Inertial Sensor-Based Stride Parameter Calculation From Gait Sequences in Geriatric Patients

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***Abstract*—A detailed and quantitative gait analysis can provide evidence of various gait impairments in elderly people. To provide an objective decision-making basis for gait analysis, simple applicable tests analyzing a high number of strides are required. A mobile gait analysis system, which is mounted on shoes, can fulfill these requirements. This paper presents a method for computing clinically relevant temporal and spatial gait parameters. Therefore, an accelerometer and a gyroscope were positioned laterally below each ankle joint. Temporal gait events were detected by searching for characteristic features in the signals. To calculate *stride length*, the gravity compensated accelerometer signal was double integrated, and sensor drift was modeled using a piece-wise defined linear function. The presented method was validated using GAITRite-based gait parameters from 101 patients (average age 82.1 years). Subjects performed a normal walking test with and without a wheeled walker. The parameters *stride length* and *stride time* showed a correlation of 0.93 and 0.95 between both systems. The absolute error of *stride length* was 6.26 cm on normal walking test. The developed system as well as the GAITRite showed an increased *stride length,* when using a four-wheeled walker as walking aid. However, the walking aid interfered with the automated analysis of the GAITRite system, but not with the inertial sensor-based approach. In summary, an algorithm for the calculation of clinically relevant gait parameters derived from inertial sensors is applicable in the diagnostic workup and also during long-term monitoring approaches in the elderly population.**

***Index Terms*—Accelerometers, gait alterations, gait analysis, gyroscopes, stride length, stride parameters.**

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I. Introduction

GAIT analysis is an indispensable assessment tool for a variety of movement disorders in the clinical workup (e.g., neurological [1] or musculoskeletal [2] diseases). Sensor-based objective mobility data analysis is increasingly developed to identify health risk factors, to support clinical diagnostics and monitor medical treatments, and to complement easily applicable assessment of the quality of life in the elderly [3]. Sensor-based gait analysis can also provide indicators for a beginning gait alternation in the elderly. With increasing age, people have significantly lower walking speed [4], [5] and a higher variability in *stride time* [6], [7]. Hausdorff *et al.* [5] and Verghese *et al.* [8] also showed that the *stride length*, the corresponding variability, as well as the *swing time* variability are key parameters for gait characteristics in elderly adults.

Specialists for movement disorders are able to identify and classify the above mentioned impairments in the everyday clinical workup. However, typical examinations require long-time experience and remain arbitrary and subjective. Several electronic measurement systems have been developed to improve assessment of temporal and spatial gait parameters in a clinical population. One example for an electronic measurement system is a camera-based stationary 3-D tracking system [7]. Here, markers have to be affixed to the body to track motion with submillimeter accuracy. Such a system is expensive and requires a complex and time-consuming preparation of the subject. The usage of these systems requires special laboratory environment and is therefore not suitable for standard clinical settings.

In contrast, computerized walkways need almost no preparation of the subjects. The GAITRite system (GAITRite; CIR Systems Inc., Havertown, PA, USA) consists of a carpet with embedded pressure sensors placed on 1.27-cm centers [9]. However, application of the GAITRite system in the clinical workup requires a laboratory environment for gait analysis. Also, 3-D parameters like *heel strike* (HS) and *toe-off* (TO) angles, or foot clearance during one gait cycle cannot be assessed.

Gait impairment in the elderly often requires the use of walking aids. Four-wheeled walkers (WW) are prescribed routinely during geriatric rehabilitation. Thus, it is important to analyze gait characteristics with and without the use of walking aids, in particular, to assess their clinical benefit. Due to technical difficulties of external gait assessment strategies, the automated distinction between the WW track and the spatiotemporal gait parameters is limited for external motion analysis systems.

Inertial sensors are often used for a mobile and unobtrusive gait analysis [10], [11]. Various studies report a spatiotemporal analysis of human gait using gyroscopes only [12]–[15]. From gyroscope data, the orientation of the sensor can be determined. However, accelerometers provide valuable information for spatial parameters, since a double integration of acceleration leads to distance [16], [17]. Consequently, this additional sensor data can be used to improve the quality of spatial parameters.

Yet, the double integration amplifies sensor noise, which results in a drift of the signal. To compensate drift, points in time where the foot is assumed to have no velocity were defined [18], [19]. The drift can be modeled as a function defined between these zero velocity points and can be subtracted from the signal. Most of the studies used a linear model [16], [17], [20] for drift compensation. Mariani *et al.* [21] showed that a nonlinear drift model can make *stride length* more accurate, as it takes into account that most measurement errors occur during swing phase. This shows that a sophisticated design of the drift model is promising. There were no studies so far, which adapted the drift model to the length of each individual stride.

In the literature, a wide variation of validation procedures for stride parameter calculation from inertial sensors exist. An established gold standard for gait parameter calculation is the instrumented walkway with embedded pressures sensors GAITRite [7], [8], [14], [22]. The mentioned gait parameters: *stride length*, *stride time*, *swing time,* and *stance time* can be validated by the usage of this system.

In the field of inertial sensor-based stride analysis, one major problem is the handling of altered gait that is often found in geriatric patients. The work of Greene *et al.* [23] shows, for example, that algorithms have difficulties detecting temporal gait events, like initial contact or terminal contact when shuffling gait is recorded. Presented methods were validated with young and healthy subjects [14]–[16], [21], as well as elderly healthy subjects [12]. There are a few studies like [13], [20], where patients with Parkinsons disease or subjects with joint impairments [24] were addressed. However, the number of participants here were less than 21, except [24] who included 42 participants. To investigate the performance in a real-world scenario, it is important to develop the algorithms on a greater amount of subjects with gait alternations.

The purpose of the present study was twofold. First, to built an improved method for the calculation of the parameters *stride length*, *stride time*, *swing time,* and *stance time* from a large amount of altered gait data and with an individualized drift model. The results were compared to the gold standard system GAITRite. Second, to show that the mobile gait analysis system is applicable without interference by the use of walking aids. To strengthen this importance, we compared the automatically detected difference in *stride length* by the inertial sensor-based gait analysis and by the GAITRite system with and without a WW. We believe that our validation study describing a mobile gait analysis system provides the basis for a long-term monitoring of a large cohort of patients with gait impairment during every day life.

