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Consistency of gait characteristics as determined from acceleration data collected at different trunk locations

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ABSTRACT

Estimates of gait characteristics may suffer from errors due to discrepancies in accelerometer location. This is particularly problematic for gait measurements in daily life settings, where consistent sensor positioning is difficult to achieve. To address this problem, we equipped 21 healthy adults with tri-axial accelerometers (DynaPort MiniMod, McRoberts) at the mid and lower lumbar spine and anterior superior iliac spine (L2, L5 and ASIS) while continuously walking outdoors back and forth (20 times) over a distance of 20 m, including turns. We compared 35 gait characteristics between sensor locations by absolute agreement intra-class correlations (2, 1; ICC). We repeated these analyses after applying a new method for off-line sensor realignment providing a unique definition of the vertical and, by symmetry optimization, the two horizontal axes. Agreement between L2 and L5 after realignment was excellent (ICC > 0.9) for stride time and frequency, speed and their corresponding variability and good (ICC > 0.7) for stride regularity, movement intensity, gait symmetry and smoothness and for local dynamic stability. ICC values benefited from sensor realignment. Agreement between ASIS and the lumbar locations was less strong, in particular for gait characteristics like symmetry, smoothness, and local dynamic stability (ICC generally < 0.7). Unfortunately, this lumbar-ASIS agreement did not benefit consistently from sensor realignment. Our findings show that gait characteristics are robust against limited repositioning error of sensors at the lumbar spine, in particular if our off-line realignment is applied. However, larger positioning differences (from lumbar positions to ASIS) yield less consistent estimates and should hence be avoided.

1. Introduction

Because of their ease of use, low cost and low power requirements, accelerometers have become increasingly popular as a measurement tool for human movement. The trunk is often recommended for sensor placement, based on the assumption that it reflects the body's center of mass movement [1,2]. Accelerometers have been placed at belt [3] or waist height [4], at the hip [5] or at the sternum [6], and at the front [7] or back [8] of the trunk. Do signals obtained from these various anatomical landmarks allow for estimating equivalent characteristics of gait? Thus far, a general mapping between these different sensor placements has not yet been reported. The recorded accelerations may differ in a non-trivial way, e.g., due to relative movement of the sensor locations with trunk deformation, which cannot be compensated for when estimating gait characteristics. Potential differences may also occur if locations differ only by small amounts. This is unfortunate, for instance, when monitoring daily life activities with self-(re-)attachment of sensors so that precise positioning of the sensor cannot be guaranteed. Whenever sensor location affects the estimated gait characteristic, the way subjects wear the sensor may bias scientific results and interpretations. In that case estimates reflect individuals' dressing preferences rather than proper gait characteristics.

Earlier studies investigated validity [9,10] and consistency [11,12] of gait characteristics based on accelerometry, but consistency was typically assessed through measurements at different times or using different sensors and/or estimation methods. Studies particularly addressing effects of sensor location typically focused on activity monitoring and estimates of energy

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consumption [13–15] but hardly on generic gait characteristics. To fill the resulting lacuna we investigated the effect of sensor location on estimates of gait characteristics derived from trunk accelerations. These characteristics included standard gait parameters like gait speed, stride time, stride frequency and their corresponding variability, as well as parameters that are considered informative about fall risk and movement disorders like local dynamic stability, gait symmetry, gait smoothness and various measures of gait variability [16]. The characteristics derived from literature were typically developed and validated for a location in the lumbar region. In our study we tested whether these characteristics can be consistently achieved over a broader range of locations, which can occur in daily life measurements by repeated self-attachment or shifting during sensor use.

We studied (outdoors) over-ground walking over repeated short-distances where we included turns to investigate gait parameters obtained from activities such as in a daily life setting. The consistency of characteristics' estimators was assessed by the absolute agreement between estimates from different locations. Since sensor positioning can affect sensor orientation, we also tested the effect of a new off-line data realignment method.

2. Methods

2.1. Participants

In this study 21 healthy adults (9 males, age 27.7 ± 3.3 years, height 1.75 ± 0.10 m, weight 66 ± 10 kg) participated. All participants provided written informed consent before entering the experiment.

