University of Verona,

School of Exercise and Sport Science,

Laurea magistrale in Scienze motorie preventive ed adattate

(Laurea magistrale in Scienze dello sport e della prestazione fisica)

Metodologia delle misure delle attività sportive

Friday 16/11/2018 10:30÷12

Luca P. Ardigò Ph.D.

A class within an eight-class module

Accelerometers

Actiwatch  -> Actical 

Actitrac 

Biotrainer 

Accelerometers

Nokia N79

Carlson Jr et al., 2012

Accelerometers

measures

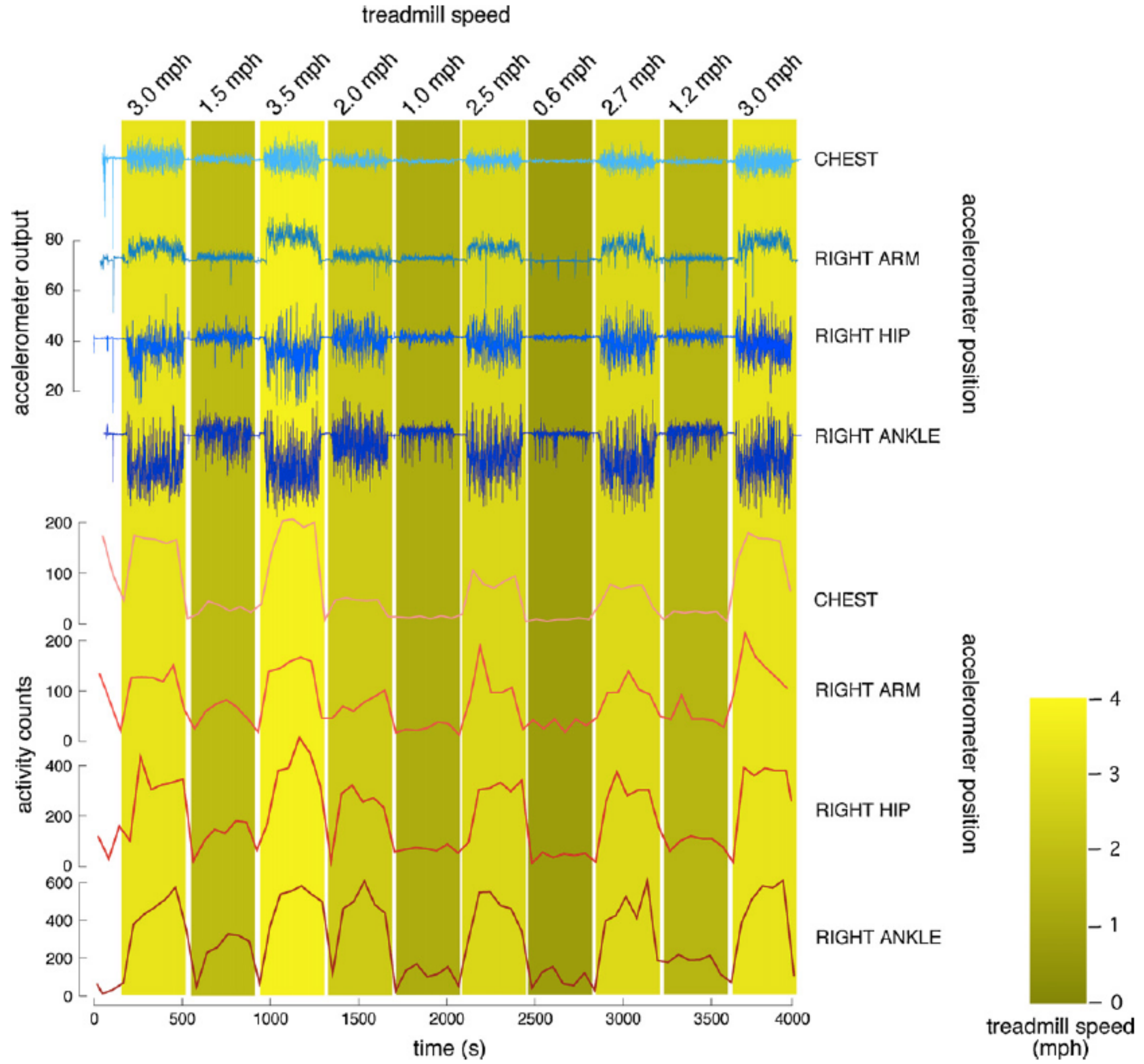


Fig. 1. Activity counts from cell-phone accelerometers provide an accurate measure of treadmill gait speed regardless of where the sensor is worn. The top four traces depict raw data from a representative trial (43 y/o man) showing acceleration magnitude *versus* time for sensors worn at the chest, right arm, right hip, and right ankle (1st through 4th traces from top, respectively). For all traces the baseline is centered at 64 (midscale between sensor output of 0 for −2 g, and 128 for +2 g), the amount of deflection from this baseline is per the common scale provided left of these traces. The bottom four traces show activity counts *versus* time for the sensors worn at the chest, right arm, right hip, and right ankle, respectively. Counts were calculated over 1 min nonoverlapping bins. Treadmill speed is given at the top of each epoch bar.

Accelerometers

measures

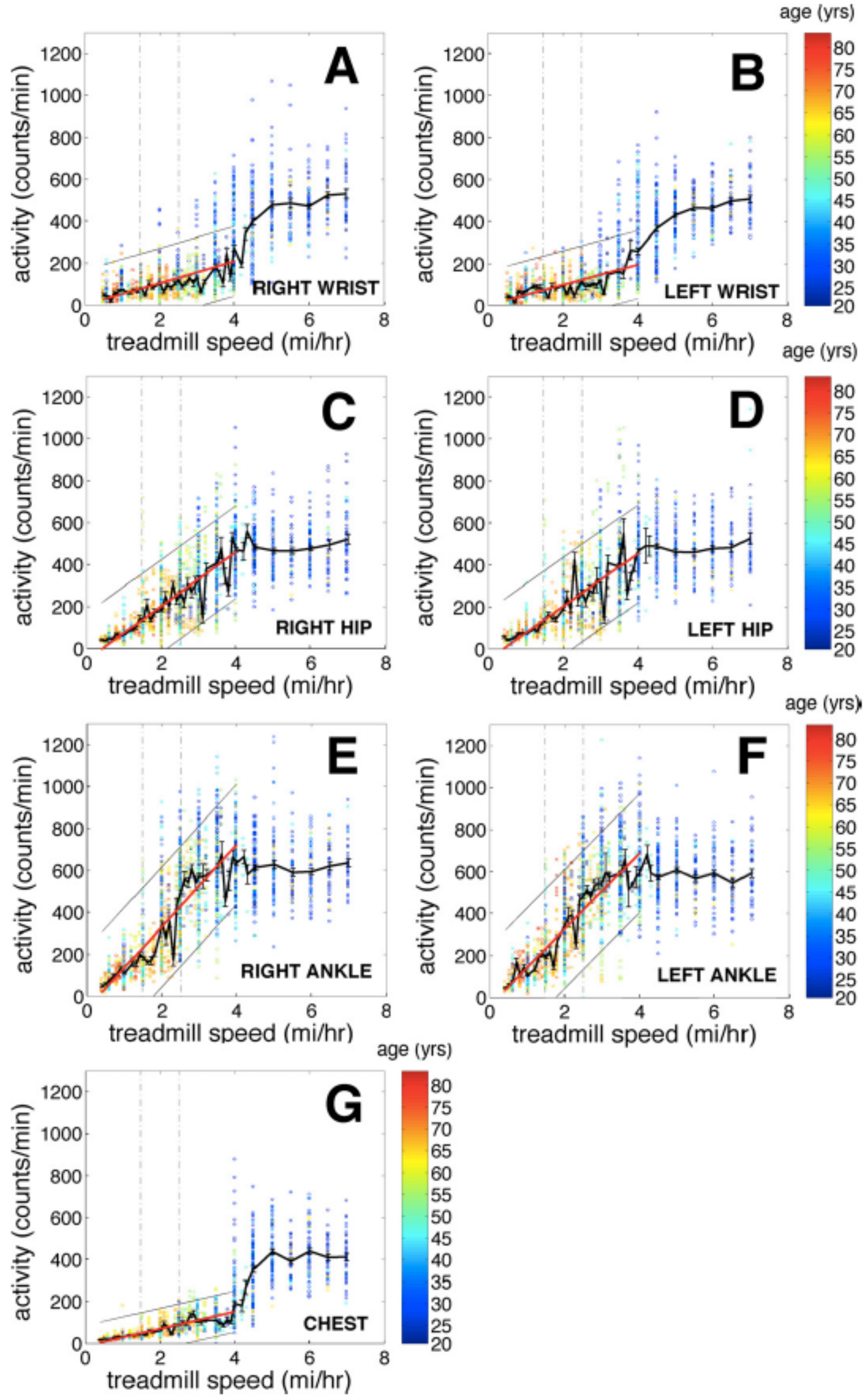


Fig. 3. Activity count versus treadmill speed relationships for all sensor locations. For all figures, the solid red line shows the linear regression between treadmill speed and activity counts (fit for all data between 0.0 and 6.4 km/h (0–4 mi/h) gait speeds); the thin surrounding black lines are 95% confidence boundaries on this regression. The thick black line connects mean activity count values for each of the evaluated treadmill speeds; bars surrounding this point are ± 1 standard error of the mean. Individual observations of activity counts are shown as open colored circles. Subject age is color coded as circle color; refer to colorbar at right side for key. The dashed lines at gait speeds of 2.35 km/h (1.46 mi/h) and 4 km/h (2.5 mi/h) highlight system performance at two critical functional thresholds. These relationships come from cell phones placed at the right wrist (A), left wrist (B), right hip (C), left hip (D), right ankle (E), left ankle (F), and neck (G).

