Adaptive Method for Detecting Zero-Velocity Regions to Quantify Stride-to-Stride Spatial Gait Parameters using Inertial Sensors

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Abstract: We present a new adaptive method that robustly detects zero-velocity regions to accurately and precisely quantify (1) individual stride lengths (SLs), (2) individual stride velocities (SVs), (3) the average of SL, (4) the average of SV, and (5) the cadence during slow, normal, and fast overground walking conditions in young and healthy people. The measurements involved in the estimation of these spatial gait parameters are obtained using only one inertial measurement unit attached on a regular shoe at the level of the heel. This adaptive method reduced the integration drifts across consecutive strides and improved the accuracy and precision in the spatial gait parameter estimation. The validation of the proposed algorithm has been carried out using reference spatial gait parameters obtained from a kinematic reference system. The accuracy ± precision results were for SLs: 0.0 ± 4.7 cm, −0.7 ± 4.4 cm, and −5.8 ± 5.8 cm, during slow, normal, and fast walking conditions, respectively, corresponding to −0.1 ± 4.2 %, −0.5 ± 3.2 %, and −3.3 ± 3.0 % of the respective mean SL. The accuracy ± precision results were for SVs: 0.0 ± 2.9 cm/s, −0.7 ± 3.8 cm/s, and −6.7 ± 6.7 cm/s, during slow, normal, and fast walking conditions, respectively, corresponding to −0.6 ± 3.3 %, −0.1 ± 4.5 %, and −3.5 ± 3.1 % of the respective mean SV. These validation results show a good agreement between the proposed method and the reference, and demonstrate a fairly accurate and precise estimation of these spatial gait parameters. The proposed method paves the way for an objective quantification of spatial gait parameters in routine clinical practice.

1 INTRODUCTION

Stride length (SL) and stride velocity (SV) are gait parameters of importance in multiple health-related applications. For example, reduced gait speed in the early stage of Parkinson's disease is primarily related to reduced SL (e.g., Morris et al., 1996; Hausdorff; 2009); SL estimation could thus help neurologists in the early diagnosis of this disease. Conventional gait analysis techniques, such as optoelectronic motion capture systems, are often used as gold standards to quantify such spatial gait parameters with high accuracy (e.g., Woltring, et al., 1980; Schwartz et al., 2015). Nevertheless, these systems are often expensive and can only be used in a controlled laboratory environment, which hinders their widespread use. Besides, systems based on inertial measurement units (IMUs) including miniaturized inertial sensors such as accelerometers and gyroscopes are becoming a reliable solution to handle the extraction of relevant gait features outside the laboratory environment (e.g., Aminian, et al. 2002; Del Din et al., 2016; Song et al., 2018).

In this context, we have previously developed a signal-processing algorithm to automatically extract stride-to-stride temporal gait parameters and sub-phase durations of a single stride. This algorithm was based on accelerometer signals recorded at the level of the heel and toe of the left/right foot during the overground walking of young and healthy subjects and older people (Boutaayamou et al., 2015; Boutaayamou et al., 2018).

In this work, we extend this extraction algorithm to include the estimation of spatial gait parameters,

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such as SL and SV. In order to minimize the integration drifts across consecutive strides and to improve the accuracy and precision in the estimation of these spatial gait parameters, we present a new adaptive method that robustly detects zero-velocity update regions to further apply adequate initial conditions in the integration of considered quantities. In this work, we use this adaptive method to quantify (1) individual SLs, (2) individual SVs, (3) the average of SL, (4) the average of SV, and (5) the cadence during slow, normal, and fast overground walking conditions. The measurements involved in the estimation of these spatial gait parameters are obtained using only one IMU attached on a regular shoe at the level of the heel. In addition, we consider a concurrent, stride-to-stride, validation of the proposed method/algorithm in young and healthy people. In this validation, we compare the results to reference spatial gait parameters (time-synchronously) provided by a kinematic 3D system.