II. Methods

A. Sensor Platform and Setup

For data collection, the inertial sensor platform Shimmer 2R [25] was used. It consists of a three-axis gyroscope (range: $\pm 500\,^{\circ}/s$) and a three-axis accelerometer (range: $\pm 6\,g$). Subjects wore shoes with a sensor placed laterally right below each ankle joint (see Fig. 1). Every subject wore the same shoe model (adidas Duramo 3) to avoid influences on gait parameters caused by different shoe models [26], [27]. Data were collected with a sampling rate of 102.4 Hz, and a resolution of 12 bits. The x-axis was defined in posterior–anterior direction, y-axis was in superior–inferior direction, and z-axis was in medio-lateral direction (see Fig. 1). No manual filtering for accelerometer and gyroscope signals, and no automatic filtering for the accelerometer signal was applied. However, the Shimmer2R sensor units use an integrated low-pass filter with a cutoff frequency of 140 Hz for the gyroscope signals. The established analysis system GAITRite [22], [28] consisting of an electronic walkway containing pressure sensors and a computer with a software that derived the gait parameters from the sensor signals was defined as the gold standard. The device used in this study had a sensitive area of 609.60 cm × 60.96 cm, a spatial accuracy of ±1.27 cm, and a track width of 84 cm. Data were sampled at 120 Hz and processed using GAITRite Platinum software version 4.7.1.

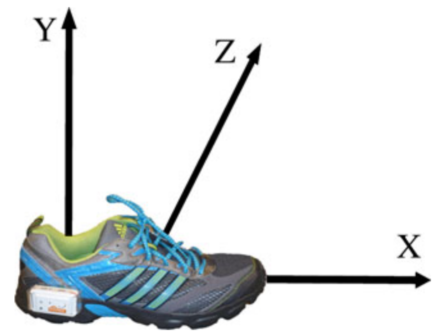


Fig. 1. Placement of the sensor and direction of axes.

B. Data Collection

Data of 116 geriatric inpatients (see Table B1 in the appendix for most frequent diagnoses) were collected at the Geriatrics Centre Erlangen (Waldkrankenhaus St. Marien, Erlangen, Germany). In all patients, inertial sensor and GAITRite data were recorded and analyzed by the same physical therapist (Samuel Schülein, with ten years of experience in physical therapy and three years of experience in clinical gait analysis).

Written informed consent was obtained prior to data collection in accordance with the approval by the ethical committee of the medical faculty of Friedrich-Alexander University Erlangen-Nürnberg (Re.-No. 4208).

Sixty two percent of the subjects had been using a four-WW for five days or more. Each subject used the same WW (Bischoff and Bischoff GmbH, Model B) for the trials. The WW got adjusted by the therapist to the subject's height, and every subject was introduced to usage of the walking aid.

The patients performed tests of a detailed geriatric assessment that took about 1 h. The assessment included, for example, an orthostatic hypotention test, an eye test, depth sensitivity test,

TABLE I
SUBJECT CHARACTERISTICS

Characteristic	Normal walk	WW
N	101	84
Sex (m/f)	46 / 55	38 / 46
Age (y)	82.1 ± 6.5	82.1 ± 6.3
Height (cm)	164.0 ± 10.0	164.0 ± 10.0

Age and height in mean ± standard deviation.

posturography analysis, timed "up and go" test, and a dual task test. The protocol of the walking tests can be seen in Table A1 in the appendix.

We included data from 1) Normal walking: Subjects passed 10-m distance at their subjective comfortable walking speed over the GAITRite instrumentation and 2) WW: Subjects repeated test 1) walking with the help of a WW. In both tests, subjects were asked to walk at save and comfortable speed. Each subject performed both tests within a time period of several minutes. Subjects that were using a WW for less than five days (similar to [29]), were asked to walk 1–2 min with the assistive device. No practice trials were performed on the GAITRite system. During testing time each subject was allowed to rest for 1–2 min between each trail to avoid symptoms or signs of fatigue.

Datasets of ten subjects had to be excluded completely—eight for medical reasons and two for recording errors from inertial sensor data (malfunction of a sensor). Furthermore, there were five exclusions in the normal walk test and 23 exclusions in the WW test due to measurement errors of the GAITRite system. A measurement error of the GAITRite system was defined as a stride with a measured *stride length* being higher than $\mu + 2\sigma$ or lower than $\mu - 2\sigma$, where μ is the mean and σ is the standard deviation of all strides of all subjects. Consequently, we included 101 subjects in the normal walk and 84 subjects in the WW test (see Table I).

To exclude the gait initiation from the sensor data recordings, subjects started walking 2 m prior to reaching the electronic walkway and stopped 2 m beyond it [30]. To establish a relationship between strides derived from the GAITRite system and strides from inertial sensors, the number of strides a subject took to reach the carpet were counted and removed manually from the inertial sensor signals.

C. Stride Segmentation

For stride segmentation, a previously developed algorithm on the basis of subsequent dynamic time warping was used [31]. To apply the stride segmentation, a template of a single stride was defined manually from the gyroscope z-axis. To segment strides, the algorithm searched for parts in the continuous signal that were similar to the template. This approach provided a method for a time-invariant template matching. The results of stride segmentation (dashed vertical lines in Fig. 2) were verified manually and corrected if segmentation errors occurred. In test 1), five (0.4 %) missed strides out of three subjects had to be inserted and one (0.1 %) stride had to be removed. In test 2), 19 (1.6 %) missed strides out of 14 subjects had to be inserted.

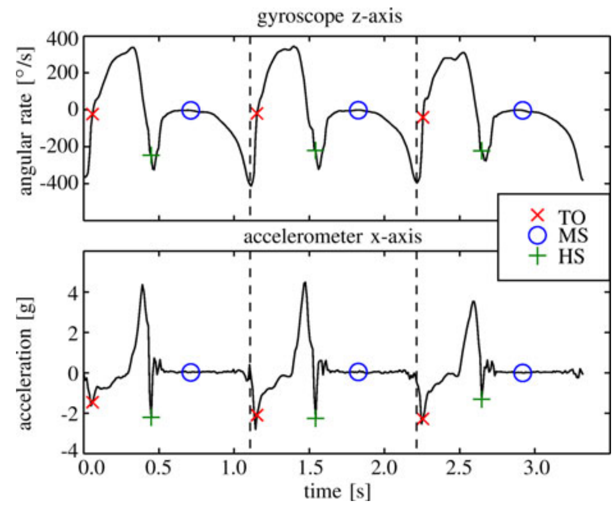


Fig. 2. Three segmented strides with TO, HS, and MS events of a typical gait signal.