2.2. Protocol

Participants were asked to self-attach three tri-axial acceleration sensors sampling at 100 Hz with a [−6 g, 6 g] range (DynaPort MiniMod, McRoberts, The Hague, NL) fitted on elastic bands to their trunk by closing the elastic bands with Velcro straps in order to fit it secure but still comfortable. They were instructed to place the sensors at the back of the trunk at belt height (the lower lumbar spine, L5), at waist height (on the middle of the lumbar spine, L2) and on the front hip at belt height (the anterior superior iliac spine, ASIS). The effect of selecting the different locations simulates positioning errors that can occur when subjects (repeatedly) self-attach sensors and wear it for longer periods in daily life. The L2 and L5 locations could span a range of (intended) initial positions and effects of unintended shifting of the sensors, and ASIS represents extreme unintended displacement of the sensor. Fitted with the sensors, participants were instructed to walk outdoors on a tarmac surface at their preferred speed continuously twenty times up and down around two markers placed 20 m apart. The experiment had been approved by the ethics committee of the Faculty of Human Movement Sciences, VU University Amsterdam, before it was conducted.

2.3. Data analysis

2.3.1. Realignment

Each session to be analyzed was selected from the start of walking until the end of walking the 40×20 m, including all turns, by visual evaluation of the recordings. These data were subjected to further analysis realized in Matlab™ (Mathworks, Natwick, MA, version R2011a). Data were also aligned to a common, body-centered reference frame with axes in the vertical (VT), medio-lateral (ML) and anterior–posterior (AP) directions, to correct for the orientation component of positioning differences. The VT direction was defined as the direction of the average acceleration equivalent to the method proposed by Moe-Nilssen [17]. This method assumes that the average acceleration with respect to the ground is negligible, and the mean acceleration measured must thus oppose gravitation. We extended the method with the estimation of the orthogonal ML and AP directions by maximizing the product of their harmonic ratios (gait symmetry [18]) in the two-dimensional plane perpendicular to the (pre-)determined VT direction (see Appendix A). The realigned data underwent the same analysis as the raw data to evaluate the effect of the realignment.

2.3.2. Gait characteristics

We selected a set of 35 characteristics based on their potential value for determining gait stability and quality. All these characteristics have been shown or are promising to differ between old and young subjects, between patients and controls and/or between fallers and non-fallers (e.g. [16,19]). We determined one estimate for the characteristics per sensor. Data from the start to the end of walking, including all turns, were processed for each estimation.

Gait speed and *speed variability* estimations were based on step lengths using the method proposed by Zijlstra and Hof [3], i.e., as the average speed over the total estimated distance and the standard deviation of speed per stride, respectively. For the estimation of speed variability, the minimum and maximum 10% of stride speeds were excluded.

Movement intensity was estimated for each of the three directions as the signal's standard deviation, which is equivalent

Table 1
Mean (standard deviation) of estimated gait characteristics after sensor realignment.