2 METHOD

2.1 Participants and Overground Walking Setting

Three healthy young volunteers without any known gait and lower limb pathology (one woman and two men; mean (min–max) age = 26 years (24–27 years); mean height = 1.79 m; mean weight = 74 kg) participated in the walking experiments. Each of them was equipped with a newly developed stand-alone IMU-based hardware system. This system integrated memory, microcontroller, battery, and four small IMU modules (2 cm × 0.7 cm × 0.5 cm) including three-axis gyroscopes (range: 2000 degree/second) and three-axis accelerometers (range: ±16 g). This IMU-based system can measure accelerations denoted by a_x, a_y, and a_z, and angular velocity signals denoted by ω_x, ω_y, and ω_z along IMUs' sensitive axes as schematically illustrated in Figure 1.

The participants wore their own regular shoes. Four IMUs were directly attached to the heel and toe of each shoe. Gait data were synchronously recorded at 200 Hz from these four IMUs. The participants were also equipped with four active markers. Each marker was attached on each IMU, i.e., the four markers were also attached to the shoes at the level of the heel and toe. A four-camera Codamotion system (Charnwood Dynamics; UK) recorded gait data from these active markers at 200 Hz. In this work, we quantify SLs, SVs, and the cadence – for each foot – from only the heel IMU measurements.

Before starting the measurements, volunteers took sufficient time to get used to the instrumentation tools and to the experimental procedure. During the tests, they were asked to walk back and forth on a 10-meter long track in a wide, clear, and straight hallway, at their slow, normal, and fast speeds. Each participant performed (in the following order) 5 slow, 5 normal, and 5 fast walking tests. The total number of recorded gait tests is then 45 tests. The duration of a single gait test was 60 s. All of the walking tests were performed at the Laboratory of Human Motion Analysis (LAMH) of the University of Liège, Belgium.

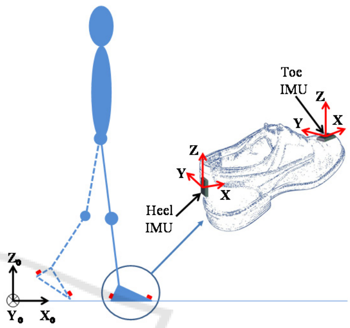

Figure 1: The newly developed stand-alone IMU-based hardware system is applied to left and right foot using four three-axis IMUs. The schematic illustration shows the position of the sensors, i.e., IMUs and the Codamotion active markers. Two of these sensors are attached to each shoe at the level of the heel and toe, respectively. The proposed algorithm quantifies SLs and SVs – for each foot – only from the heel IMU measurements.

2.2 Adaptive Method for Detecting Zero-Velocity Update Regions

The proposed extraction algorithm relies on the assumption of foot movements in sagittal plane. In order to accurately and precisely quantify individual SLs and SVs during overground slow, normal, and fast walking, it is important to robustly detect zero-velocity update regions to further determine suitable initial conditions to be used in integration steps of considered quantities. The principal originality of this algorithm is the use of an adaptive method to robustly detect these zero-velocity update regions without the need of empirical threshold values.

To reduce the number of sensors, we consider hereafter only heel IMU measurements in the sagittal plane. For clarity, we consider only one foot for the description of the algorithm. The algorithm would be applied in the same way for the left and right foot.

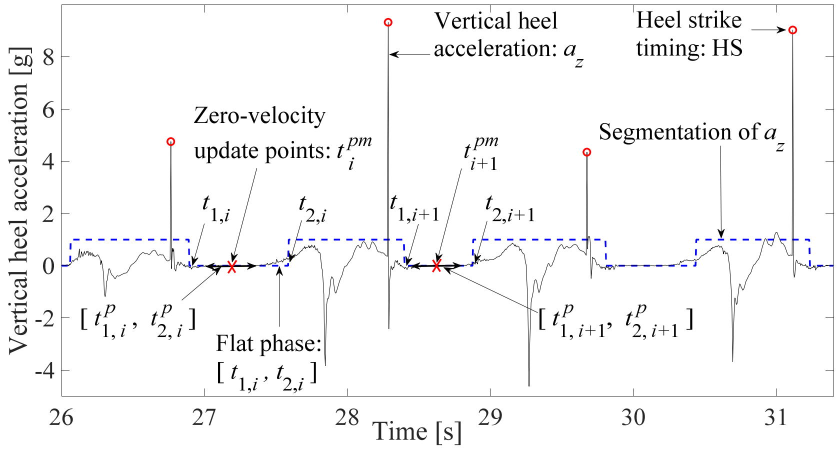

Figure 2: The proposed adaptive method is applied to the vertical heel acceleration and automatically detects set of points t_i^{pm} that are candidates to be zero-velocity points where initial conditions are updated for each stride i and for each partition p.