TABLE II
WW DATA OF 23 EXCLUDED PATIENTS FROM GAITRITE

	Without correction	With correction
Strides per subject	14.3 ± 4.7	11.5 ± 1.9
Stride length (cm)	132.1 ± 89.2	92.1 ± 5.3
Stride time (s)	3.24 ± 2.20	1.26 ± 0.08

Table shows parameters before and after manual data correction. Values are given in mean values ± standard deviation.

D. Calculation of Gait Parameters

1) Gait Events: At TO, the movement of the ankle joint changes from an plantar flexion to a dorsal extension in the sagittal plane [32]. This change results in a zero crossing of the gyroscope's z-axis signal, which was defined as TO [15] (red cross in Fig. 2).

At HS, the foot decelerates abruptly when the heel hits the ground. To detect HS, only the segment between the absolute maximum and the end of the first half of the gyroscope's z-axis signal was considered. Within this segment, HS was found by searching for the minimum between the point of the steepest negative slope and the point of steepest positive slope in following signal. After that the x-axis of the accelerometer signal was searched for a minimum (green cross in Fig. 2) in the area 50 ms before and 20 ms after the described minimum in the gyroscope signal.

At *mid stance* (MS), the foot has the lowest velocity. It was defined to be the middle of the window with the lowest energy in all axes of the gyroscope signal [19] (blue circle in Fig. 2). The window size was 140 ms (similar to [19]) and the windows overlapped by 70 ms.

2) Temporal Gait Parameters: Temporal gait parameters were calculated on the basis of above mentioned gait events.

Borders of the used stride segmentation results were not identical to these gait events and could not directly be used. Therefore, temporal parameters were defined from two consecutive strides as defined in the following. Definitions of TO, HS, and MS were modeled as functions $t_{\mathrm{TO}}(i)$, $t_{\mathrm{HS}}(i)$, and $t_{\mathrm{MS}}(i)$. These functions delivered the point in time within the stride i, where the event occurred. To get the results in seconds, each temporal gait parameter was divided by the sampling frequency f_s

$$\mathrm{StrideTime}(i) = \frac{t_{\mathrm{HS}}(i+1) - t_{\mathrm{HS}}(i)}{f_s} \tag{1}$$

$$\mathrm{SwingTime}(i) = \frac{t_{\mathrm{HS}}(i) - t_{\mathrm{TO}}(i)}{f_s} \tag{2}$$

$$\mathrm{StanceTime}(i) = \frac{t_{\mathrm{TO}}(i+1) - t_{\mathrm{HS}}(i)}{f_s}. \tag{3}$$

3) Spatial Gait Parameter—Stride length: To calculate the *stride length*, a double integration of the gravity corrected accelerometer signal was carried out. To minimize sensor drift, the signal was segmented at MS events assuming that the velocity of the foot is zero at these points. The following section describes the calculation of the *stride length* of one single stride that contains n samples between two subsequent MS events. Therefore, sample 0 is equal to $t_{\mathrm{MS}}(i)$ and sample n is equal to $t_{\mathrm{MS}}(i+1)$.

Orientation estimation at MS: To describe the orientation of the sensor, quaternions were used. They depict the mapping between the sensor frame and the world frame. The *y*-axis of the world frame was aligned with the gravity axis of the earth frame. At MS events, orientation was estimated by using the accelerometer as a tilt sensor. It was assumed that there is no movement at this point in time. With this assumption, rotations around *x*- and *z*-axes could be described in context to the world frame. Due to the parallelism of the *y*-axis to the gravity vector, rotation around the *y*-axis is negligible and assumed to be zero.

A quaternion that describes orientation in context of *x*- and *z*-axes at this time instance was defined as the quaternion product

$$q = q_x \otimes q_z \tag{4}$$

where

$$q_x = \left[\cos\frac{\phi}{2} \quad \sin\frac{\phi}{2} \quad 0 \quad 0\right] \tag{5}$$

and

$$q_z = \left[\cos\frac{\psi}{2} \quad 0 \quad 0 \quad \sin\frac{\psi}{2}\right]. \tag{6}$$

The angles ϕ and ψ are rotation angles that describe the displacement between sensor and world frame in rotations around *x*- and *z*-axes. These angles were calculated from the accelerometer signals a_x, a_y, and a_z [33, eq. 25f]

$$\tan\phi = \frac{-a_y}{-a_z} \tag{7}$$

$$\tan\psi = \frac{-a_x}{\sqrt{a_y^2 + a_z^2}}. \tag{8}$$

These equations defined the orientation at one specific MS event. The next paragraph shows how to get a continuous orientation for each time point in a stride.

Orientation estimation during stride: Between MS events, orientation was computed by integrating the gyroscope signals. The rate of change $\hat{q}(j)$ at sample j was defined as the quaternion product of a previously estimated orientation $q(j-1)$ and the current angular rates $g_x(j), g_y(j), g_z(j)$ scaled with f_s [34]

$$\hat{q}(j) = \frac{1}{2f_s} \cdot (q(j-1) \otimes [0 \quad g_x(j) \quad g_y(j) \quad g_z(j)]). \tag{9}$$

This rate was added to the previous estimate [35]

$$q'(j) = q(j-1) + \hat{q}(j) \tag{10}$$

and the interim result $q'(j)$ was normalized by its two norm to fulfill the unit quaternion constraint

$$q(j) = \frac{q'(j)}{\|q'(j)\|_2}. \tag{11}$$

Gravity removal: To remove gravity from the accelerometer signal a method described in [17] was used. The gravity component of the signal at sample j was described as a vector $a_G(j)$. It was computed by projecting the gravity vector of the world frame with the orientation quaternions estimated before [17]

$$\vec{a}'_G(j) = q(j) \otimes [0 \quad 0 \quad -1 \quad 0] \otimes q^*(j) \tag{12}$$

$$\vec{a}_G(j) = \frac{\vec{a}'_G}{\|\vec{a}'_G\|_2} \tag{13}$$

$q^*(j)$ is the conjugate of quaternion $q(j)$ defined as

$$q^*(j) = [q_1(j) \quad -q_2(j) \quad -q_3(j) \quad -q_4(j)] \tag{14}$$

over $q(j)$'s components $q_1(j)$, $q_2(j)$, $q_3(j)$, and $q_4(j)$.