Sensors	L5	L2	ASIS
Gait speed (m/s)	1.41 (0.15)	1.43 (0.15)	1.43 (0.13)
Speed variability (m/s)	0.06 (0.01)	0.06 (0.01)	0.06 (0.01)
Stride time (s)	1.01 (0.06)	1.01 (0.06)	1.01 (0.06)
Stride time variability (0.01 s)	1.70 (0.43)	1.63 (0.45)	1.63 (0.42)
Stride frequency (Hz)	0.99 (0.05)	0.99 (0.05)	0.99 (0.05)
Stride frequency variability VT	0.14 (0.04)	0.14 (0.04)	0.15 (0.05)
Stride frequency variability ML	0.16 (0.03)	0.16 (0.03)	0.15 (0.03)
Stride frequency variability AP	0.14 (0.04)	0.14 (0.04)	0.15 (0.04)
Stride regularity VT	0.83 (0.06)	0.81 (0.07)	0.84 (0.05)
Stride regularity ML	0.59 (0.14)	0.62 (0.11)	0.60 (0.10)
Stride regularity AP	0.71 (0.07)	0.69 (0.08)	0.73 (0.06)
Movement intensity VT (m/s^2)	3.41 (0.69)	3.42 (0.64)	3.38 (0.59)
Movement intensity ML (m/s^2)	2.02 (0.57)	1.75 (0.40)	1.81 (0.39)
Movement intensity AP (m/s^2)	2.25 (0.45)	2.16 (0.38)	2.41 (0.43)
Low-frequency percentage VT	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)
Low-frequency percentage ML	1.03 (0.98)	2.11 (1.72)	2.54 (2.11)
Low-frequency percentage AP	0.76 (0.48)	1.97 (1.12)	1.41 (0.74)
Gait smoothness VT	0.80 (0.08)	0.83 (0.07)	0.87 (0.06)
Gait smoothness ML	0.09 (0.09)	0.10 (0.12)	0.36 (0.15)
Gait smoothness AP	0.53 (0.08)	0.50 (0.09)	0.53 (0.07)
Gait symmetry VT	4.61 (1.24)	4.97 (0.96)	2.59 (0.68)
Gait symmetry ML	2.98 (0.76)	2.91 (0.61)	2.49 (0.64)
Gait symmetry AP	3.91 (0.79)	3.92 (0.71)	2.42 (0.52)
Local dynamic stability Wolf VT (s^{-1})	0.74 (0.16)	0.80 (0.17)	0.69 (0.14)
Local dynamic stability Wolf ML (s^{-1})	1.20 (0.27)	1.13 (0.21)	1.19 (0.19)
Local dynamic stability Wolf AP (s^{-1})	1.01 (0.19)	1.09 (0.17)	0.95 (0.14)
Local dynamic stability Ros. VT (s^{-1})	0.60 (0.07)	0.64 (0.08)	0.54 (0.06)
Local dynamic stability Ros. ML (s^{-1})	0.55 (0.06)	0.53 (0.07)	0.49 (0.08)
Local dynamic stability Ros. AP (s^{-1})	0.54 (0.05)	0.50 (0.05)	0.52 (0.07)
Local dynamic stability Wolf VT/stride	0.75 (0.17)	0.81 (0.18)	0.70 (0.16)
Local dynamic stability Wolf ML/stride	1.22 (0.30)	1.15 (0.24)	1.21 (0.23)
Local dynamic stability Wolf AP/stride	1.02 (0.21)	1.10 (0.20)	0.96 (0.16)
Local dynamic stability Ros. VT/stride	0.60 (0.08)	0.64 (0.09)	0.55 (0.07)
Local dynamic stability Ros. ML/stride	0.56 (0.07)	0.54 (0.08)	0.50 (0.08)
Local dynamic stability Ros. AP/stride	0.55 (0.07)	0.51 (0.07)	0.52 (0.08)

to the acceleration root mean square or RMS as described by Menz et al. [18].

Stride time was estimated as the time lag between 0.4 and 4.0 s with the highest auto-covariance summed over the three directions, with the additional condition that auto-covariance had to be positive for each and any direction. This method was similar to the one used by Moe-Nilssen et al. [20], with the addition of combining three directions.

Stride regularity was estimated for each direction as the normalized auto-covariance for a lag of exactly one estimated stride time [20].

Stride time variability was estimated from the durations between a minimum (maximum) in the vertical positions and the second next minimum (maximum). Vertical positions agreed with those used for gait speed and speed variability estimations; see above. In line, the stride time variability was estimated as the standard deviation of these durations, with exclusion of the highest and lowest 10%.

Stride frequency was estimated from the median of the modal frequencies (half the modal frequency for VT and AP) for all three directions. Whenever the median of the three frequencies fell outside the range 0.6–1.2 Hz, it was replaced by one of the other two frequencies, if available, within this range. Finally, if all modal frequencies were within 10% of an integer multiple of the resulting frequency, it was replaced by the mean of the three associated base frequencies.

Stride frequency variability was estimated for each of the three directions as the strength of the relative fluctuations in phase progression; see Appendix B for details. These relative fluctuations were estimated per harmonic from the corresponding analytic signals, which were obtained via the Hilbert transform after applying a band-pass filter around the harmonic with a width of two-thirds of the stride frequency. The estimations were then averaged over the harmonics, weighted by their power.

Gait symmetry was estimated for each of the three directions as the harmonic ratio, which was described earlier by Menz et al. [18] and which was shown to measure gait symmetry by Bellanca et al. [21].

Gait smoothness was estimated for each of the three directions as the index of harmonicity which is the spectral power of the basic harmonic divided by the sum of the power of first six harmonics [22].

Low-frequency percentage was estimated as the sum of spectral power of the frequencies below 0.5 Hz for a direction, expressed as the percentage of the total power for that same direction. The low frequencies are fluctuations below the stride frequency and thus represent between-strides variability. The power spectrum was estimated after subtraction of the mean, using a Hamming window corresponding to 10 s.

Local dynamic stability was estimated for each direction with the methods of Wolf [23] and Rosenstein [24], using an embedding of seven dimensions [12] with ten samples (0.1 s) time delay [25]

Table 2

Between-location ICCs (95% confidence interval) after sensor realignment. Good and excellent agreements (ICC of 0.7 or higher) are printed in bold face.