All measured heel accelerations and angular velocities are defined in the reference frame of the heel IMU denoted by XYZ as illustrated in Figure 1. We apply the proposed adaptive method to the vertical heel acceleration signal to further estimate SLs, SVs, and the cadence.

We first use our previously developed segmentation method to parse heel acceleration data into flat (motionless periods) and non-flat phases (Boutaayamou et al., 2015). This segmentation method has the advantage that it only determines rough heel flat/non-flat phases and avoids to look directly for specific gait events. Moreover, we identify the heel strike (HS) timings adopting the method from (Boutaayamou et al., 2015). We denote time intervals corresponding to these flat phases by $[t_{1,i}, t_{2,i}]$ during each stride i. Time intervals $[t_{1,i}, t_{2,i}]$ refer to the zero-velocity update regions.

For each interval $[t_{1,i}, t_{2,i}]$ having a length greater than 20 samples, we consider partitions p of $[t_{1,i}, t_{2,i}]$ into segments $[t_{1,i}^p, t_{2,i}^p]$ of a length varying from 10 samples to the length of $[t_{1,i}, t_{2,i}]$, with an overlap of 5 samples (see Figure 2). Given the sampling frequency of 200 Hz, a sample corresponds here to 5 milliseconds. For a given partition p, we calculate the variance of the vertical heel acceleration signal in all associated segments and determine the segment having the minimum variance value, denoted by $[t_{1,i}^{pm}, t_{2,i}^{pm}]$. The midpoint of $[t_{1,i}^{pm}, t_{2,i}^{pm}]$ is denoted by t_i^{pm}.

Considering a given $[t_{1,i}, t_{2,i}]$ – having a length greater than 20 samples – for stride i, we emphasize that we obtain a set of points t_i^{pm} that are candidates to be zero-velocity update points and not just one zero-velocity update point as reported in the literature (e.g., Mariani et al., 2010; Rebula et al., 2013). Initial conditions are then updated at these points t_i^{pm} for each stride i and for each partition p.

For each interval $[t_{1,i}, t_{2,i}]$ having a length strictly less than 20 samples, we consider the midpoint of $[t_{1,i}, t_{2,i}]$ as a zero-velocity update point to be added to the list of points t_i^{pm}.

The extraction algorithm relies on successive integrations in intervals $[t_i^{pm}, t_{i+1}^{pm}]$. For each stride i and for each partition p, we estimate the inclination of the foot in the sagittal plane, θ_i^p, by integrating the angular velocity in y-axis ω_y (i.e., the yaw) in the time interval $[t_i^{pm}, t_{i+1}^{pm}]$. The drift of this integration is modeled as a straight line between t_i^{pm} and t_{i+1}^{pm}, and is subtracted from θ_i^p to minimize this drift and to ensure the initial conditions of this integration: $\theta_i^p(t_i^{pm}) = \theta_{0,i}^p$ and $\theta_i^p(t_{i+1}^{pm}) = \theta_{0,i+1}^p$. Initial conditions $\theta_{0,i}^p$ and $\theta_{0,i+1}^p$ correspond to the inclination of the foot during the flat phases $[t_{1,i}^{pm}, t_{2,i}^{pm}]$ and $[t_{1,i+1}^{pm}, t_{2,i+1}^{pm}]$, respectively. We use the accelerometer as an inclinometer in these flat phases to determine $\theta_{0,i}^p$ as the mean value of $\tan^{-1}(a_x/a_z)$ in $[t_{1,i}^{pm}, t_{2,i}^{pm}]$, and $\theta_{0,i+1}^p$ as the mean value of $\tan^{-1}(a_x/a_z)$ in $[t_{1,i+1}^{pm}, t_{2,i+1}^{pm}]$.