Finally, projected gravity $a_G(j)$ was subtracted from sensor measurements $a_S(j)$ to get a gravity corrected acceleration vector $\hat{\vec{a}}_E(j)$

$$\hat{\vec{a}}_E(j) = \vec{a}_S(j) - \vec{a}_G(j). \tag{15}$$

De-drifted integration: The acceleration vector $\hat{\vec{a}}_E$ contains drift that occurred when integrating the gyroscope signal. This drift was modeled by a drift function $\vec{d_a}(j)$. The values of y_0 and y_1 are the mean of the first kn and the last ln samples of the acceleration vector $\hat{\vec{a}}_E$ of the current stride and defined as

$$y_0 = \frac{1}{\mathrm{rnd(kn)}} \sum_{j=0}^{\mathrm{rnd(kn)}-1} \hat{\vec{a}}_E(j) \tag{16}$$

$$y_1 = \frac{1}{\mathrm{rnd(ln)}} \sum_{j=n-\mathrm{rnd(ln)}+1}^{n} \hat{\vec{a}}_E(j) \tag{17}$$

where $\mathrm{rnd}()$ is the round function. Between these plateaus, the drift function interpolates a straight line

$$\vec{d_a}(j) = \begin{cases} y_0, & \text{if} \quad j \leq \mathrm{rnd(k \cdot n)} \\ y_1, & \text{if} \quad j \geq n - \mathrm{rnd(l \cdot n)} \\ y_0 + (y_1 - y_0)\frac{j-k}{n-l-j}, & \text{else.} \end{cases} \tag{18}$$

TABLE III
RESULTS OF OUR INERTIAL SENSOR-BASED SYSTEM (INERTIAL SENSORS) ARE COPARED TO THE RESULTS OF THE GOLD STANDARD (GAITRITE)

Test	Parameter	Unit	Inertial sensors	GAITRite	Mean error	Abs. error	CC	n
Normal walk	Stride time	s	1.227 ± 0.189	1.226 ± 0.189	0.002 ± 0.068	0.029 ± 0.062	0.95	1220 strides 101 subjects
	Swing time	s	0.364 ± 0.068	0.372 ± 0.081	-0.008 ± 0.045	0.025 ± 0.038	0.90	
	Stance time	s	0.863 ± 0.154	0.854 ± 0.161	0.009 ± 0.069	0.033 ± 0.061	0.95	
	Stride length	cm	79.76 ± 24.25	80.02 ± 23.41	-0.26 ± 8.37	6.26 ± 5.56	0.93	
WW	Stride time	s	1.239 ± 0.181	1.233 ± 0.197	0.006 ± 0.084	0.030 ± 0.079	0.95	797 strides 84 subjects
	Swing time	s	0.405 ± 0.057	0.405 ± 0.076	0.000 ± 0.046	0.023 ± 0.040	0.89	
	Stance time	s	0.833 ± 0.141	0.828 ± 0.157	0.006 ± 0.083	0.030 ± 0.077	0.94	
	Stride length	cm	96.52 ± 18.07	98.51 ± 16.83	-1.99 ± 11.87	8.27 ± 8.75	0.80	

Quality of the measurement is denoted as the difference of the measured values (mean error), the mean of the absolute error (abs. error), and Spearman correlation coefficient (CC). Results, mean error, and abs. error are given as mean $\pm$ standard deviation.

In this study, the length of y_0 was defined empirical as 4% ($k = 0.04$), and the length of y_1 was defined as 2% ($l = 0.02$) of the current *stride length*.

A drift compensated acceleration signal was computed by subtracting the drift from the estimate $\hat{\vec{a}}_E(j)$

$$\vec{a}_E(j) = \hat{\vec{a}}_E(j) - \vec{d}_a(j). \tag{19}$$

By integrating this acceleration signal, a velocity estimate

$$\hat{\vec{v}}(j) = \int_0^n \vec{a_E}(j)\,\mathrm{dj} \tag{20}$$

was calculated. Integration of the discrete signal values was accomplished using the trapezoidal rule.

To eliminate the drift from the integration of the accelerometer signal, the effect of the zero velocity assumption was used. The zero velocity assumption is shown by Peruzzi *et al.* [18] and says that on each MS event, the velocity is zero $\vec{v}(0) = \vec{v}(n) = \vec{0}$. Hence, the estimate $\hat{\vec{v}}(n)$ describes the drift accumulated by integration.

This drift was modeled as a straight line between the origin and the mean of the last five integrated points

$$\vec{d}_v(j) = j\frac{y_1}{n} \tag{21}$$

$$y_1 = \frac{1}{5}\sum_{j=n-4}^{n} \hat{\vec{v}}(j). \tag{22}$$

Again, drift was compensated by subtraction

$$\vec{v}(j) = \hat{\vec{v}}(j) - \vec{d}_v(j). \tag{23}$$

After that, the position of the sensor was calculated by trapezoidal integration of the velocity

$$\vec{p}(j) = \int_0^n \vec{v}(j)\,\mathrm{dj}. \tag{24}$$

Finally, the *stride length* was defined as the two norm of a 2-D vector containing the distance in *x*- and *z*-direction at the end of the stride

$$\mathrm{SL} = \left\| \begin{pmatrix} p_x(n) \\ p_z(n) \end{pmatrix} \right\|_2 = \sqrt{p_x(n)^2 + p_z(n)^2}. \tag{25}$$

E. Evaluation Strategy

The precision of our method was quantified by the measures accuracy, absolute error, and correlation coefficient.

Accuracy was defined as mean and standard deviation over the signed difference of each stride. This measure shows if results of the evaluated method tend to be smaller or larger compared to the gold standard. Due to cancellation of negative and positive values, it cannot quantify the discrepancy between gold standard and results of the evaluated method.

The absolute error was defined as mean and standard deviation over the absolute difference of each stride. It quantifies the discrepancy between gold standard and evaluated method in absolute values.

The correlation coefficient quantifies the statistical dependence between the results of the evaluated method and the gold standard. For this evaluation, we used the Spearman correlation coefficient as it is more robust against outliers.

