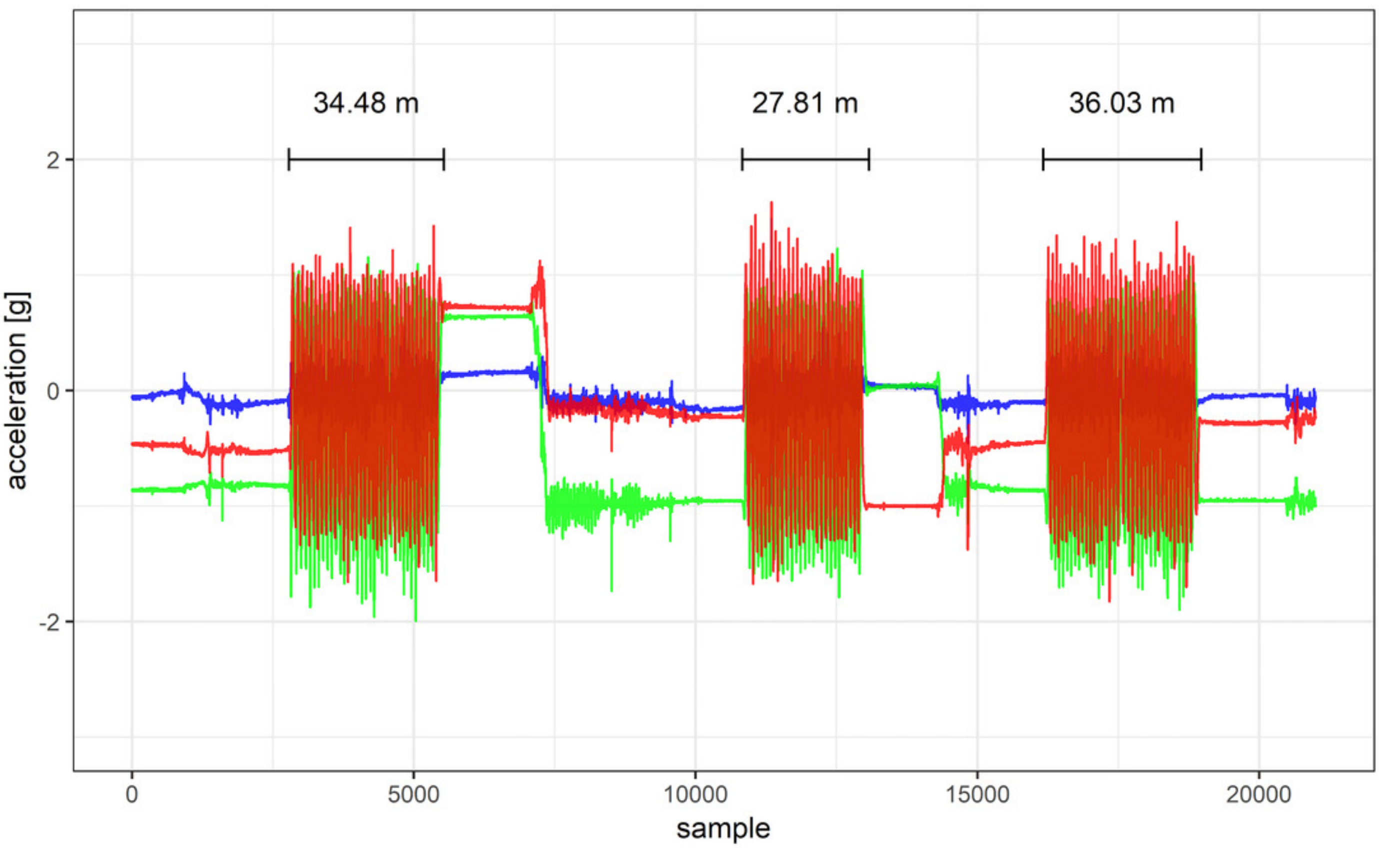

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Figure 6

Speed measurement validation: Output from the spoke-mounted accelerometer and speed algorithm (black) versus the stepped treadmill settings (red).