This is followed by a projection of the acceleration on the horizontal axis of the lab reference frame, $A_x = \mathrm{a_x}\cos(\theta_i^p) + \mathrm{a_z}\sin(\theta_i^p)$. We obtain the horizontal velocity V_x by integrating A_x in $[t_i^{pm}, t_{i+1}^{pm}]$. Again, the drift of this integration is modeled as a straight line between t_i^{pm} and t_{i+1}^{pm}, and is subtracted from V_x to minimize this drift and to ensure the initial conditions of this integration: $V_x(t_i^{pm}) = 0$ m/s and $V_x(t_{i+1}^{pm}) = 0$ m/s for each i

Table 1: Mean and standard deviation (STD) of SLs, SVs, and cadence for each volunteer during slow (S), normal (N), and fast (F) walking speed conditions with the associated mean, STD, minimum (Min) and maximum (Max) values of the flat phase length (corresponding to the number of samples of 5 milliseconds).

		SL (cm)	SV (m/s)	Cadence	Flat phase length	
		Mean (*STD*)	*Mean* (*STD*)		*Mean* (*STD*)	*Min – Max*
Volunteer 1	S	105.7 (8.3)	0.675 (0.069)	0.64	47 (10)	30 – 94
	N	118.8 (7.4)	0.906 (0.054)	0.76	34 (10)	21 – 72
	F	144.8 (7.2)	1.357 (0.078)	0.94	23 (6)	14 – 59
Volunteer 2	S	119.4 (7.1)	0.731 (0.045)	0.61	52 (9)	32 – 84
	N	161.0 (7.1)	1.402 (0.073)	0.87	21 (7)	13 – 44
	F	201.2 (7.7)	2.252 (0.103)	1.12	12 (2)	6 – 24
Volunteer 3	S	106.6 (11.7)	0.618 (0.138)	0.58	58 (19)	12 – 105
	N	141.3 (5.2)	1.210 (0.069)	0.86	37 (6)	13 – 80
	F	186.9 (7.9)	2.725 (0.188)	1.46	9 (2)	4 – 16

and p. The horizontal position of the heel, X, is obtained by integrating V_x in $[t_i^{pm}, t_{i+1}^{pm}]$, for each i and p.

Finally, the stride length value of each stride i, SL_i, is obtained by averaging all $X(t_{i+1}^{pm})$ found for p. For each stride i, the stride velocity SV_i is calculated as $SL_i/(HS_{i+1} - HS_i)$. The average values of SL and SV are thus estimated as the mean of SL_i and SV_i, respectively. Moreover, the cadence is calculated as the average of $1/(HS_{i+1} - HS_i)$; this average corresponds to the average number of strides performed during one second.

2.3 Concurrent Validation and Evaluation Methods

We extracted reference spatial gait parameters from the kinematic 3D Codamotion system to validate concurrently, stride-to-stride, those extracted using our algorithm, namely: (1) individual SLs, (2) individual SVs, (3) the average of SL, (4) the average of SV, and (5) the cadence.

Prior calculating these reference parameters, we extracted reference HSs from measured heel coordinates using the kinematic method reported in (Boutaayamou et al., 2014). We extracted then reference individual SLs from the horizontal heel position signal. For each stride i, reference individual SVs are determined as $SL_i/(HS_{i+1} - HS_i)$. Reference average values of SL and SV are thus estimated as the mean of SL_i and SV_i, respectively. Reference cadence is calculated as the average of $1/(HS_{i+1} - HS_i)$.

We evaluated the level of agreement between our method and the reference method in the extraction of spatial gait parameters by quantifying

- The mean and standard deviation (STD) of differences and relative differences,
- The mean and STD of absolute differences and relative absolute differences,
- The root-mean-square (RMS) of differences and relative differences,

for (1) individual SLs, (2) individual SVs, (3) averages of SL, (4) averages of SV, and (5) the cadence. The extraction accuracy and precision are given by the mean and STD of differences, respectively.

3 RESULTS

In this work, we focused on the results of gait tests performed at speeds less than 11 km/h. We thus excluded the last four fast walking tests of volunteer 3 who walked at speeds ranging from 11.262 to 12.475 km/h.

A total of 551 gait cycles/strides – performed at speeds less than 11 km/h – have been synchronously recorded by both IMU-based system and reference system. These strides have been obtained during slow, normal, and fast walking conditions in young and healthy volunteers with:

- Mean (STD) of SL = 110.8 cm (6.0 cm), mean (STD) of SV = 0.675 m/s (0.051 m/s), and cadence = 0.61 strides/s in slow walking condition (n = 172 strides),

Table 2: Concurrent, stride-to-stride, validation results of the quantification of individual SLs and SVs, and averages of SL and SV using our method (IMU) and the reference method (Ref) during slow (S), normal (N), fast (F) walking speed conditions in young and healthy volunteers. These results are given as mean and standard deviation (STD) of differences and relative differences, mean and STD of absolute differences (Abs) and relative absolute differences, and root-mean-square (RMS) of differences and relative differences.