Sensors	L5-L2	L5-ASIS	L2-ASIS
Gait speed	**0.98 (0.94–0.99)**	**0.94 (0.84–0.98)**	**0.96 (0.91–0.98)**
Speed variability	**0.96 (0.87–0.99)**	**0.94 (0.84–0.98)**	**0.89 (0.56–0.96)**
Stride time	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**
Stride time variability	**0.98 (0.82–0.99)**	**0.95 (0.87–0.98)**	**0.96 (0.91–0.99)**
Stride frequency	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**
Stride frequency variability VT	**1.00 (0.99–1.00)**	**0.98 (0.96–0.99)**	**0.98 (0.92–0.99)**
Stride frequency variability ML	**0.94 (0.86–0.98)**	**0.78 (0.53–0.90)**	**0.79 (0.55–0.91)**
Stride frequency variability AP	**0.97 (0.89–0.99)**	**0.98 (0.95–0.99)**	**0.95 (0.68–0.98)**
Stride regularity VT	**0.92 (0.71–0.97)**	**0.90 (0.76–0.96)**	**0.83 (0.27–0.95)**
Stride regularity ML	**0.91 (0.62–0.97)**	**0.73 (0.46–0.88)**	**0.76 (0.51–0.90)**
Stride regularity AP	**0.83 (0.60–0.93)**	**0.74 (0.48–0.89)**	**0.71 (0.27–0.89)**
Movement intensity VT	**0.98 (0.95–0.99)**	**0.92 (0.81–0.97)**	**0.94 (0.86–0.98)**
Movement intensity ML	0.65 (0.16–0.86)	0.65 (0.28–0.84)	0.64 (0.30–0.83)
Movement intensity AP	0.68 (0.36–0.85)	**0.89 (0.29–0.97)**	0.59 (0.11–0.83)
Low-frequency percentage VT	**0.71 (0.01–0.91)**	0.64 (−0.02–0.88)	0.60 (0.24–0.81)
Low-frequency percentage ML	0.37 (−0.04–0.68)	0.36 (−0.07–0.68)	0.30 (−0.14–0.64)
Low-frequency percentage AP	0.27 (−0.11–0.63)	0.37 (−0.10–0.71)	0.35 (−0.04–0.66)
Gait smoothness VT	**0.74 (0.45–0.89)**	0.43 (−0.07–0.74)	0.58 (0.08–0.83)
Gait smoothness ML	**0.76 (0.49–0.89)**	0.11 (−0.07–0.40)	0.19 (−0.08–0.55)
Gait smoothness AP	**0.75 (0.48–0.89)**	0.61 (0.25–0.82)	0.50 (0.12–0.76)
Gait symmetry VT	0.63 (0.29–0.83)	0.16 (−0.08–0.49)	0.03 (−0.05–0.18)
Gait symmetry ML	**0.86 (0.69–0.94)**	0.22 (−0.13–0.56)	0.18 (−0.17–0.53)
Gait symmetry AP	0.22 (−0.25–0.59)	0.08 (−0.07–0.33)	0.08 (−0.07–0.33)
Local dynamic stability Wolf VT	**0.86 (0.41–0.95)**	**0.77 (0.50–0.90)**	0.67 (−0.00–0.89)
Local dynamic stability Wolf ML	**0.85 (0.63–0.94)**	**0.70 (0.38–0.86)**	0.67 (0.36–0.85)
Local dynamic stability Wolf AP	0.66 (0.29–0.85)	0.66 (0.32–0.85)	0.57 (−0.09–0.85)
Local dynamic stability Ros. VT	**0.77 (0.09–0.93)**	0.48 (−0.06–0.78)	0.35 (−0.10–0.73)
Local dynamic stability Ros. ML	**0.81 (0.54–0.93)**	0.47 (−0.05–0.77)	0.54 (0.13–0.79)
Local dynamic stability Ros. AP	0.42 (−0.01–0.71)	0.50 (0.12–0.76)	0.51 (0.13–0.77)
Local dynamic stability Wolf VT/stride	**0.87 (0.44–0.96)**	**0.81 (0.57–0.92)**	**0.72 (0.03–0.91)**
Local dynamic stability Wolf ML/stride	**0.88 (0.69–0.95)**	**0.76 (0.49–0.89)**	**0.75 (0.47–0.89)**
Local dynamic stability Wolf AP/stride	**0.71 (0.37–0.88)**	**0.71 (0.40–0.88)**	0.62 (−0.07–0.88)
Local dynamic stability Ros. VT/stride	**0.83 (0.18–0.95)**	0.60 (0.00–0.85)	0.47 (−0.10–0.81)
Local dynamic stability Ros. ML/stride	**0.87 (0.65–0.95)**	0.51 (−0.04–0.79)	0.60 (0.19–0.82)
Local dynamic stability Ros. AP/stride	0.62 (0.15–0.84)	0.66 (0.34–0.85)	0.66 (0.35–0.85)