Furthermore, the results were visualized with Bland–Altman plots [36]. These plots show the mean of the measurement on the *x*-axis and the differences of the measurements on the *y*-axis. It also shows a dashed line at $\pm 1.96\sigma$—so 95% of the measurements are within these two bounds.

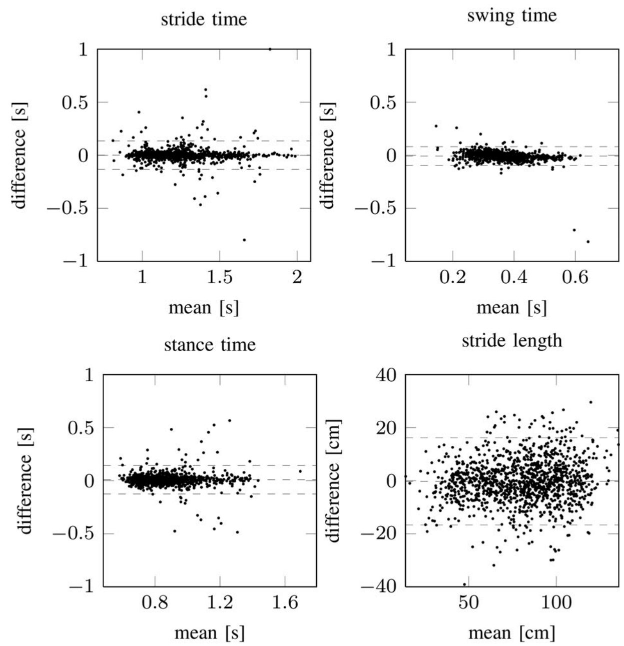
III. RESULTS

Table III shows evaluation results of the presented method.

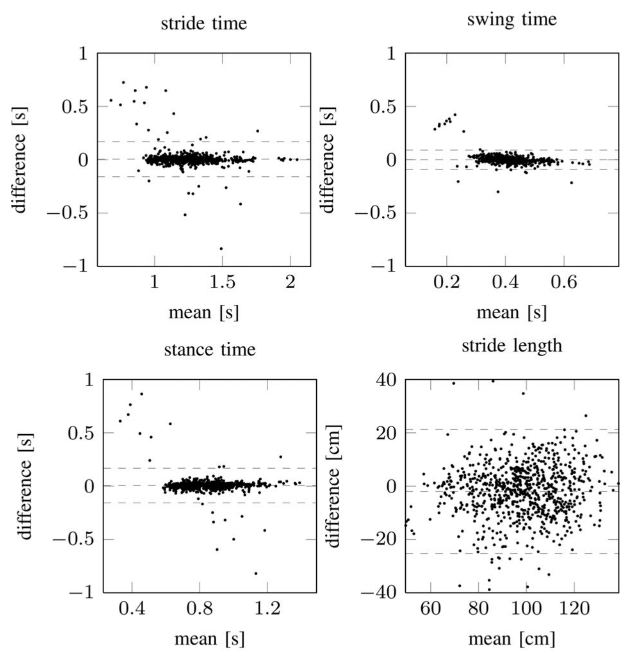
Temporal parameters could be estimated with an absolute error $\leq$33 ms in both tests. Spearman correlation between results of our method and results of the gold standard was $\geq$0.94 for *stride time* and *stance time,* and $\geq$0.89 for *swing time*. *stride length* could be calculated with 6.27-cm mean absolute error and correlation 0.93 in normal walk, and 8.27-cm mean absolute error and correlation 0.80 in the WW test.

Fig. 3 shows Bland–Altman plots comparing the two measurement results. In both tests, accuracy of temporary parameters suffered from outliers, while most differences of *stride length* were within the 1.96σ line.

Both systems showed, in tests for statistical significance, that the *stride length* increased significantly when subjects used a WW (see Fig. 4, $p < 0.0001$). Furthermore, both systems showed that *stance time* decreased and *swing time* increased significantly ($p < 0.004$). No significant difference was shown in *stride time* (see Table III, $p > 0.42$).



(a)



(b)

Fig. 3. Bland–Altman plots of the evaluation results. The x-axis shows the arithmetic mean of results of our method and the gold standard, the y-axis shows the difference between the results. The dashed line in the middle is the arithmetic mean of the differences, the lines above and below denote 1.96σ ($\sigma =$ standard deviation), where 95% of the differences are in between. (a) Normal walk. (b) WW.

Both systems showed a substantial increase in *stride length* in the group that used a WW compared to the normal walk group (see Fig. 4, $p < 0.0001$). *Stance* and *swing time* could also be analyzed in both groups and showed decreased/increased values in the WW group for all strides ($p < 0.004$). No significant difference was found for *stride time* (see Table III, $p > 0.42$).

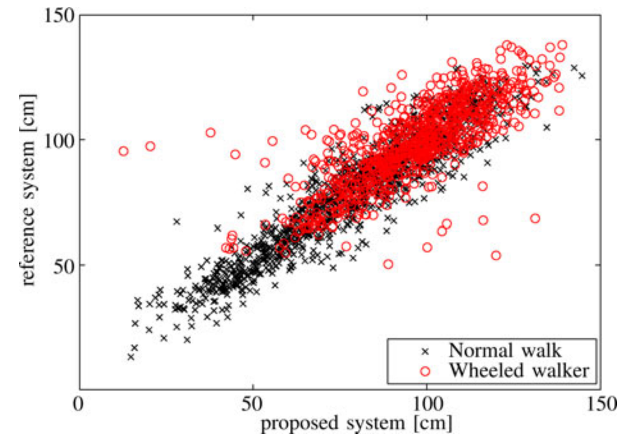


Fig. 4. Scatter plot comparing results of both systems in both tests. Both systems showed that the *stride length* increased significantly when subjects used a WW ($p < 0.0001$).

(a)

(b)

Fig. 5. GAITRite recorded the tracks of the walking aid [see Fig. 5(a)] additionally to the strides of the subject. When using the automatic removal tool of the GAITRite software, those tracks caused errors in the stride parameter calculation. For that reason the tracks were removed manually [see Fig. 5(b)]. (a) GAITRite signal containing tracks of the WW. (b) GAITRite signal after manual removed tracks of the WW.

IV. Outlier Analysis of GAITRite Data

Due to errors in the measurements of the gold standard system, 23 datasets of the WW data were excluded from the analysis. As the main focus was on *stride length* calculation, an outlier and measurement error was defined as a *stride length* with a difference higher than 2σ from the mean over all strides of all subjects.