Accelerometers

Apple iPod Touch
(iPhone)

Ellis et al., 2015

Accelerometers

measures

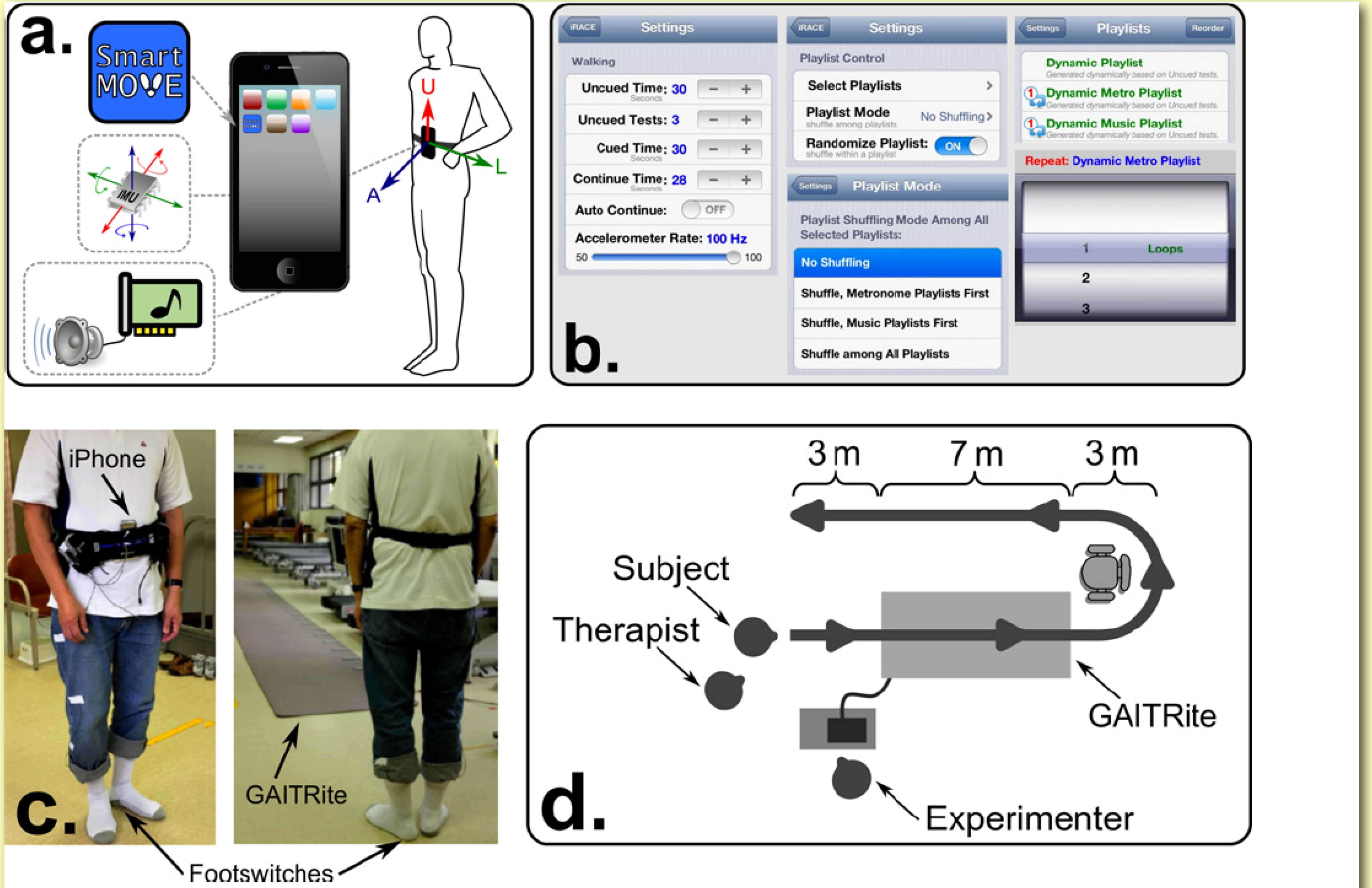


Fig 1. Key experimental features. The SmartMOVE mobile app (a.) utilizes the smartphone's inertial measurement unit to record gait movements during walking. Flexible parameter settings (b.) enable precise control over testing parameters. SmartMOVE outcome measures were validated against heel-mounted footswitches and a GAITRite sensor walkway (c.) while subjects walked along a prescribed path (d.).

Accelerometers

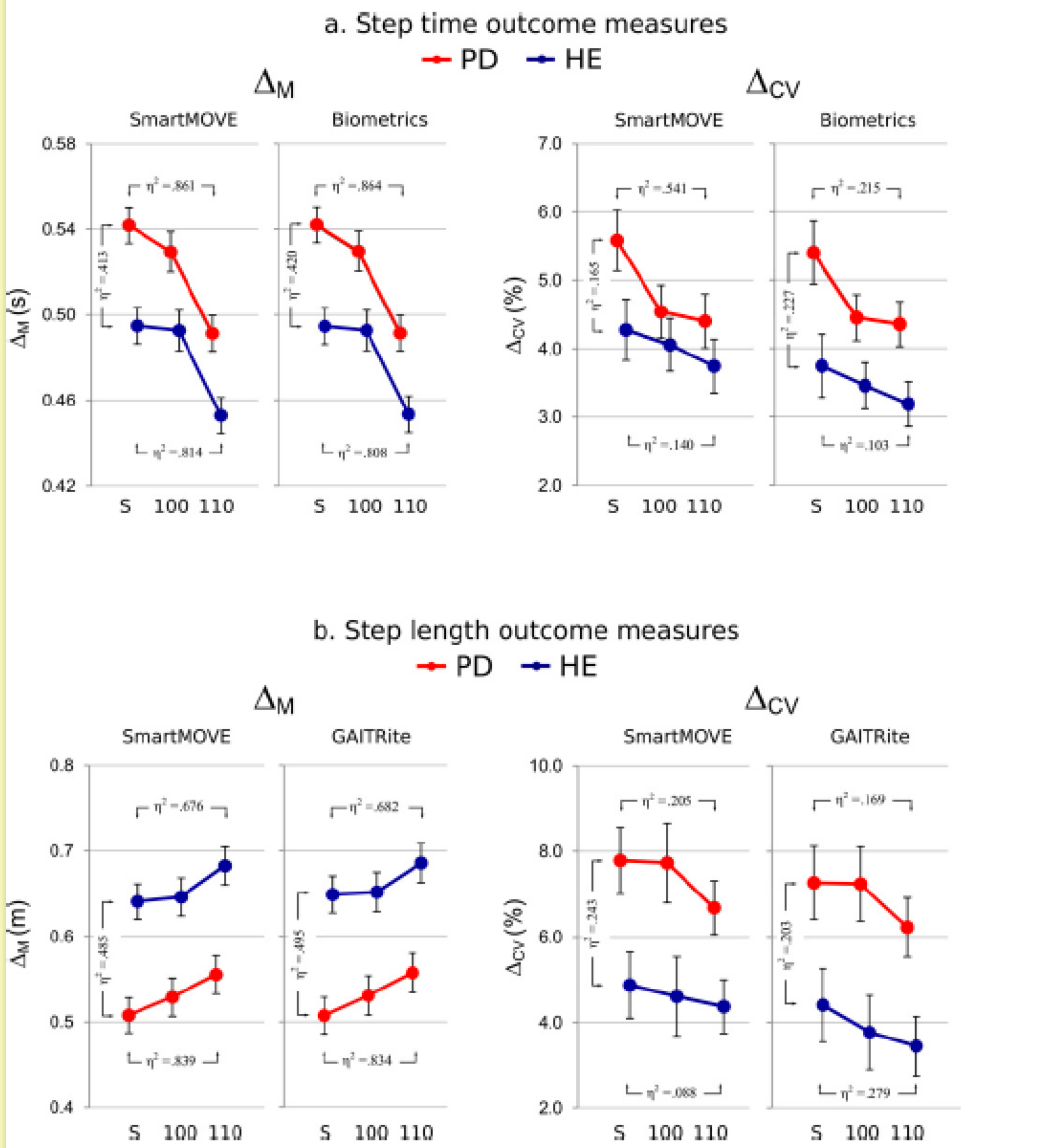


Fig 2. Outcome measure results. Results of the *Group* (separate lines: PD vs. HE) × *Condition* (x-axis: self-paced, 100% RAC, 110% RAC) × *Device* (separate panels: SmartMOVE vs. heel contact–based) ANOVAs for step time (a.) and step length (b.) outcome measures.

doi:10.1371/journal.pone.0141694.g002

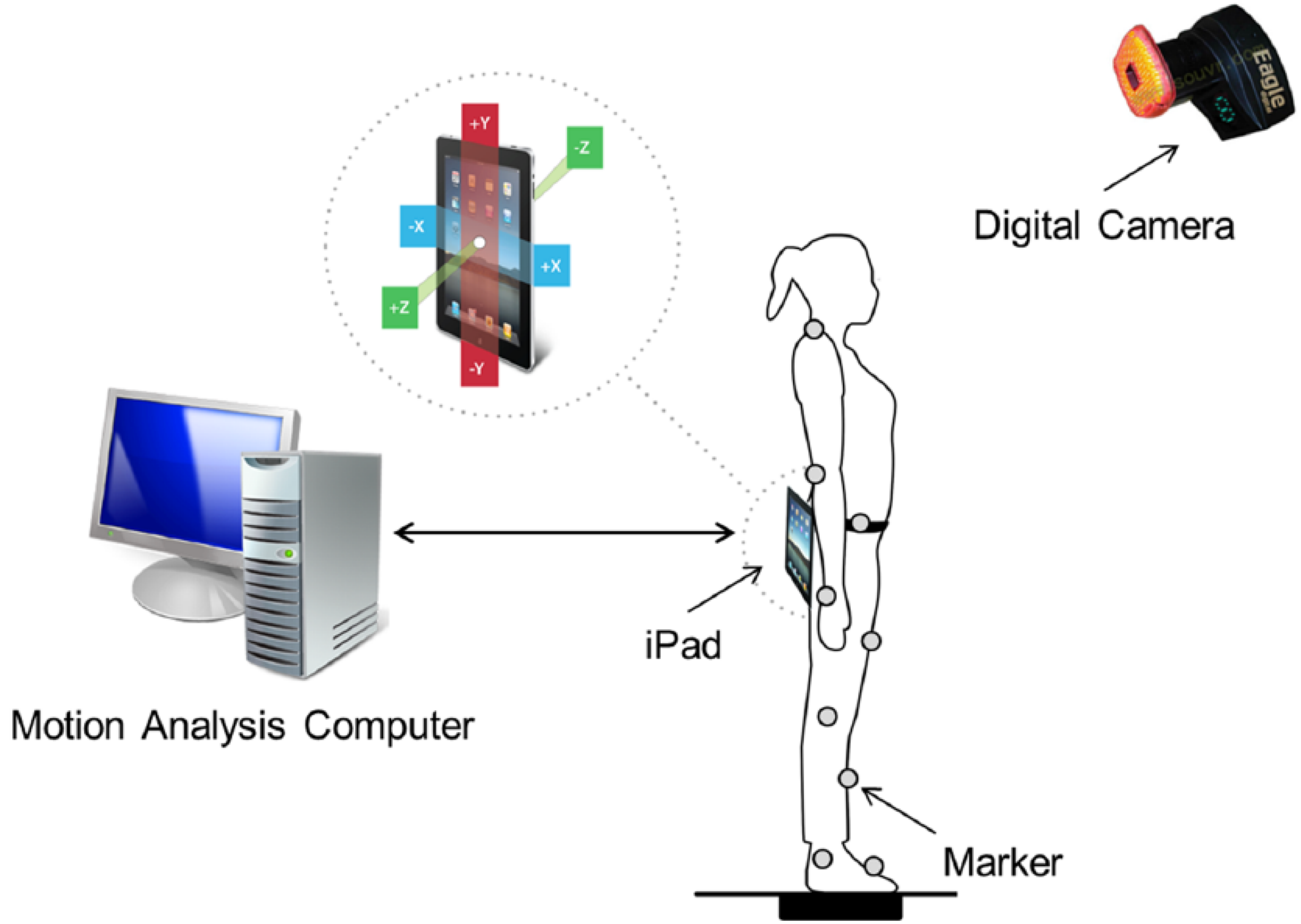
Accelerometers

iPad (third generation)