		Individual SLs and SVs[(a)]						Averages of SL and SV[(b)]					
		Differences[(c)]: SL (cm); SV(cm/s)			Relative differences[(c)] (%)			Differences: SL (cm); SV(cm/s)			Relative differences (%)		
		Mean (STD)	*Abs (STD)*	*RMS*	*Mean (STD)*	*Abs (STD)*	*RMS*	*Mean (STD)*	*Abs (STD)*	*RMS*	*Mean (STD)*	*Abs (STD)*	*RMS*
SL	S	0.0 (4.7)	3.7 (2.8)	4.6	−0.1 (4.2)	3.4 (2.6)	4.2	−0.1 (2.3)	1.9 (1.3)	2.2	−0.1 (2.0)	1.7 (1.1)	2.0
	N	−0.7 (4.4)	3.5 (2.7)	4.4	−0.5 (3.2)	2.5 (2.1)	3.3	−0.7 (1.2)	1.0 (0.9)	1.3	−0.5 (0.8)	0.7 (0.6)	0.9
	F	−5.8 (5.8)	6.8 (4.6)	8.2	−3.3 (3.0)	3.8 (2.3)	4.4	−5.6 (1.4)	5.6 (1.4)	5.8	−3.2 (0.9)	3.2 (0.9)	3.3
SV	S	0.0 (2.9)	2.3 (1.8)	2.9	−0.1 (4.5)	3.5 (2.8)	4.4	0.0 (1.3)	1.1 (0.7)	1.3	−0.1 (2.0)	1.6 (1.1)	1.9
	N	−0.7 (3.8)	3.0 (2.4)	3.8	−0.6 (3.3)	2.6 (2.2)	3.4	−0.7 (0.9)	0.9 (0.7)	1.1	−0.6 (0.8)	0.7 (0.6)	0.9
	F	−6.7 (6.7)	7.7 (5.4)	9.4	−3.5 (3.1)	4.0 (2.4)	4.7	−6.4 (1.8)	6.4 (1.8)	6.7	−3.4 (1.0)	3.4 (1.0)	3.5

[(a)] Total number of individual strides = 551, with n=172, 193, and 186 strides, for S, N, and F, respectively.

[(b)] Total number of gait tests = 41, with n=15, 15, and 11 averages, for S, N, and F, respectively.

[(c)] The differences and relative differences are defined here as IMU−Ref and 100 × (IMU−Ref)/Ref, respectively.

Table 3: Results of the comparison between global average values (STD) of SL and SV, and the cadence obtained by our IMU-based system and those obtained by the reference system.

		IMU-based system	Reference system	Mean differences	Mean relative absolute differences (%)
SL (cm)	S	110.7 (7.4)	110.8 (6.0)	−0.1	0.05
	N	140.3 (17.9)	140.9 (17.7)	−0.7	0.46
	F	174.2 (29.0)	179.8 (29.2)	−5.6	3.12
SV (m/s)	S	0.675 (0.061)	0.675 (0.051)	0.000	0.02
	N	1.172 (0.213)	1.179 (0.212)	−0.007	0.57
	F	1.886 (0.533)	1.950 (0.543)	−0.064	3.30
Cadence (strides/s)	S	0.61 (0.04)	0.61 (0.04)	−0.001	0.09
	N	0.83 (0.05)	0.83 (0.05)	−0.001	0.13
	F	1.07 (0.16)	1.07 (0.16)	−0.002	0.22

- Mean (STD) of SL = 140.9 cm (17.7 cm), mean (STD) of SV = 1.179 cm/s (0.212 cm/s), and cadence = 0.83 strides/s in normal walking condition (n = 193 strides),
- Mean (STD) of SL = 179.8 cm (29.2 cm), mean (STD) of SV = 1.950 cm/s (0.543 cm/s), and cadence = 1.07 strides/s in fast walking condition (n = 186 strides).