and, for Rosenstein's method, using the first 0.6 s of the divergence curve to determine its slope.

Local dynamic stability per stride was estimated as the local dynamic stability divided by the stride frequency. This characteristic was included because of the recent discussion on normalization of local dynamic stability to stride time [26,27].

2.3.3. Statistics

Group means and standard deviations of the 35 gait characteristics were estimated for each of the three sensor locations over the estimates obtained for each of the 21 participants. For each pair of sensor locations, the between-sensor-locations agreement was quantified as the intra-class correlation absolute agreement (2, 1 [28]; ICC). Agreements were considered excellent, good, moderate and poor when the ICC values were above 0.9, between 0.7 and 0.9, between 0.5 and 0.7, and below 0.5, respectively. These limits were inspired by the limits advised for group comparisons (0.7) and for individual comparisons (0.9–0.95) [29].

3. Results

For reference, Table 1 shows the means and standard deviations of the estimated gait characteristics.

Most of the characteristics (26 out of 35) showed good to excellent agreement between sensor locations L5 and L2 after realignment of the sensor data (Table 2). As regards the agreement with the ASIS location, the results were mixed with 18 of the 35 characteristics showing good or excellent agreement for L5 with ASIS and 14 of the 35 characteristics showing good to excellent agreement for L2 with ASIS. Some of the common gait parameters showed excellent (stride time, stride frequency, gait speed and their variability) or good (stride regularity) agreement between all sensor locations. Other characteristics displayed good agreement between locations L5 and L2, but poor (gait smoothness) or mixed (local dynamic stability) agreement between L2 and ASIS or L5 and ASIS. Movement intensity had excellent agreement for the VT direction, but moderate agreement for the ML and AP directions. The negative exceptions were the low-frequency percentage and gait symmetry, with poor to moderate agreement for most comparisons.

Table 3 shows the effect of the data realignment performed in the pre-processing step on the between-location agreement. Generally, there was a positive effect on the agreement between the L5 and L2 locations, i.e. ICC values for the realigned data were higher than for the raw, unaligned data. However, for the agreement of either lumbar location with the ASIS location, the effects on the ICCs varied between characteristics and directions, ranging from −0.28 to +0.61.

Table 3
Effect of realignment on between-location ICCs. Values displayed are the ICC with realignment applied minus the ICC without realignment applied. Positive effects of realignment are printed in bold face and negative effects are underlined. Effects between −0.02 and +0.02 are faded.