Ozinga et al., 2014

Accelerometers

Fig. 1 Illustration of experimental paradigm and measurement setup



Accelerometers

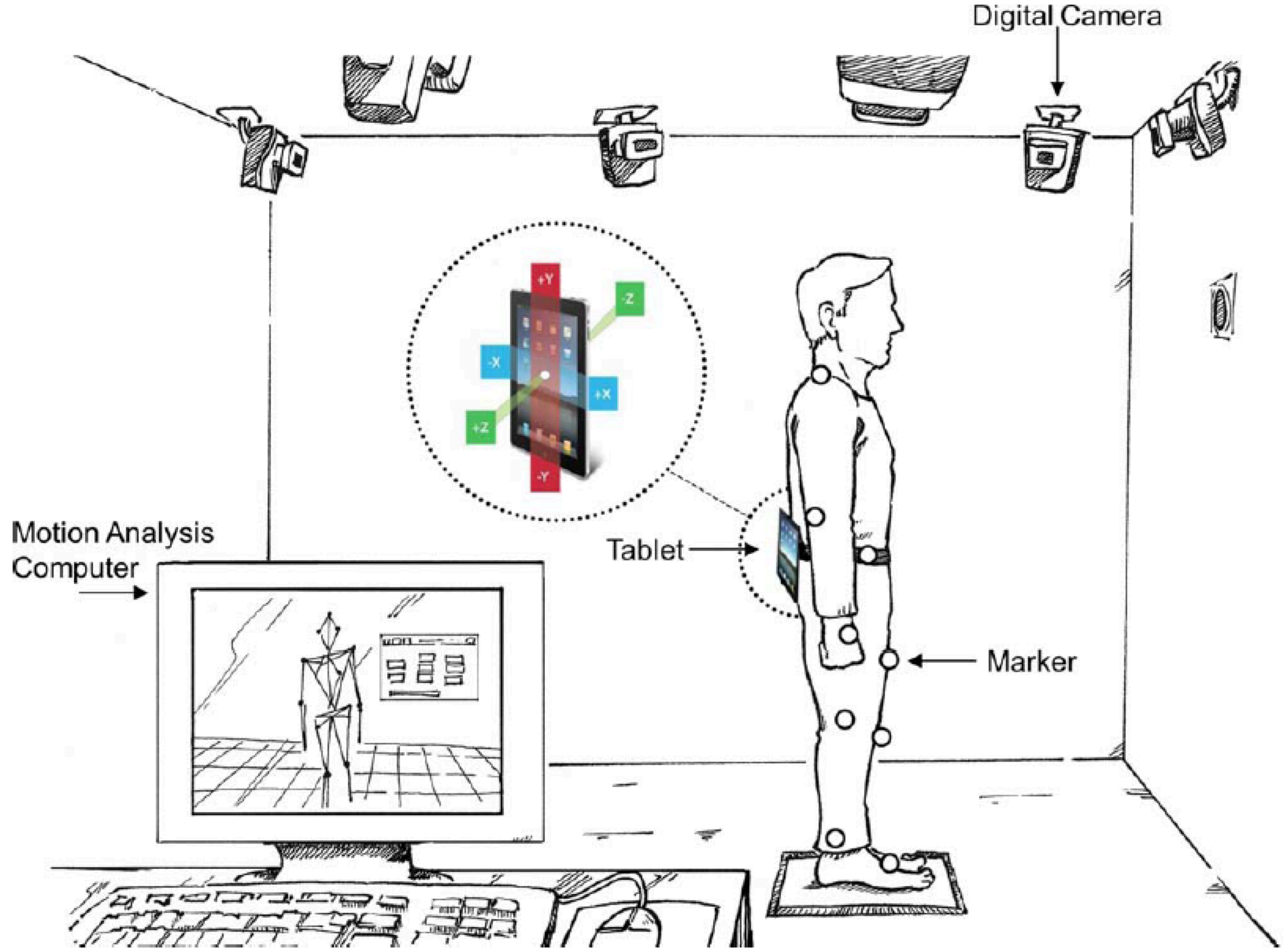


FIG. 1. Illustration of experimental paradigm and measurement setup. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Ozinga et al., 2015

Accelerometers

Samsung Galaxy II

Zhang et al., 2014

Accelerometers

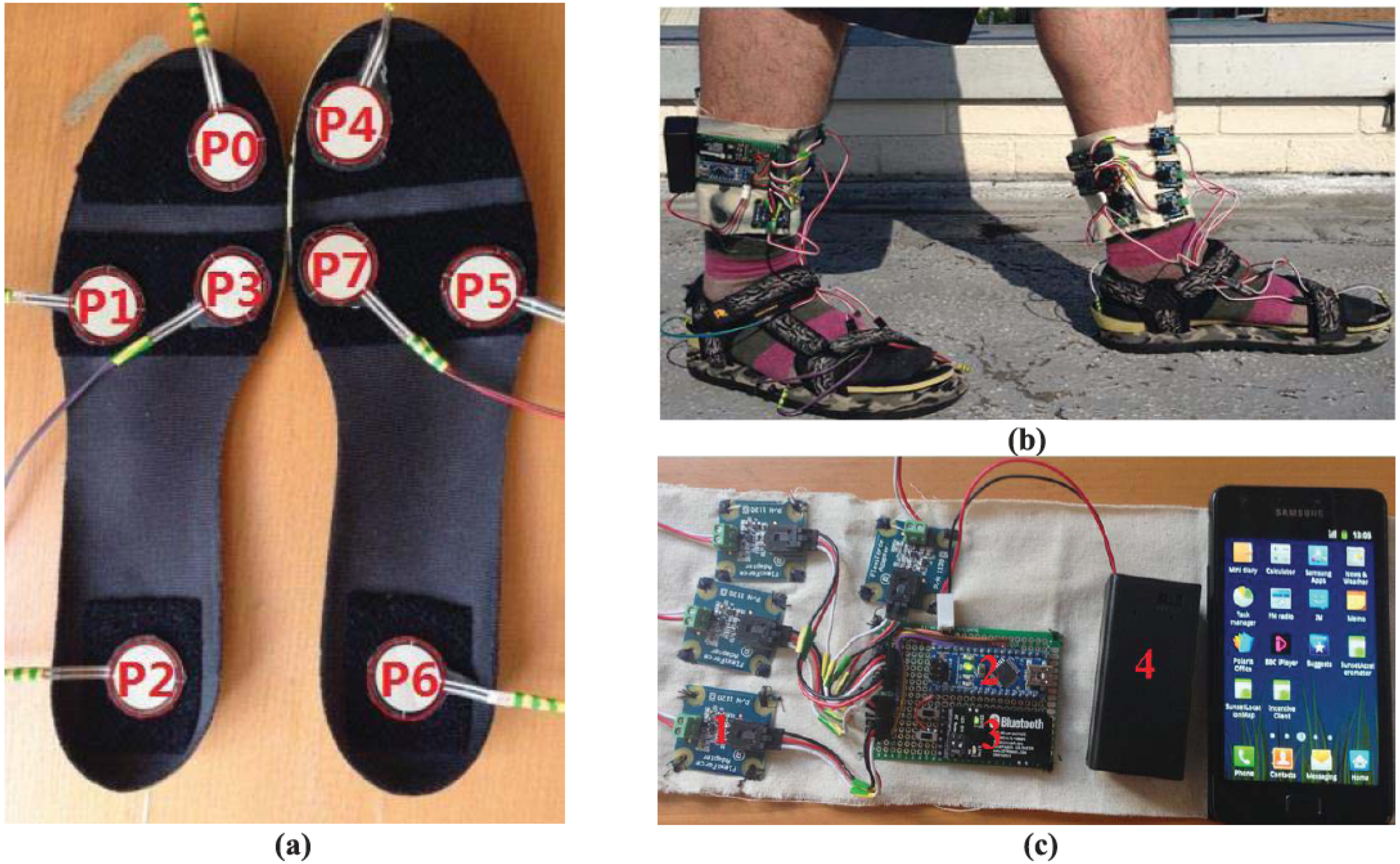


Fig. 2. Experiment equipment: (a) experimental insoles with 8 Flexiforce sensors instrumented; (b) the scene of foot force measurements; and (c) the foot force sensing system and a Samsung galaxy II smart phone.

Accelerometers

measures

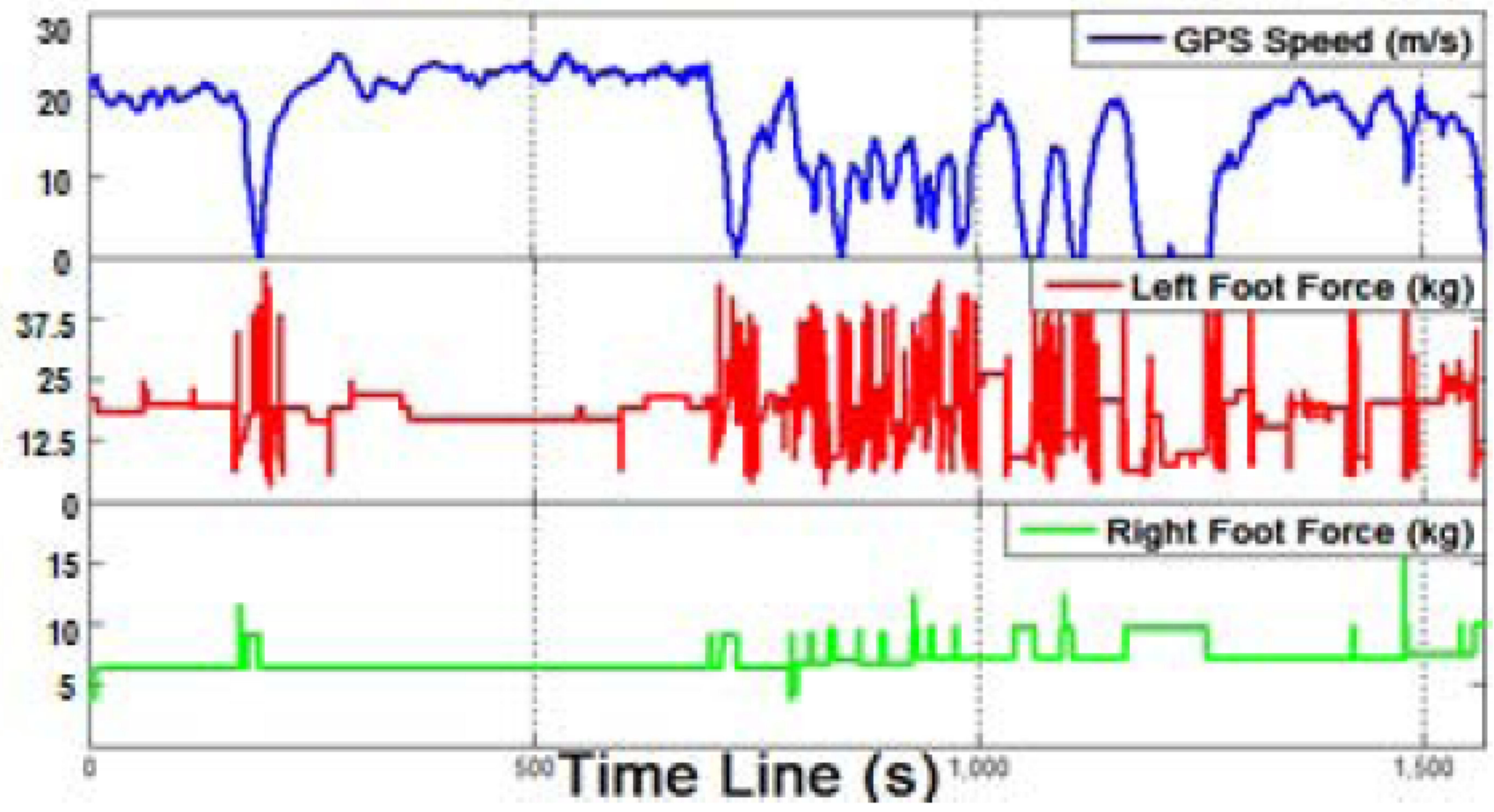


Fig. 8. GPS speed, foot force variations during a 30 minutes driving process.