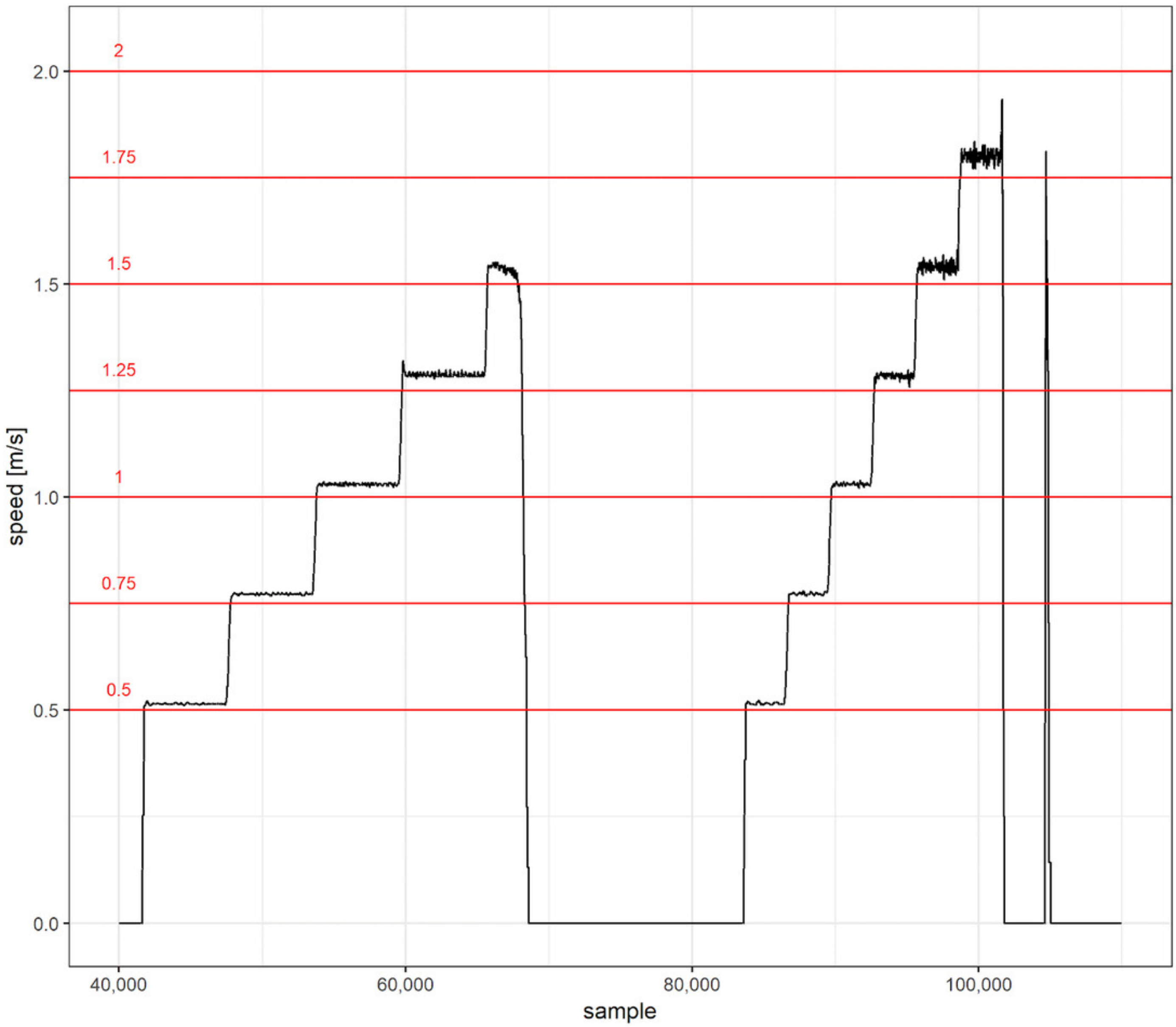

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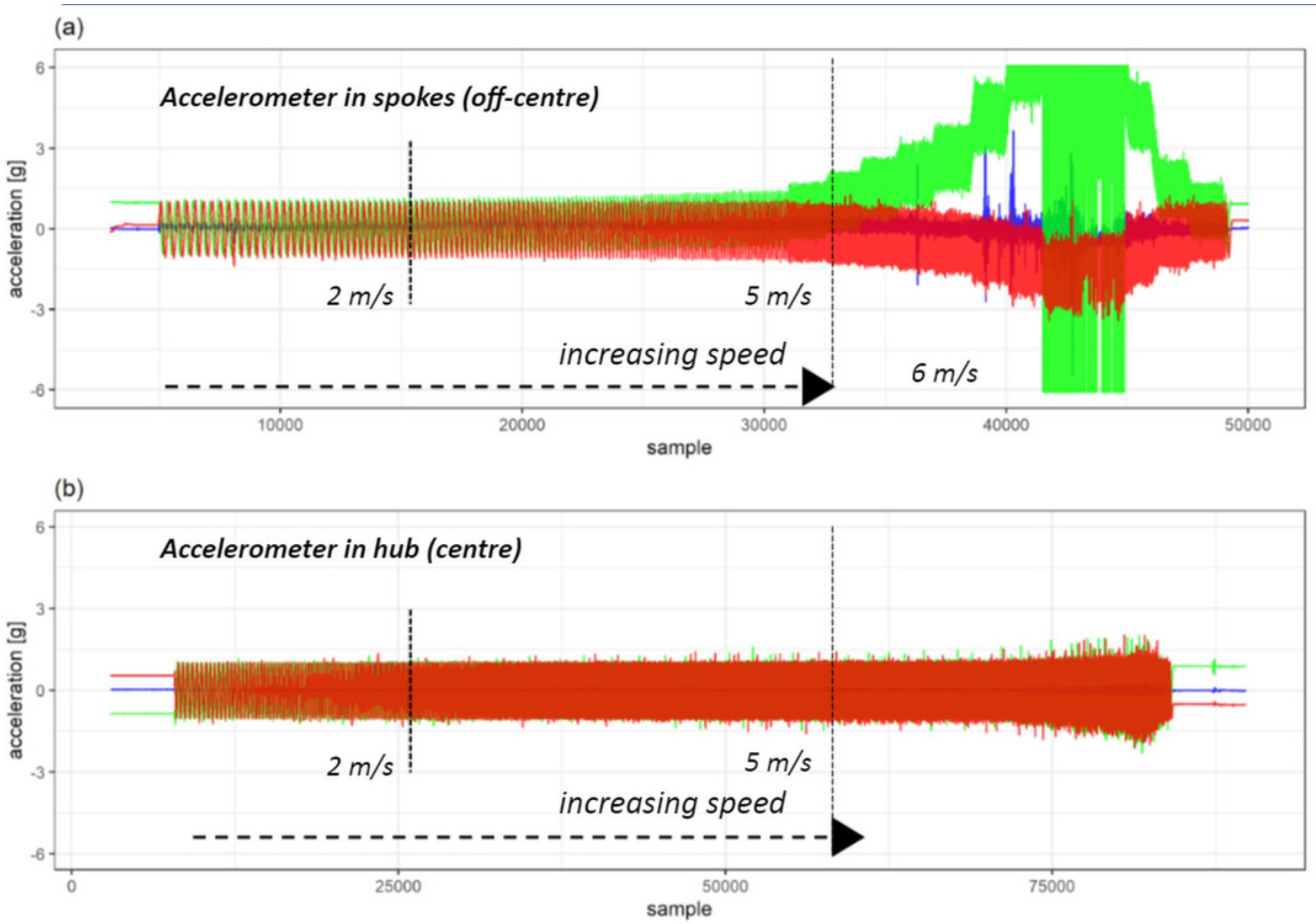
Figure 7

Influence of centrifugal force on raw accelerometry signal depending on wheel speed (from 0 in steps of 0.25 m/s) and sensor position (spoke and hub).

Red and green: axes in wheel plane, blue: axis perpendicular to wheel plane.



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