Sensors	L5-L2	L5-ASIS	L2-ASIS
Gait speed	**0.1**	**0.07**	−0.01
Speed variability	**0.16**	**0.07**	0.01
Stride time	0	0	0
Stride time variability	**0.08**	**0.07**	**0.04**
Stride frequency	0	0	0
Stride frequency variability VT	0.01	0	0
Stride frequency variability ML	**0.05**	**0.29**	**0.2**
Stride frequency variability AP	0.01	0	0
Stride regularity VT	0.02	**0.05**	0.01
Stride regularity ML	0.01	**0.22**	**0.18**
Stride regularity AP	**0.13**	**0.13**	**0.03**
Movement intensity VT	**0.04**	**0.03**	0.01
Movement intensity ML	**0.03**	−<u>0.12</u>	**0.23**
Movement intensity AP	**0.07**	**0.12**	−<u>0.17</u>
Low-frequency percentage VT	**0.57**	**0.21**	**0.61**
Low-frequency percentage ML	0.02	**0.11**	**0.27**
Low-frequency percentage AP	**0.09**	**0.26**	**0.22**
Gait smoothness VT	**0.24**	**0.11**	−<u>0.07</u>
Gait smoothness ML	**0.09**	**0.06**	0.02
Gait smoothness AP	**0.54**	**0.5**	**0.32**
Gait symmetry VT	**0.1**	−0.02	0.01
Gait symmetry ML	**0.1**	**0.14**	**0.1**
Gait symmetry AP	**0.15**	**0.03**	**0.1**
Local dynamic stability Wolf VT	0.01	−0.01	0.02
Local dynamic stability Wolf ML	−<u>0.03</u>	**0.14**	0.09
Local dynamic stability Wolf AP	−<u>0.03</u>	**0.06**	−<u>0.04</u>
Local dynamic stability Ros. VT	**0.1**	−0.01	**0.03**
Local dynamic stability Ros. ML	**0.03**	−<u>0.28</u>	−<u>0.12</u>
Local dynamic stability Ros. AP	**0.23**	**0.16**	−<u>0.05</u>
Local dynamic stability Wolf VT/stride	0.01	−0.02	0.02
Local dynamic stability Wolf ML/stride	−<u>0.03</u>	**0.14**	**0.1**
Local dynamic stability Wolf AP/stride	−<u>0.02</u>	**0.04**	−<u>0.04</u>
Local dynamic stability Ros. VT/stride	**0.08**	−0.02	**0.04**
Local dynamic stability Ros. ML/stride	**0.03**	−<u>0.27</u>	−<u>0.13</u>
Local dynamic stability Ros. AP/stride	**0.24**	**0.18**	−0.01

4. Discussion

We investigated the effect of accelerometer sensor location on estimates of various gait characteristics. Values obtained from the two locations on the back of the trunk, L5 at 'belt height' and L2 at 'waist height', showed good or excellent agreement for 26 of the 35 characteristics. When comparing L2 or L5 with ASIS, however, estimates appeared less consistent: while basic characteristics like stride time, stride frequency, gait speed and the corresponding variability showed good or excellent agreement, more 'complex' characteristics like symmetry, smoothness and local dynamic stability in most cases had moderate to poor agreement, which is partly caused by systematic differences (see Table 1). In consequence, estimates of gait characteristics from accelerometer data can be considered robust against sensor mis- or replacement at the mid to lower back, provided that the sensor is (kept) placed in the midline.

By and large, consistency between estimates for the sensors that were placed at L2 or L5 had improved by application of the new realignment method. However, this was not the case for the consistency between the estimates based on the ASIS data and those from L2 or L5. These results imply that sensor realignment is beneficial for sensors positioned in the lumbar region, but not necessarily for other regions.

Several of our characteristics were estimated per direction. This called for our off-line sensor realignment, which, admittedly, is only one specific way to correct for possible orientation errors. Alternatively one may opt for measures that are by definition invariant against sensor orientation. We followed this idea by formulating nine orientation-independent values for the corresponding characteristics. These orientation-independent values were determined by applying the algorithm for a characteristic to the length of the three-dimensional acceleration vector or to the sum of the three variances, autocorrelations or power spectra, instead of applying it to the acceleration, variance, autocorrelation or power spectrum from a single dimension. The orientation-independent estimates did not agree consistently better or worse than the averages for the realigned estimates per direction. However, the orientation-independent estimates of stride regularity and local dynamic stability (per stride) with Wolf's method had a better agreement than any of their corresponding direction-dependent estimates, which suggests that the use of this approach is beneficial specifically for these nonlinear characteristics.

If a sensor is worn on the back with a band around the waist in daily life measurement settings, there is a possibility that the sensor moves along or around the vertical body axis. The orientation parameters determined in the realignment step might be useful to identify or even exclude measurements in which large sensor location deviations occur, especially for lateral deviations. Assuming that the more lateral the sensor is located, the more the medio-lateral axis of the sensor will be rotated (yaw rotation), the identification of such measurements might be possible with a threshold based on the realignment parameters.

Although the inclusion of turns in our protocol is a first approximation of the variations that are present in daily life, we cannot be certain that our findings will hold in uncontrolled circumstances. Moreover, the population we tested consisted of young healthy adults, whereas measurement of daily life gait patterns might be opportune for other populations. A change in environment or population may affect our realignment procedure: the identification of the anterior–posterior and medio-lateral directions was driven by optimization of gait symmetry, but in daily life and in older or patient populations, gait may be expected to be less symmetric and have a lower harmonic ratio [30] than in our data. Our protocol should thus be seen as a first but good approximation which yields a welcome improvement of the reliability of gait characteristics' estimates. Even if a less symmetric gait would bias the orientation estimates, the resulting realigned signal can be expected to be independent of sensor orientation. This does improve reproducibility of results. However, a complete assessment of the effect of a less symmetric gait on the orientation estimates requires further investigation.