Cameras

iPhone 4s

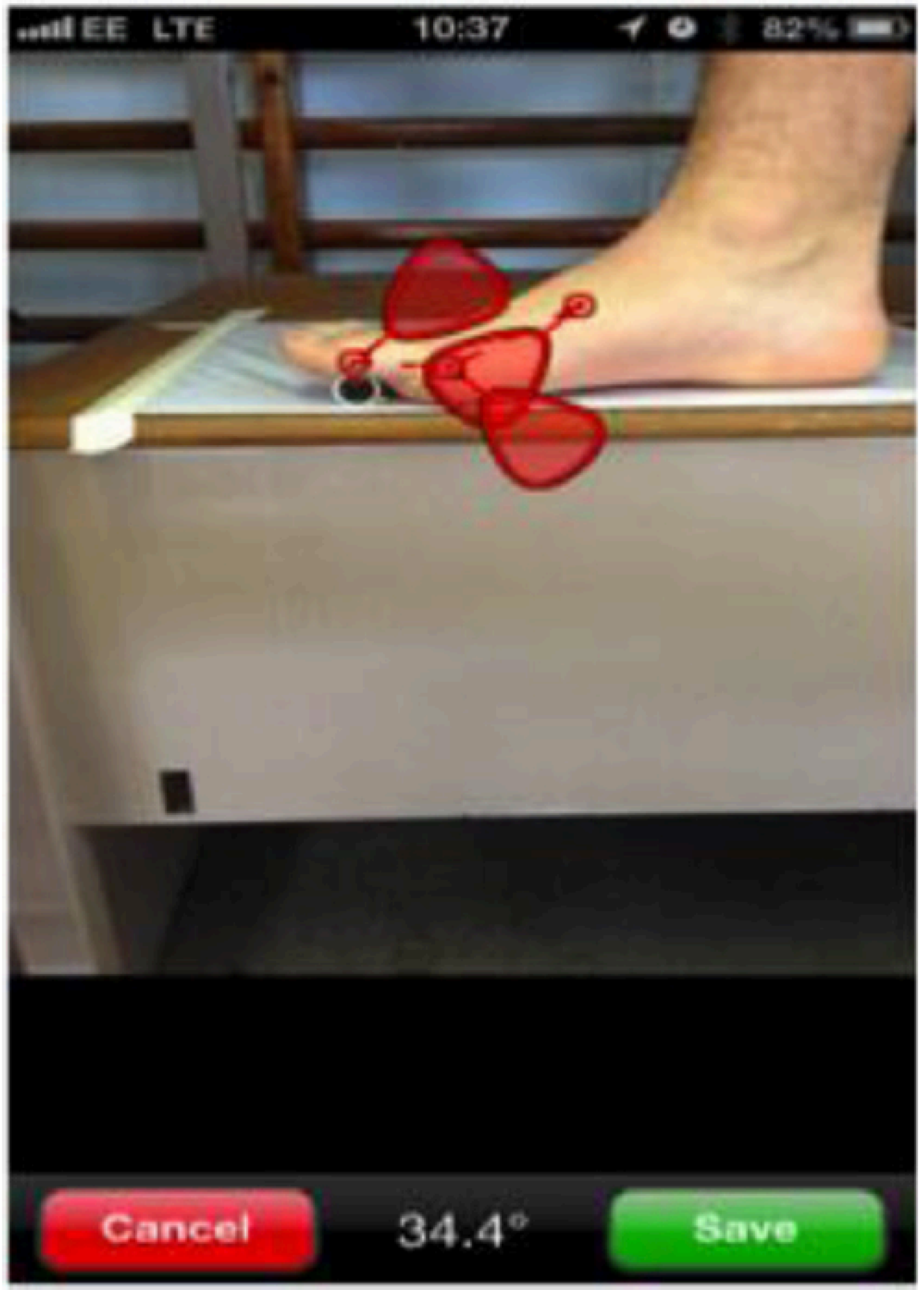


Fig. 2 Screenshot of smartphone app

Otter et al., 2015

Pedometer

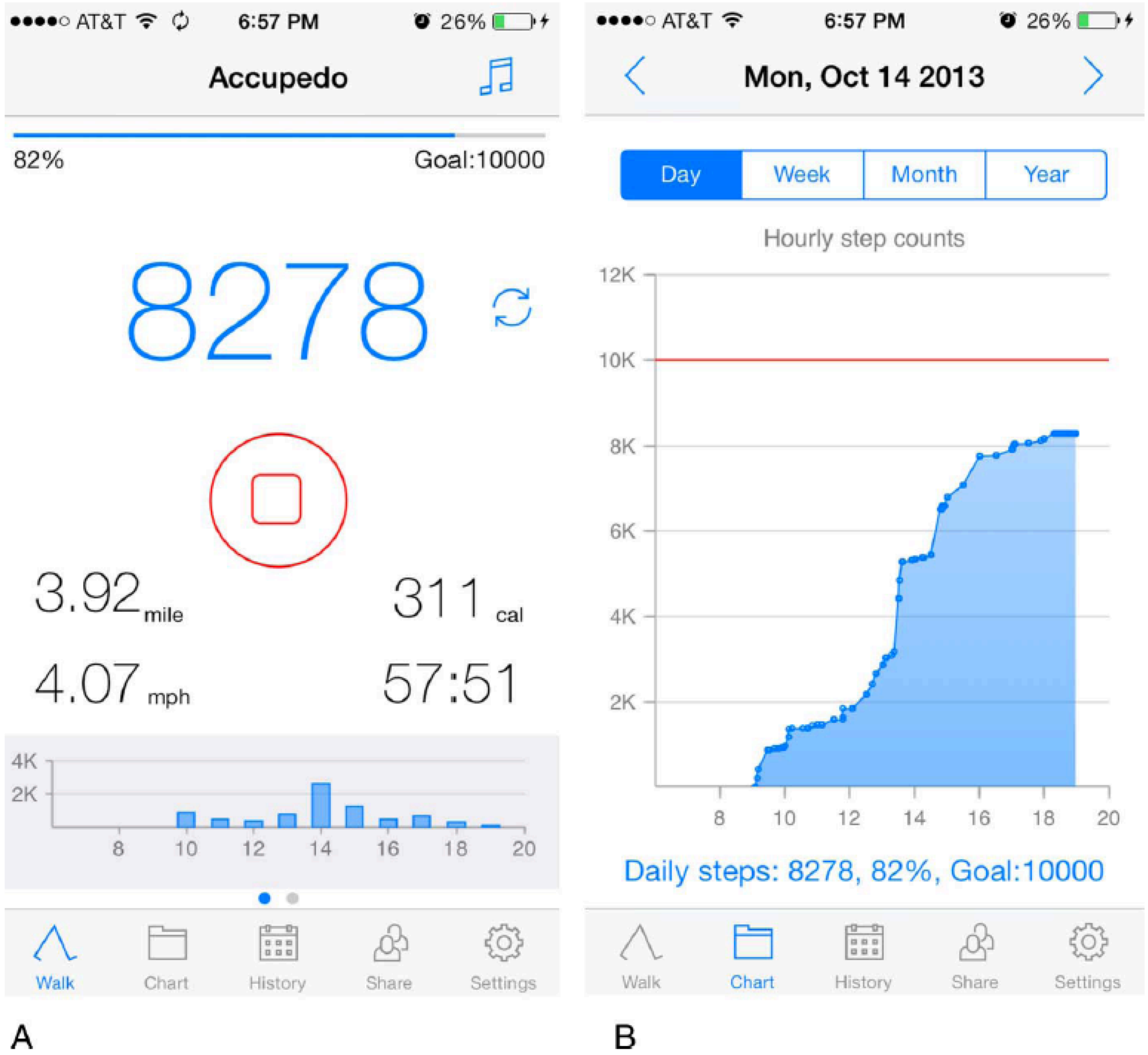


Figure 1 Screenshot of iOS Accupedo-Pro Pedometer user interface: (A) daily log history (step counts, distance, calories and walking time) and (B) charts (daily, weekly, monthly and yearly step counts).