A detailed analysis of these outliers showed that the tracks from the WW caused these errors [see Fig. 5(a)]. After manual removal of the tracks [see Fig. 5(b)], gait parameters were recalculated and are shown in Table II.

The main difference can be observed in the standard deviation. Especially for *stride length*, the standard deviation decreased after recalculation by a factor of 16.

V. Discussion

This study described a method to calculate clinically relevant gait parameters using inertial sensors. The method was validated by comparing results to measurements of the valid gold standard

GAITRite [22], [28]. The inertial sensor system was able to measure and analyze the same indications of gait alternation as the gold standard.

Mariani *et al.* [21] calculated *stride length* with a similar correlation (0.96), but a lower standard deviation of the mean error (1.5 $\pm$ 6.8 cm). Compared to Salarian *et al.* [13], *stride length* was similar (mean error: 3.5 $\pm$ 8.5 cm), but their method was more accurate in *stride time* (mean error: 0.0022 $\pm$ 0.0232 s) and *stance time* (mean error: 0.0059 $\pm$ 0.0296 s). This accuracy was achieved by using six gyroscopes, which is not applicable for a non stigmatizing day-by-day long-time monitoring system. Doheny *et al.* [14] calculated *stride length* using two gyroscopes placed on the shank (mean error: 9 $\pm$ 7 cm), but they already discussed that their method could have problems with altered gait.

In general, comparison with results from other studies is difficult because there are various statistical measures which cannot be compared with each other. Moreover, the source of the analyzed data was very diverse ([14] had young, [13] had old subjects, [14], [21] had healthy subjects, and [13] had patients as well as healthy controls) and the number of subjects differed (from 7 to 20). To improve the comparability in the future, we published our data on the Internet (http://www.activitynet.org). We invite other studies to run their algorithm on the published data and calculate the validation parameters suggested in our study.

Stride segmentation was achieved using a previously published method [31]. There were some erroneously detected strides that had to be corrected by hand. This step was necessary to ensure clearly initial conditions, namely correctly segmented data, because stride segmentation was not at the focus of this study.

In order to calculate the important gait events during one stride, methods out of the literature were used for TO and MS calculation [15], [19], [32]. For detecting HS, previous studies showed that this event is just before the change in angular velocity between swing and stance phase [15]. While other studies used the gyroscope signal solely, we used the accelerometer signal as an additional source of information. A HS always causes a deceleration of the foot, which results in a peak in the accelerometer signal, and should therefore be a more accurate estimation of this event. To make HS detection more robust, we considered just the relevant part of the signal. As the swing phase lasts 40% of a stride [32], it is sufficient to search in the first half of the stride's signal. Moreover, it is obvious that the HS event occurs after the *mid swing* event, which can be easily detected as the absolute maximum of the gyroscope's z-axis signal [13]. However, with the signal of one particular subject, HS detection still caused problems, which shows up as outliers in the temporal parameter plots of Fig. 3.

The window size for MS detection was derived from an assumed common *stride time* of 1s, where the MS phase lasts 19 % of a stride [37]. Since MS occurs during a small ammount of time, a smaller window size is sufficient. However, the actual ammount of the window size for MS as well as the window size for HS detection were adapted to our data and need further evaluation for generalization.

For the intermediate task of orientation estimation and gravity removal of the accelerometer signal, a quaternion-based calculation was used. This method had the advantages compared to Euler angles that it required less computational operations as well as avoided the problem of a gimbal lock [34].

To compensate the drift that appears in gyroscope integration, a piece-wise defined linear function was used. This function takes into account that the foot is assumed to stand still at the beginning and end of every stride. In contrast to all other studies that used a static function to model drift, we adapted the drift function individually to every single stride. This approach is very promising as it takes into account that most drift occurs during swing phase and the duration of the swing phase depends on the duration of the whole stride.

Furthermore, the calculation of *stride length* is based on the assumption that a foot has zero velocity at a specific point in time during stride. In reality, velocity reaches minimum at this point [18]. Results tend to get better when setting the velocity not to zero but to a small amount when resetting the integration. This relationship should be examined in a separate study where subjects walk at different paces, since it can be assumed that the relationship is highly dependent on the gait speed.

Results of the validation procedure of our system compared to the gold standard GAITRite showed that the absolute differences and also the correlation coefficients are comparable to the literature [15], [21]. Together with the high number of subjects and their advanced age, it can be supposed that the method is applicable in geriatric medicine. Since it works for altered gait, it can also be assumed that the developed method is usable in a lot of other settings, for example, analyzing gait disorders in general or searching for indicators of an increased fall risk.

The presented method also tracked sensor's orientation for gravity removal using quaternions. These quaternions made it possible to quantify angles between foot and floor during the complete stride and for example, at the HS and TO events. As the GAITRite system is not able to measure angles, there is no validation for these parameters so far.

However, the time of double support is also an important parameter in clinical gait analysis [7]. So far, there is no synchronization between left and right sensor in the used measurement system. Consequently, it is not possible to calculate the double-support time. This would be a necessary improvement for further studies with the described sensor system.

Another aspect of the study was to show that the developed system was able to quantify clinically relevant differences in gait parameters. As a concrete example, the parameters from both systems were compared for normal walk and walk with a walking aid. Results of our system as well as results of the gold standard system showed a significant increase of the parameters *stride length*, *stride time*, and *swing time* when subjects used a WW.

However, the use of walking aids interfered with the correct automated detection of gait parameters in the GAITRite system. Our study showed that the WW influences the measurement of stride parameters by the automated GAITRite analysis setup. In particular, the *stride length* was longer than 200 cm in individual cases. Therefore, we analyzed outliers based on the *stride length*. However, further outliers showed up in temporal parameters, which were not detected by the outlier analysis. In the WW trial, eight strides from six subjects can be assumed to be errors that were caused by GAITRite. In seven strides, the *swing time* was <0.01s, in one stride it was >0.7s. Furthermore, five strides from one subject in normal walk and two strides from two subjects in the WW trial caused outliers due to improper HS detection. An implementation of the presented method could detect these outliers and exclude them from the further analysis.