5. Conclusion

Gait characteristics estimated from simultaneous measurements of three-dimensional accelerations at three trunk locations (L5, L2 and ASIS) were compared. Consistency in stride time, stride frequency, gait speed and their corresponding variability was excellent (most ICC > 0.9). Movement intensity, gait smoothness, gait symmetry and local dynamic stability showed good agreement (most ICC > 0.7) between L5 and L2 but not between ASIS and L5 or L2. We introduced a novel approach to realign measurements in order to correct for sensor orientation errors. This realignment improves the agreement between the estimations from locations on the back, and is therefore recommended when data are collected without precisely controlled location and orientation, as is typically the case in daily life recordings. Our results indicate that estimation of gait characteristics is robust against location differences within the lumbar region, allowing for reliable estimates of gait characteristics in daily life studies.

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Appendix A. Off-line sensor realignment

After data recording the orientation of the sensor with respect to VT, ML and AP axes was estimated. The VT direction was, as in the method of Moe-Nilssen [17], determined as the direction of the average acceleration. Here, we assumed that the average acceleration with respect to the ground is in general negligible and that the mean acceleration recorded thus opposes gravitation. We extended this method with the estimation of the ML and AP directions by maximizing the product of their harmonic ratios (gait symmetry [21]) in the two-dimensional horizontal plane perpendicular to the (pre-) determined VT direction. Consider the case in which a sensor is placed in a medial position and symmetric gait is produced. Then the recorded accelerations of a left step would be identical to that of a right step in the sagittal plane and thus the AP axis, but opposite in the ML axis. This becomes manifest in a power spectrum as peaks at even harmonics of the stride frequency for AP accelerations, but at odd harmonics of the stride frequency for ML accelerations. The symmetry of gait can thus be estimated by the harmonic ratio, i.e. the summed amplitude in the even harmonics divided by the summed power in odd harmonics for the AP axis, and the inverse for the ML axis. If, due to error in the orientation of the sensor, the sensor AP and ML axes contained part of the anatomical ML and AP axes signal, respectively, we expect the harmonic ratios to decrease: left and right steps in the signal of the sensor AP axis would no longer be identical but would contain a partly opposite signal from the anatomical ML axis, and left and right steps in the signal of the sensor ML axis would no longer be opposite but contain a partly identical signal from the anatomical ML axis. We estimated the orientation of the anatomical AP and ML axes such that the product of their harmonic ratios was maximal, provided that they were perpendicular to each other and to the VT axis. Harmonic ratios for AP and ML directions were estimated as [18]

$$\mathrm{HR_{AP}} = \frac{\sum_{i=1}^{10} P_{\mathrm{AP}}(f_{\mathrm{STR}} \times 2i)}{\sum_{i=1}^{10} P_{\mathrm{AP}}(f_{\mathrm{STR}} \times (2i-1))}$$

$$\mathrm{HR_{ML}} = \frac{\sum_{i=1}^{10} P_{\mathrm{ML}}(f_{\mathrm{STR}} \times (2i-1))}{\sum_{i=1}^{10} P_{\mathrm{ML}}(f_{\mathrm{STR}} \times 2i)}$$

where f_{STR} is the stride frequency, and $P_{\mathrm{AP}}(f)$ and $O_{\mathrm{ML}}(f)$ are the amplitude spectra for AP and ML acceleration signals, respectively.

Appendix B. Stride frequency variability

Given a direction's acceleration signal and an average stride frequency, the stride frequency variability was estimated as the relative fluctuations in phase progression. To determine this 'phase progression' we first subsequently applied a band-pass filter around every harmonic with a width of two-thirds of the stride frequency. The filtered signal contains mainly the selected harmonic. Using the filtered signal's Hilbert transform one can construct the so-called analytic signal, from which we use the instantaneous phase, which is a steadily increasing signal. Phase progression is then defined as the difference between the phases at times t and $t + 1/f_{\mathrm{STR}}$, where f_{STR} is the stride frequency. Dividing the standard deviation of the phase progression by the harmonic number gives us an estimation of relative fluctuations in phase progression. Stride frequency variability is finally estimated as the average of the relative fluctuations in phase progression. The average is taken over the harmonics, weighted by the harmonics' power.

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