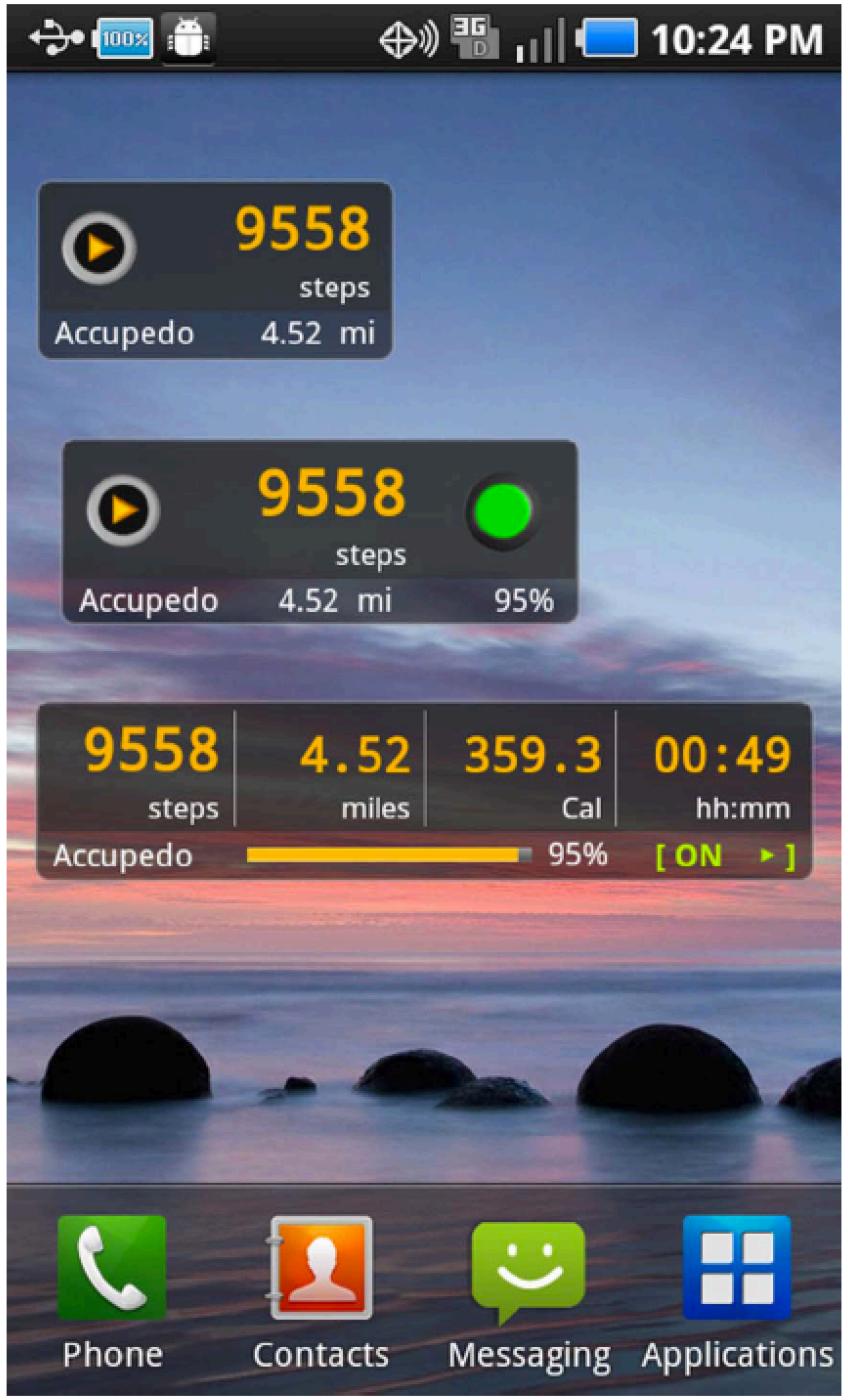


Figure 2 Screenshot of Android Accupedo-Pro Pedometer widget.

Milanović et al., 2016

Smartphone accelerometer

2018 study example 1

KINEMATIC ANALYSIS BY GENDER IN DIFFERENT JUMP TESTS BASED ON A SMARTPHONE INERTIAL SENSOR

ANÁLISE CINEMÁTICA POR GÊNERO COM BASE NO SENSOR INERCIAL DE UM SMARTPHONE EM DIFERENTES TESTES DE SALTOS

ANÁLISIS CINEMÁTICO POR GÉNERO COM BASE EN EL SENSOR INERCIAL DE UN SMARTPHONE EN DIFERENTES PRUEBAS DE SALTO

ORIGINAL ARTICLE
ARTIGO ORIGINAL
ARTÍCULO ORIGINAL

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ABSTRACT

Introduction: Vertical jump tests can be used as estimators of muscular power, physical capacity, motor development and functional capacity. The ability to jump can be analyzed with different methods, including the use of inertial sensors. Objective: To describe and analyze kinematic characteristics using the inertial sensor integrated into the iPhone 4S® and jump contact mat variables in the squat jump (SJ) and countermovement jump (CMJ) tests, and to determine the interaction between kinetic and kinematic variables. Methods: A cross-sectional study was conducted with 27 healthy young adults. The primary outcome measures were linear acceleration, flight time, contact time, jump height and dynamometry of the knee extensors. Spearman's rho was used to investigate the correlation between variables. The Mann–Whitney U rank-sum test was used for the analysis of intergender variance. Results: The greatest difference between groups (gender) was in the dynamometry variables ($p<0.001$) and contact mat variables ($p<0.001$). Between the jump tests, the greatest difference between groups (gender) was in the CMJ test ($p<0.001$). Conclusion: The inertial sensor embedded in the smartphone demonstrated a correlation with the jump mat and the dynamometry. Finally, the higher kinetic and kinematic scores observed in the jumps performed by male participants than in those performed by female participants suggest that

Smartphone accelerometer

2018 study example 1

Table 1. Jump Kinetic and kinematic characteristic and differences of the jumps by gender (n=81).

	All Jumps (n=81)	Female Jumps (n=36)	Male Jump (n=45)	p Value
	Mean ± SD	Mean ± SD	Mean ± SD	
Dynamometry Variables				
Right dynamometry (N)	251.93 ± 53.03	213.17 ± 21.44	282.93 ± 50.35	0.000
Left dynamometry (N)	234.96 ± 45.85	204.08 ± 21.13	259.67 ± 45.41	0.000
Contact Mat Variables				
Jump Height SJ (m)	0.22 ± 0.08	0.17 ± 0.04	0.26 ± 0.07	0.000
Jump Time SJ (s)	0.42 ± 0.08	0.37 ± 0.05	0.46 ± 0.07	0.000
Jump Height CMJ (m)	0.33 ± 0.10	0.24 ± 0.04	0.40 ± 0.06	0.000
Jump Time CMJ (s)	0.51 ± 0.08	0.44 ± 0.04	0.57 ± 0.05	0.000
SJ Inertial Senor Variables				
Max Acceleration X SJ (m/s^2)	0.58 ± 0.45	0.46 ± 0.35	0.69 ± 0.49	0.037
Min Acceleration X SJ (m/s^2)	-0.55 ± 0.44	-0.37 ± 0.21	-0.69 ± 0.51	0.002
Max Acceleration Z SJ (m/s^2)	0.84 ± 0.49	0.72 ± 0.45	0.94 ± 0.51	0.011
Max Acceleration RV SJ (m/s^2)	2.20 ± 0.68	2.05 ± 0.51	2.32 ± 0.78	0.005
CMJ Inertial Senor Variables				
Max Acceleration X CMJ (m/s^2)	0.82 ± 0.54	0.52 ± 0.28	1.06 ± 0.58	0.000
Min Acceleration Y CMJ (m/s^2)	-2.04 ± 0.64	-1.77 ± 0.46	-2.25 ± 0.70	0.001
Max Acceleration Z CMJ (m/s^2)	1.05 ± 0.55	0.79 ± 0.48	1.25 ± 0.52	0.000
Max Acceleration RV CMJ (m/s^2)	2.47 ± 0.63	2.17 ± 0.48	2.71 ± 0.64	0.000

SD, Standard deviation; Max, maximum; Min, minimum; RV, resultant vector; X, x axis; Y, y axis; Z, z; CMJ, Countermovement Jump Test; SJ, Squat Jump Test; s, second; m, meters; N, Newton.

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2018 study example 1

Table 2. SJ best correlations indexes.

Jump Height SJ – Right dynamometry	ρ 0.312 (p=0.005)
Jump Height SJ – Left dynamometry	ρ 0.292 (p=0.008)
Jump Height SJ – Max Acceleration ML SJ	ρ 0.301 (p=0.006)
Jump Height SJ – Min Acceleration ML SJ	ρ -0.257 (p=0.020)
Jump Time SJ – Right dynamometry	ρ 0.337 (p=0.002)
Jump Time SJ – Left dynamometry	ρ 0.309 (p=0.005)
Jump Time SJ – Max Acceleration ML SJ	ρ 0.285 (p=0.010)
Jump Time SJ – Min Acceleration ML SJ	ρ -0.234 (p=0.035)

Max, maximum; Min, minimum; X, x axis; SJ, Squat Jump Test.

Smartphone accelerometer

Table 3. CMJ best correlation indexes.

Jump Height CMJ – Right dynamometry	ρ 0.409 (p=0.000)
Jump Height CMJ – Left dynamometry	ρ 0.392 (p=0.000)
Jump Height CMJ – Max Acceleration ML CMJ	ρ 0.579 (p=0.000)
Jump Height CMJ – Min Acceleration VT CMJ	ρ -0.338 (p=0.002)
Jump Height CMJ – Max Acceleration AP CMJ	ρ 0.497 (p=0.000)
Jump Height CMJ – Min Acceleration AP CMJ	ρ -0.300 (p=0.007)
Jump Height CMJ – Max Acceleration RV CMJ	ρ 0.498 (p=0.000)
Jump Time CMJ – Right dynamometry	ρ 0.436 (p=0.000)
Jump Time CMJ – Left dynamometry	ρ 0.417 (p=0.000)
Jump Time CMJ – Max Acceleration ML CMJ	ρ 0.561 (p=0.000)
Jump Time CMJ – Min Acceleration VT CMJ	ρ -0.328 (p=0.003)
Jump Time CMJ – Max Acceleration AP CMJ	ρ 0.487 (p=0.000)
Jump Time CMJ – Max Acceleration RV CMJ	ρ 0.483 (p=0.000)

Max, maximum; Min, minimum; RV, resultant vector; X, x axis; Y, y axis; Z, z axis; CMJ, Countermovement Jump Test.

Smartphone camera

2018 study example 2


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ORIGINAL ARTICLE
EXERCISE PHYSIOLOGY AND BIOMECHANICS

Validation of the iPhone app using the force platform to estimate vertical jump height

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Smartphone camera

2018 study example 2

TABLE I.—*Descriptive and reliability statistics for all methods to calculate CMJ height.*

	Mean±SD	Range	ICC (95% CI)	α	CV (cm)
TIA, cm	28.674±7.213	31.44	0.985	0.985	0.062
Jump 1	27.645±7.324	30.0			
Jump 2	28.838±7.731	32.6			
Jump 3	29.054±7.454	31.7			
Jump 4	28.908±7.621	32.6			
Jump 5	28.845±7.155	33.4			
TOV, cm	28.379±6.846	29.44	0.978	0.978	0.063
Jump 1	27.268±6.578	28.7			
Jump 2	28.979±7.697	30.1			
Jump 3	28.590±7.248	31.1			
Jump 4	28.456±7.256	30.6			
Jump 5	28.555±7.075	32.4			
APP, cm	28.602±7.215	31.52	0.983	0.983	0.062
Jump 1	27.553±7.321	30.3			
Jump 2	28.575±7.730	33.1			
Jump 3	29.018±7.344	31.7			
Jump 4	28.077±7.694	32.6			
Jump 5	28.787±7.150	33.5			

CMJ: countermovement jump SD: standard deviation; ICC: intraclass correlation coefficient; α: Cronbach's alpha reliability coefficients; CV: coefficients of variation; TIA: time in the air method from force platform; TOV: velocity at take-off method from force platform; APP: My Jump application method.

Smartphone camera

2018 study example 2

TABLE II.—*Intraclass-correlation between APP-TIA and APP-TOV.*

	ICC	95% CI	α
APP-TIA	1.000	1.000-1.000	1.000
APP-TOV	0.996	0.993-0.998	0.996

ICC: intraclass correlation coefficient; IC: confidence interval α: Cronbach's alpha reliability coefficients; TIA: time in the air method from force platform; TOV: velocity at take-off method from force platform; APP: My Jump application method.