Table 1 provides spatial gait parameter values for each volunteers, with the associated values of the flat phase length during these three walking speed conditions. A flat phase length corresponds to the number of samples of 5 milliseconds.

Tables 2 shows the concurrent, stride-to-stride, validation results of the extraction of individual SLs and SVs during these three walking speed conditions. These results correspond to the application of the proposed adaptive zero-velocity update region method to the vertical heel acceleration signal.

The accuracy (precision) of the extraction of individual SLs was 0.0 cm (4.7 cm), −0.7 cm (4.4 cm), and −5.8 cm (5.8 cm) during slow, normal, and fats walking condition, respectively, corresponding to −0.1 % (4.2 %), −0.5 % (3.2 %), and −3.3 % (3.0 %) of the respective mean SL.

The accuracy (precision) of the extraction of individual SVs was 0.0 cm/s (2.9 cm/s), −0.7 cm/s (3.8 cm/s), and −6.7 cm/s (6.7 cm/s) during slow, normal, and fats walking condition, respectively, corresponding to −0.1 % (4.5 %), −0.6 % (3.3 %), and −3.5 % (3.1 %) of the respective mean SV.

Moreover, individual SLs could be quantified with a mean (STD) of absolute differences of 3.7 cm (2.8 cm), 3.5 cm (2.7 cm), and 6.8 cm (4.6 cm) for slow, normal, and fast walking conditions, respectively, corresponding to 3.4 % (2.6 %), 2.5 % (2.1 %), and 3.8 % (2.3 %) of the respective mean SL.

Individual SVs could be also quantified with a mean (STD) of absolute differences of 2.3 cm/s (1.8 cm/s), 3.0 cm/s (2.4 cm/s), and 7.7 cm/s (5.4 cm/s) for slow, normal, and fast walking conditions, respectively, corresponding to 3.5 % (2.8 %), 2.6 % (2.2 %), and 4.0 % (2.4 %) of the respective mean SV.

RMS differences between SLs quantified by both MU-based system and reference system were 4.6 cm, 4.4 cm, and 8.2 cm for slow, normal, and fast walking conditions, respectively, corresponding to 4.2 %, 3.3 %, and 4.4 % of the respective mean SL.

RMS differences between SVs quantified by both MU-based system and reference system were 2.9 cm/s, 3.8 cm/s, and 9.4 cm/s for slow, normal, and fast walking conditions, respectively, corresponding to 4.4 %, 3.4 %, and 4.7 % of the respective mean SV.

Table 2 provides also quantitative values of the averages of SL and SV obtained for the 41 gait tests including 15, 15, and 11 tests in slow, normal, and fast walking conditions, respectively. As mentioned above, we emphasize that we considered the results of 11 fast walking tests instead of 15 ones since we excluded four gait tests performed – by volunteer 3 – at speeds greater than 11 km/h; such walking speeds are not the focus of this work.

Tables 3 shows the validation results of the quantification of global average values of SL and SV, and the cadence during the three walking speed conditions in young and healthy volunteers. We quantified the average value of SL with a mean of differences (mean of relative absolute differences) of −0.1 cm (0.05 %), −0.7 cm (0.46 %), and −5.6 cm (3.12 %) for slow, normal, and fast walking conditions, respectively. We quantified also the average value of SV with a mean of differences (mean of relative absolute differences) of 0.000 m/s (0.02 %), −0.007 m/s (0.57 %), and −0.064 m/s (3.30 %) for slow, normal, and fast walking conditions, respectively. In addition, we quantified the cadence with a mean of differences (mean of relative absolute differences) of −0.001 strides/s (0.09 %), −0.001 strides/s (0.13 %), and −0.002 strides/s (0.22 %) for slow, normal, and fast walking conditions, respectively.

4 DISCUSSION

We have presented a new adaptive method that robustly detects zero-velocity update regions for accurately and precisely quantifying (1) individual SLs, (2) individual SVs, (3) the average of SL, (4) the average of SV, and (5) the cadence during slow, normal, and fast overground walking conditions in young and healthy people. Data involved in this quantification are the measurements obtained with only one IMU attached on a regular shoe at the level of the heel. This adaptive method aimed to reduce the integration drifts across consecutive strides and to improve the accuracy and precision in the spatial gait parameter estimation.