Results in Table II show that after manual data correction, the standard deviation decreased by a factor of 16, indicating more stable results. This time-consuming recalculation is not required if an inertial sensor-based system is used, where the sensor is directly fixed on the shoe. The quantification of clinical relevant parameters makes the usage of an inertial sensor-based system reliably and beneficial for daily use in geriatric medicine.

We ensured that the WW was setup and used correctly because it is known that gait is influenced by a not correctly set up walking aid [38]. Experience of WW use also influences gait parameters [29], [39]. Accordingly, we found differences in the averaged stride parameters when comparing normal walk to WW supported walking. This underlines the applicability of inertial sensor-based gait analysis in clinical gait diagnostics. Future studies will decipher the influence of additional clinical parameters and subgroup analysis of different patient cohorts (e.g., used, versus not used to WW, fallers versus nonfallers) on the gait parameter changes by walking aids.

An enormous advantage of the introduced mobile gait analysis system, is the possibility to record a very large number of strides over a long period of time. A specialized environment like a laboratory is not required and a measurement can be done on nearly everywhere. The usage of walking aids like WW does not influence the calculation of results of our system.

The presented algorithm can be implemented into a recording software running on a mobile device (for example a tablet computer). This allows a mobile and simple to use gait lab concept providing objective gait parameters without complex postprocessing of the data. It is also applicable in standard in- and outpatient units that do not have complex equipped motion laboratories.

VI. Conclusion

We presented a method that is able to calculate clinically relevant gait parameters from inertial sensor data of gait sequences. It was shown that the algorithm yields proper results when applying it on altered gait that is typically for geriatric patients.

To improve comparability with other studies, we published our data (http://www.activitynet.org) and invite other studies to apply their method on our data.

In the future, the sensor should be integrated in the shoe to give the possibility of a data recording over at least a complete day. This would give the possibility for a detailed long-term gait monitoring.

Appendix A
Test Protocol

Table A1 shows the whole test protocol. Data of the bold marked trials (4 and 7) were used for this study.

TABLE A1
Protocol of Tests Performed by Each Subject

#	Trial	Description
1	heel-toe-tapping	Subject sits on a chair and has to tap heel and toe alternatively.
2	timed up-and-go	Subject has to stand up from a chair, walk around a pylon and sit down again.
3	drawing circles	Subject sits on a chair and has to draw circles with the foot just above the ground.
4	**normal walk**	**Subject has to walk in a self-selected, comfortable speed over the GAITRite carpet without any help.**
5	dual tasking	Subject has to enumerate months of a year in reverse order while walking over the GAITRite carpet.
6	walk and turn	Subject has to walk 10 m, then turn in the direction the instructor tells, walk back to start and turn again in a told direction.
7	**WW**	**Subject has to walk in a self-selected, comfortable speed over the GAITRite carpet with the help of a WW.**

In this study, datasets of the tests “normal walk” and “WW” were analyzed.

Appendix B
Most Frequent Diagnoses

TABLE B1
Most Frequent Diagnoses of Subjects

Position	Diagnose	Percent
1	heart rhythm disorder	69.92
2	arterial hypertension	69.11
3	gait disorders/fall proneness	53.66
4	coronary artery disease	40.65
5	hypercholesterolemia/dislipedemia	26.83
6	cardiac valve disorder	26.02
7	kidney disease	21.95
8	diabetes mellitus	20.33
9	degenerative spine disorder	20.33
10	heart failure	20.33

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References

[1] N. Giladi, F. B. Horak, and J. M. Hausdorff, "Classification of gait disturbances: Distinguishing between continuous and episodic changes," *Mov. Disorders, Off. J. Mov. Disorder Soc.*, vol. 28, no. 11, pp. 1469–1473, 2013.

[2] J. A. Block and N. Shakoor, " The biomechanics of osteoarthritis: Implications for therapy," *Current Rheumatol. Rep.*, vol. 11, no. 1, pp. 15–22, 2009.

[3] C. NíScanaill, S. Carew, P. Barralon, N. Noury, D. Lyons, and G. M. Lyons, "A review of approaches to mobility telemonitoring of the elderly in their living environment," *Ann. Biomed. Eng.*, vol. 34, no. 4, pp. 547–563, 2006.

[4] B. Maki, "Gait changes in older adults: Predictors of falls or indicators of fear," *J. Amer. Geriatr. Soc.*, vol. 45, no. 3, pp. 313–320, 1997.

[5] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: A 1-year prospective study," *Arch. Phys. Med. Rehabil.*, vol. 82, no. 8, pp. 1050–1056, 2001.

[6] J. Hausdorff, "Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking," *Human Mov. Sci.*, vol. 26, no. 4, pp. 555–589, 2007.

[7] R. W. Kressig, R. J. Gregor, A. Oliver, D. Waddell, W. Smith, M. O'Grady, A. T. Curns, M. Kutner, and S. L. Wolf, "Temporal and spatial features of gait in older adults transitioning to frailty," *Gait Posture*, vol. 20, no. 1, pp. 30–35, 2004.

[8] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *J. Gerontol. Ser. A, Biol. Sci. Med. Sci.*, vol. 64A, no. 8, pp. 896–901, 2009.

[9] U. Givon, G. Zeilig, and A. Achiron, "Gait analysis in multiple sclerosis: Characterization of temporal-spatial parameters using GAITRite functional ambulation system," *Gait Posture*, vol. 29, no. 1, pp. 138–142, 2009.

[10] J. Klucken, J. Barth, P. Kugler, J. Schlachetzki, T. Henze, F. Marxreiter, Z. Kohl, R. Steidl, J. Hornegger, B. Eskofier, and J. Winkler, "Unbiased and mobile gait analysis detects motor impairment in Parkinson's disease," *PLoS ONE*, vol. 8, no. 2, p. e56956, 2013.

[11] J. Barth, M. Sünkel, K. Bergner, G. Schickhuber, J. Winkler, J. Klucken, and B. Eskofier, "Combined analysis of sensor data from hand and gait motor function improves automatic recognition of Parkinson's disease," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2012, pp. 5122–5125.

[12] K. Aminian, B. Najafi, C. Büla, P.-F. Leyvraz, and P. Robert, "Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes," *J. Biomech.*, vol. 35, no. 5, pp. 689–699, 2002.

[13] A. Salarian, H. Russmann, F. J. G. Vingerhoets, C. Dehollain, Y. Blanc, P. R. Burkhard, and K. Aminian, "Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring," *IEEE Trans. Bio-Med. Eng.*, vol. 51, no. 8, pp. 1434–1443, Aug. 2004.