Smartphone camera

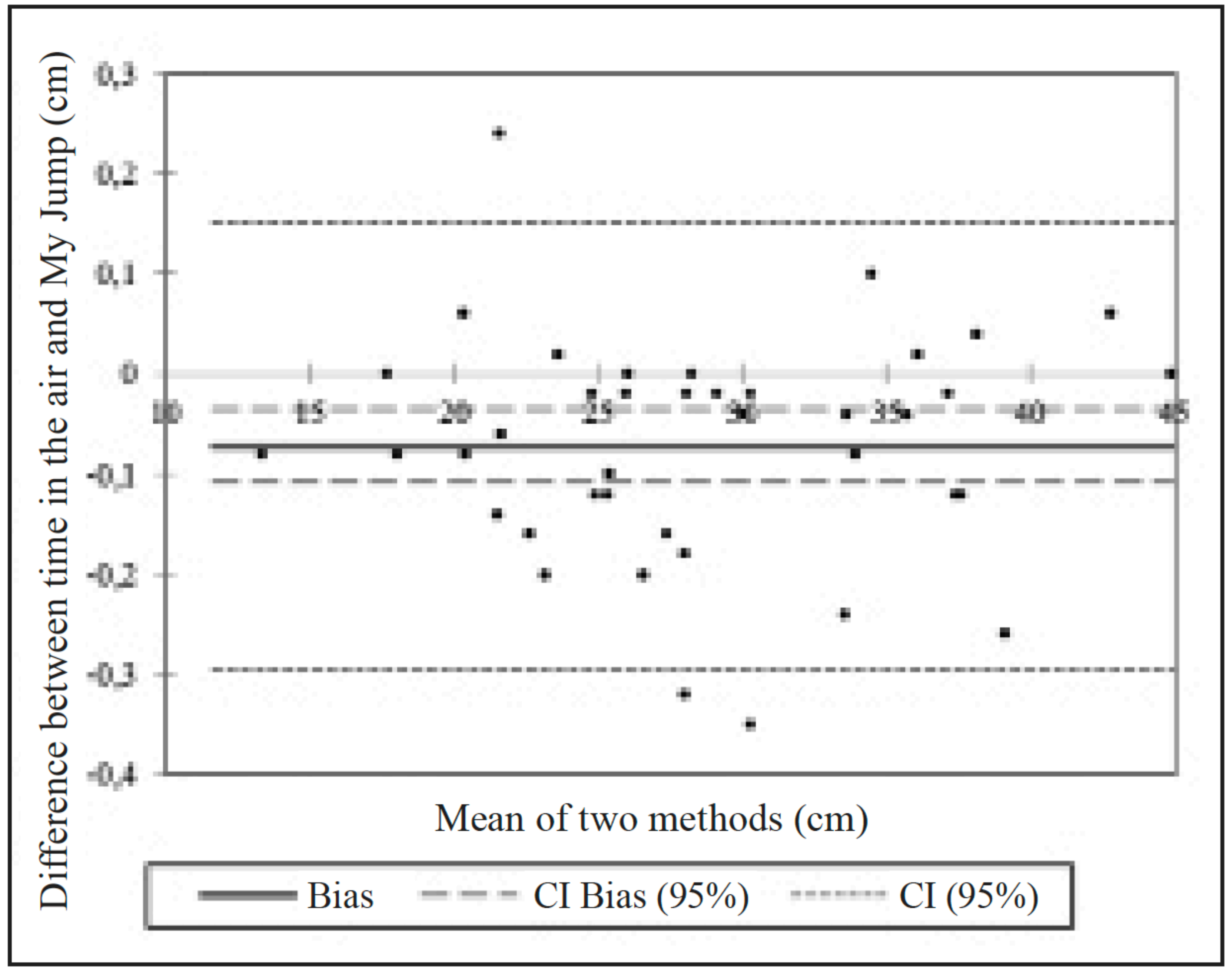

Figure 1.—Bland-Altman plots for TIA from force platform and My Jump height data. The central line represents the absolute average difference between instruments, while the upper and the lower lines represent standard deviation.

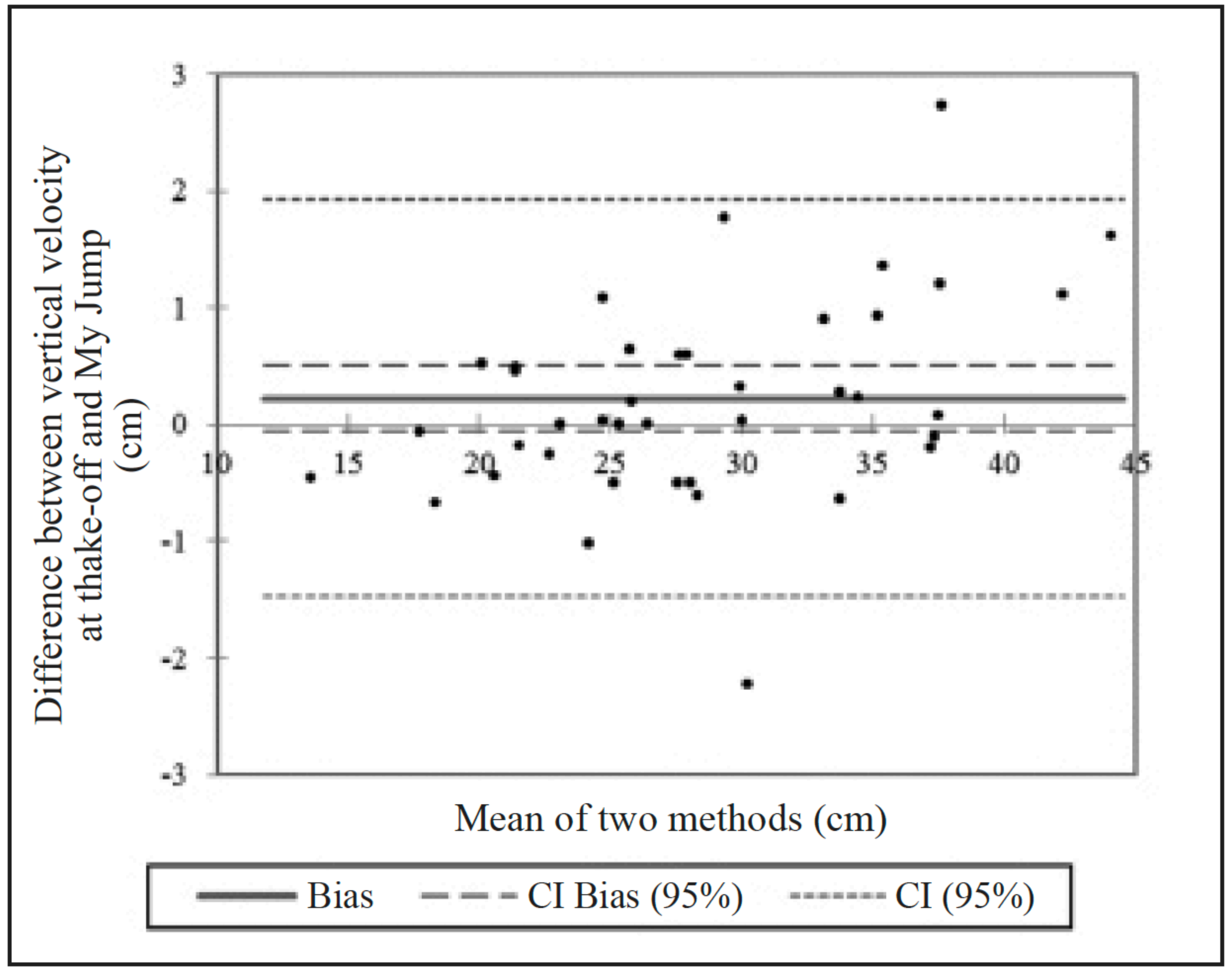

Figure 2.—Bland-Altman plots for TOV from force platform and My Jump height data. The central line represents the absolute average difference between instruments, while the upper and the lower lines represent standard deviation.

Smartphone inclinometer

2018 study example 3

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https://doi.org/10.1080/02640414.2018.1494908

Routledge
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Concurrent validity and reliability of an iPhone app for the measurement of ankle dorsiflexion and inter-limb asymmetries iPhone

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Smartphone inclinometer

2018 study example 3

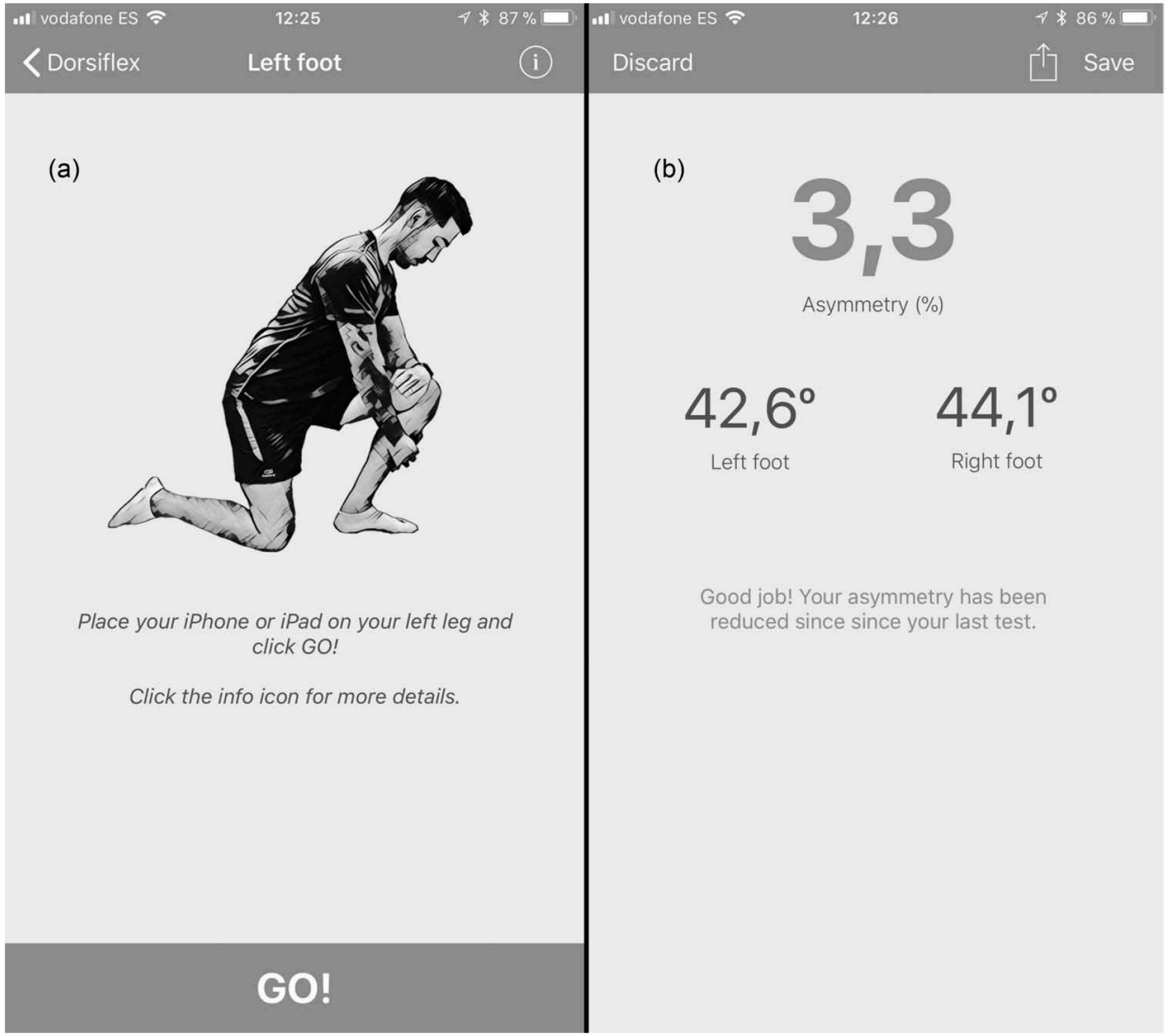

Figure 1. User interface of the app analyzed in the study. A) Instructions to proceed with the weight-bearing lunge test and B) results screen showing instant feedback about ankle dorsiflexion and inter-limb asymmetry.

Smartphone inclinometer

2018 study example 3

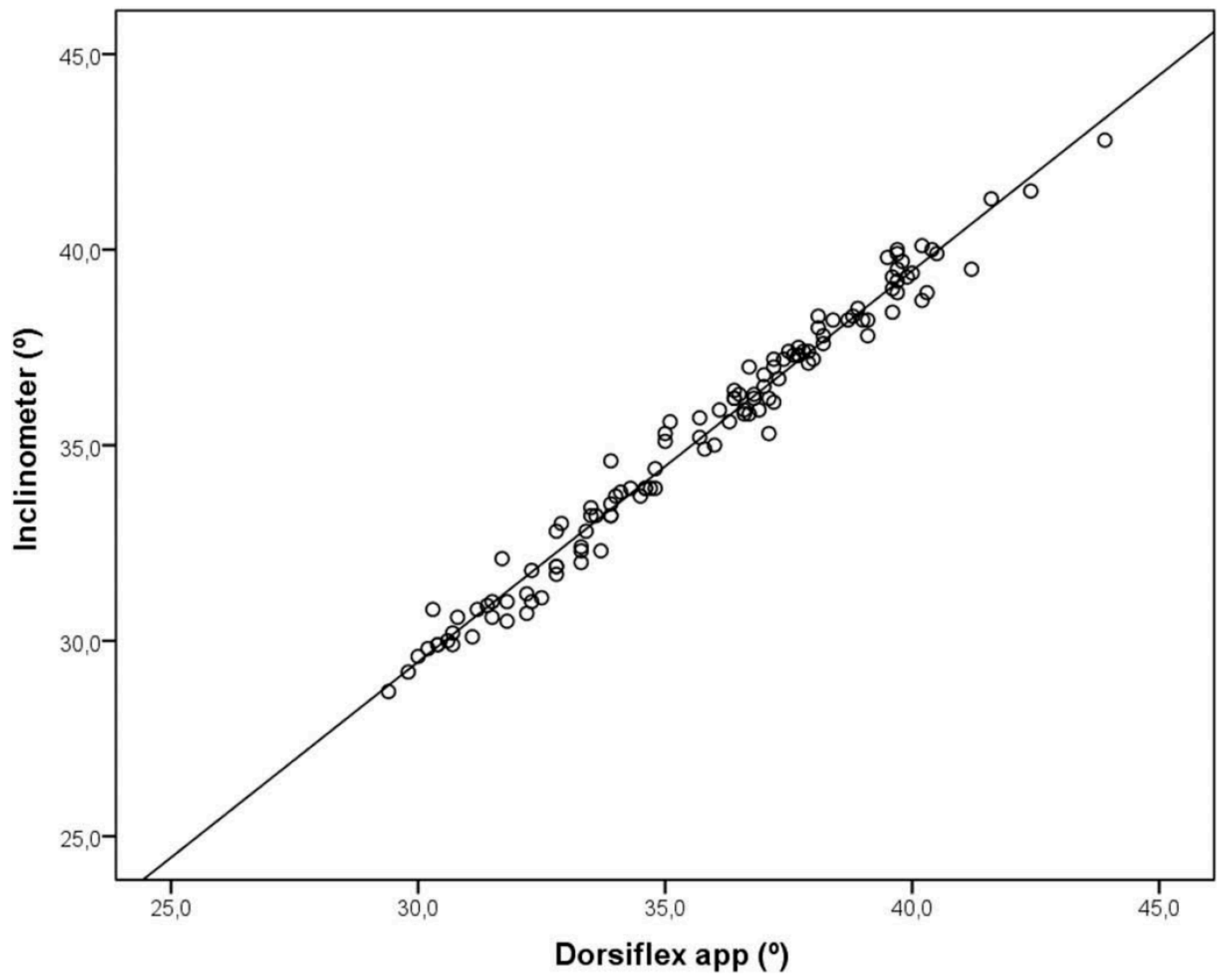

Figure 2. Correlation plot with regression line between the dorsiflexion angles obtained with the Dorsiflex app and the digital inclinometer.

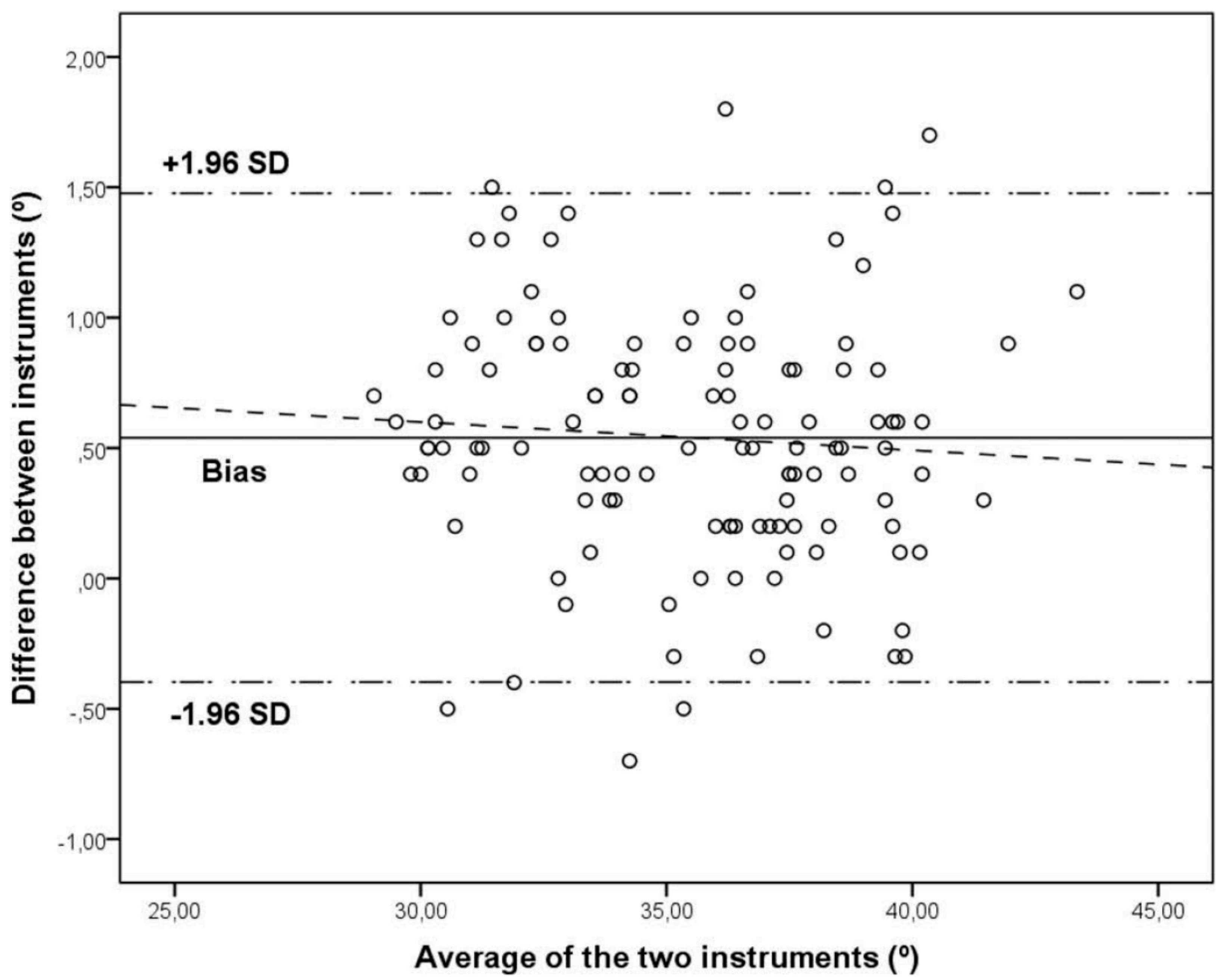

Figure 3. Bland-Altman plot showing the bias (± 1.96 SD) between instruments and the regression line of the residuals (dashed line).

Smartphone inclinometer

2018 study example 4

IOP Publishing Physiol. Meas. **39** (2018) 02NT01(12pp) https://doi.org/10.1088/1361-6579/aaa3c2

Physiological Measurement

IPEM Institute of Physics and Engineering in Medicine

CrossMark

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NOTE

Validity and reliability of smartphone orientation measurement to quantify dynamic balance function

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Keywords: smartphone sensors, measurement, gait, variability, reliability, validity, intraclass correlation