[14] E. P. Doheny, T. G. Foran, and B. R. Greene, "A single gyroscope method for spatial gait analysis," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2010, pp. 1300–1303.

[15] A. Mannini and A. M. Sabatini, "A hidden Markov model-based technique for gait segmentation using a foot-mounted gyroscope," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2011, pp. 4369–4373.

[16] A. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of walking features from foot inertial sensing," *IEEE Trans. Bio-Med. Eng.*, vol. 52, no. 3, pp. 486–494, Mar. 2005.

[17] A. Sabatini, "Quaternion-based strap-down integration method for applications of inertial sensing to gait analysis," *Med. Biol. Eng. Comput.*, vol. 43, pp. 94–101, 2005.

[18] A. Peruzzi, U. DellaCroce, and A. Cereatti, "Estimation of stride length in level walking using an inertial measurement unit attached to the foot: A validation of the zero velocity assumption during stance," *J. Biomech.*, vol. 44, no. 10, pp. 1991–1994, 2011.

[19] I. Skog, P. Händel, J.-O. Nilsson, and J. Rantakokko, "Zero-velocity detection in pedestrian navigation systems—An algorithm evaluation," *Biomed. Eng.*, vol. 57, no. 11, pp. 2657–2666, 2010.

[20] S. J. M. Bamberg, A. Y. Benbasat, D. M. Scarborough, D. E. Krebs, and J. A. Paradiso, "Gait analysis using a shoe-integrated wireless sensor system," *IEEE Trans. Inf. Technol. Biomed.*, vol. 12, no. 4, pp. 413–423, Jul. 2008.

[21] B. Mariani, C. Hoskovec, S. Rochat, C. Büla, J. Penders, and K. Aminian, "3D gait assessment in young and elderly subjects using foot-worn inertial sensors," *J. Biomech.*, vol. 43, no. 15, pp. 2999–3006, 2010.

[22] A. McDonough, M. Batavia, F. C. Chen, S. Kwon, and J. Ziai, "The validity and reliability of the GAITRite system's measurements: A preliminary evaluation," *Arch. Phys. Med. Rehabil.*., vol. 82, no. 3, pp. 419–425, 2001.

[23] B. R. Greene, D. McGrath, R. O'Neill, K. J. O'Donovan, A. Burns, and B. Caulfield, "An adaptive gyroscope-based algorithm for temporal gait analysis," *Med. Biol. Eng. Comput.*, vol. 48, no. 12, pp. 1251–1260, 2010.

[24] B. Mariani, H. Rouhani, X. Crevoisier, and K. Aminian, "Quantitative estimation of foot-flat and stance phase of gait using foot-worn inertial sensors," *Gait Posture*, vol. 37, no. 2, pp. 229–234, 2013.

[25] A. Burns, B. R. Greene, M. J. McGrath, T. J. O'Shea, B. Kuris, S. M. Ayer, F. Stroiescu, and V. Cionca, "SHIMMER—A wireless sensor platform for noninvasive biomedical research," *IEEE Sensors J.*, vol. 10, no. 9, pp. 1527–1534, Sep. 2010.

[26] J. C. Menant, J. R. Steele, H. B. Menz, B. J. Munro, and S. R. Lord, "Optimizing footwear for older people at risk of falls," *J. Rehabil. Res. Develop.*, vol. 45, no. 8, pp. 1167–1181, 2008.

[27] J. C. Menant, J. R. Steele, H. B. Menz, B. J. Munro, and S. R. Lord, "Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people," *Gait Posture*, vol. 29, no. 3, pp. 392–397, 2009.

[28] K. E. Webster, J. E. Wittwer, and J. a. Feller, "Validity of the GAITRite walkway system for the measurement of averaged and individual step parameters of gait," *Gait Posture*, vol. 22, no. 4, pp. 317–321, 2005.

[29] K. Lucki, M. Bach, W. Banzer, and L. Vogt, "Walker use affects Timed Up and Go and gait speed measures," *J. Amer. Geriatr. Soc.*, vol. 57, no. 10, pp. 1963–1965, 2009.

[30] R. W. Kressig, O. Beauchet, E. Gaitrite, and N. Group, "Guidelines for clinical applications of spatio-temporal gait analysis in older adults," *Aging Cli. Exp. Res.*, vol. 18, no. 2, pp. 174–176, 2006.

[31] J. Barth, C. Oberndorfer, P. Kugler, D. Schuldhaus, J. Winkler, J. Klucken, and B. Eskofier, "Subsequence dynamic time warping as a method for robust step segmentation using gyroscope signals of daily life activities," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2013, pp. 6744–6747.

[32] D. Beckers and J. Deckers, *Ganganalyse und Gangschulung*. Berlin, Germany: Springer, 1997, p. 297.

[33] M. Pedley. (2013). Tilt sensing using linear accelerometers. [Online]. Available: http://www.freescale.com/files/sensors/doc/app_note/AN3461.pdf

[34] J. Cooke, M. Zyda, D. Pratt, and R. Mcghee, "NPSNET: Flight simulation dynamic modeling using quaternions," *Presence*, vol. 1, no. 4, pp. 404–420, 1994.

[35] S. Madgwick, A. Harrison, and A. Vaidyanathan, "Estimation of IMU and MARG orientation using a gradient descent algorithm," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, 2011, pp. 1–7.

[36] J. Bland and D. Altman, "Statistical methods for assessing agreement between two methods of clinical measurement," *Lancet*, vol. 1, no. 8476, pp. 307–310, 1986.

[37] M. W. Whittle, *Gait Analysis: An Introduction*, 3rd ed. Burlington MA, USA: Butterworth-Heinemann, 2001.

[38] H. H. Liu, "Assessment of rolling walkers used by older adults in senior-living communities," *Geriatr. Gerontol. Int.*, vol. 9, no. 2, pp. 124–30, 2009.

[39] M. Schwenk, M. Schmidt, M. Pfisterer, P. Oster, and K. Hauer, "Rollator use adversely impacts on assessment of gait and mobility during geriatric rehabilitation," *J. Rehab. Med., Off. J. UEMS Eur. Board Phys. Rehabil. Med.*, vol. 43, no. 5, pp. 424–429, 2011.

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