Supplementary material for this article is available online

Smartphone inclinometer

2018 study example 4

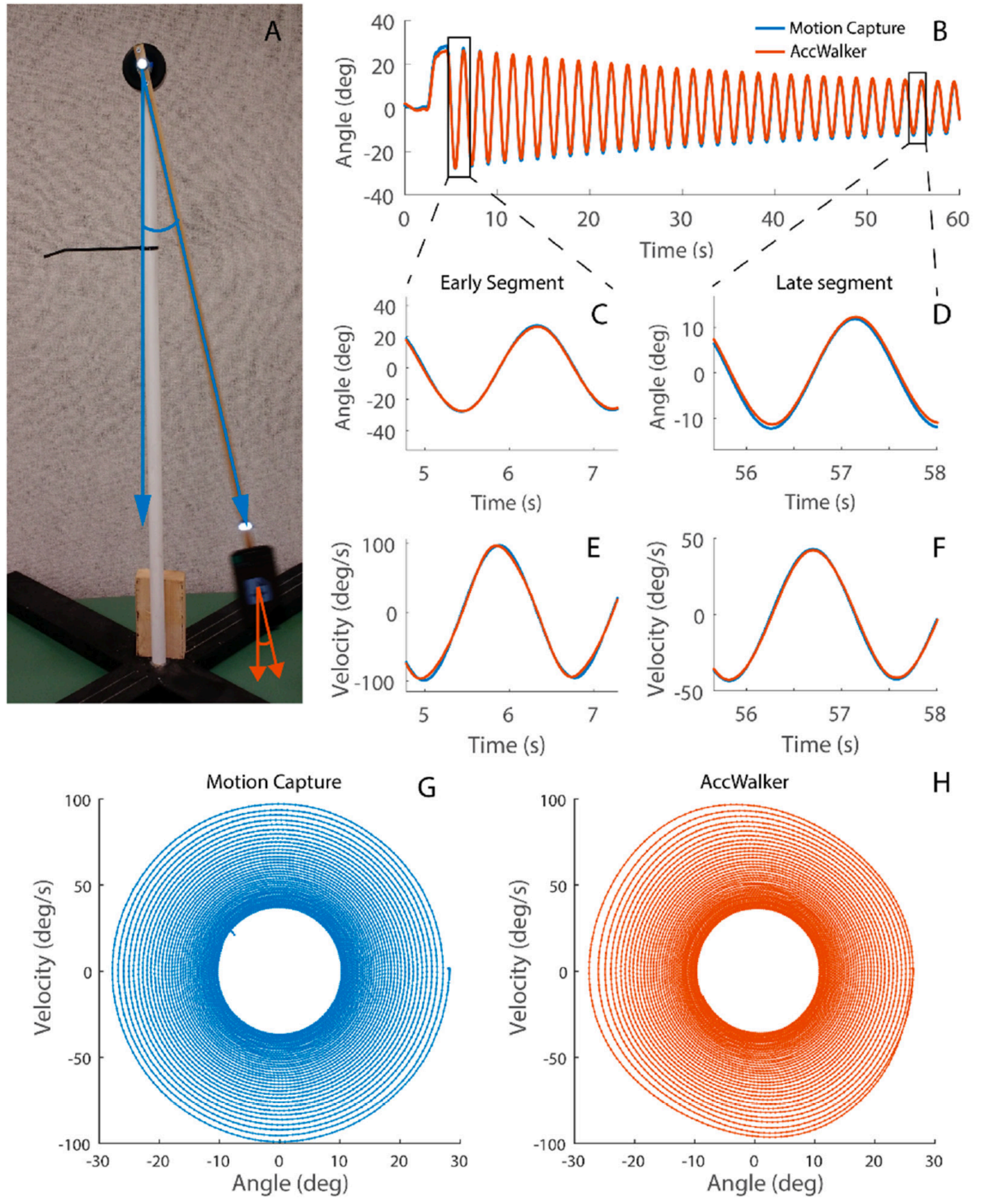

Figure 1. Testing of the AccWalker to detect pendulum angle in comparison to Qualisys motion capture system.

Smartphone inclinometer

2018 study example 4

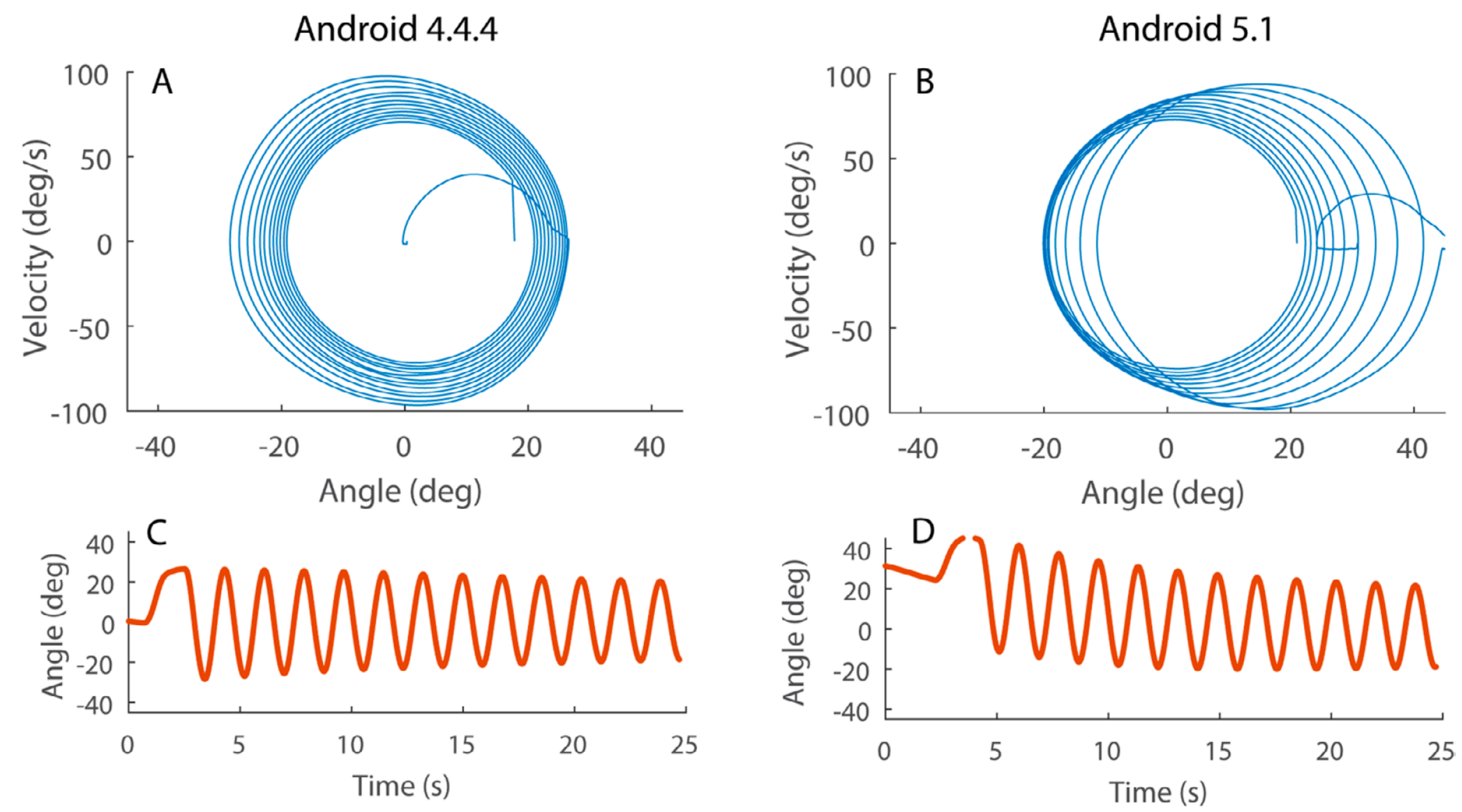

Figure 2. Performance of the AccWalker when running on Android OS 4.4.4 versus Android 5.1. Panels (C) and (D) show the time series of the pendulum angle measured by the same phone while running these two different operating systems. Drift is clearly evident in the angle measurement provided by Android 5.1. Corresponding position-velocity phase spaces are shown in Panels (A) and (B)—an ideal pendulum oscillation measurement should show circular trajectories.

Smartphone inclinometer

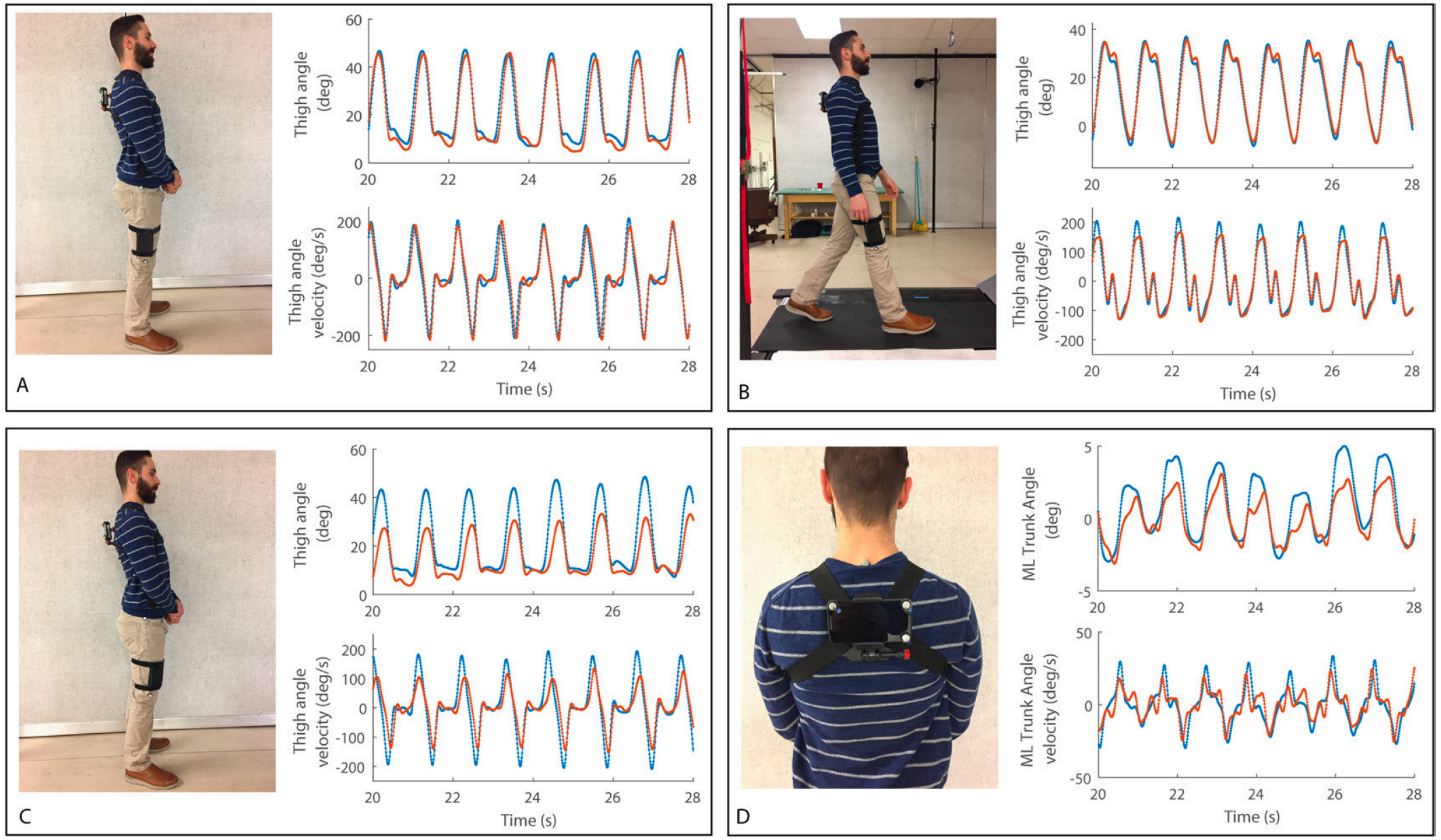

Figure 3. Examples of thigh angle and velocity time series recorded from AccWalker (orange lines) and motion capture (blue lines). Panels (A) and (B) depict the conditions with proper phone placement of the phone on the thigh during the stepping-in-place task and treadmill walking, respectively. Panel (C) indicates an anterior shift in the phone's placement on the thigh and the corresponding thigh angle and velocity time series during stepping in place to the right of the panel. Panel (D) shows the phone placed on the trunk and the corresponding ML angle and velocity time series during stepping-in-place.