A concurrent, stride-to-stride, validation of the proposed algorithm has been carried out using reference spatial gait parameters obtained from a kinematic reference system (used as gold standard). The experimental results show a good agreement between our algorithm and the reference, and demonstrate a fairly accurate and precise quantification of the spatial gait parameters.

The detection accuracy ± precision of individual SLs using the present algorithm ranged from −0.7 ± 4.4 cm to 0.0 ± 4.7 cm for walking speeds ranging from 2.43 ± 0.25 km/h to 5.05 ± 0.26 km/h, corresponding to a range of −0.5 ± 3.2 % to −0.1 ± 4.2 % of the respective mean SL. Moreover, we quantified individual SLs with an accuracy ± precision of −5.8 ± 5.8 cm for walking speeds ranging from 4.88 ± 0.28 km/h to 9.81 ± 0.68 km/h.

In addition, the detection accuracy± precision of individual SVs using the present algorithm ranged from −0.7 ± 3.8 cm/s to 0.0 ± 2.9 cm/s for walking speeds ranging from 2.43 ± 0.25 km/h to 5.05 ± 0.26 km/h, corresponding to a range of −0.6 ± 3.3 % to −0.1 ± 4.5 % of the respective mean SV. Moreover, we quantified individual SVs with an accuracy± precision of −6.7 ± 6.7 cm/s for walking speeds ranging from 4.88 ± 0.28 km/h to 9.81 ± 0.68 km/h, corresponding to −3.5 ± 3.1 % of the respective mean SV.

We compared theses obtained results to previously published results for the estimation of SL and SV during each walking speed condition in young and healthy volunteers as follows:

- Slow walking speed: compared to RMS values reported in (Song et al., 2018) (i.e., 8.2 cm for SL, 5.9 cm/s for SV), the present method improves these values by approximatively a factor of 2 (i.e., 4.6 cm for SL, 2.9 cm/s for SV),
- Normal walking speed: compared to the results reported in (Mariani et al., 2010) (i.e., 2.4 ± 7.5 cm (2.1 ± 6.8%) for SL; 2.2 ± 6.2 cm/s (2.4 ± 6.1 %) for SV), in (Aminian et al., 2002) (i.e., RMS = 7.cm (7.2%) for SL and RMS = 6 cm/s (6.7 %) for SV), in (Rampp et al., 2015), the accuracy, precision and RMS are improved by the present method (i.e., −0.7 ± 4.4 cm (−0.5 ± 3.2%) and RMS = 4.4 cm (3.3 %) for SL; −0.7 ± 3.8 cm/s (−0.6 ± 3.3 %) and RMS = 3.8 cm/s (3.4 %) for SV).
- Fast walking speed: compared to RMS values reported in (Song et al., 2018) (i.e., 21.4 cm for SL and 12.9 cm/s for SV), the present method improves these values (i.e., 8.2 cm for SL and 9.4 cm/s for SV).

Compared to commercial trunk accelerometer systems (e.g., Auvinet et al., 1999), which only provide global gait features, the proposed system (hardware and algorithm) is capable to extract stride-to-stride spatial gait parameters. The stride-to-stride extraction may be a huge advantage in the gait analysis of some specific population such as Parkinson's disease patients who experience freezing of gait, a sudden and brief episodic alteration of strides regulation.

We emphasize that the proposed IMU-based hardware system can time-synchronously record signals from up to four IMU sensors. The proposed algorithm can thus quantify the left/right step length, the symmetry, and the regularity of the spatial gait parameters.

The proposed IMU-based system can measure spatial gait parameters in a very large number of strides without the need of controlled laboratory conditions. We believe that this novel IMU-based system offers perspectives for use in a routine clinical practice to deal with abnormal gait (e.g., gait of patients with Parkinson's disease).

5 CONCLUSION

We presented a new adaptive method that robustly detects zero-velocity regions for accurately and precisely quantifying (1) individual SLs, (2) individual SVs, (3) the average of SL, (4) the average of SV, and (5) the cadence during slow, normal, and fast overground walking conditions in young and healthy people. This method reduces the number of foot-mounted IMUs for estimating spatial gait parameters. The advantages of this method can be summarized as follows:

- Only two IMUs are required, i.e., one for each shoe at the level of the heel. This contributes to a simplification of the proposed wearable IMU-based system, thus resulting in reducing the costs and time needed to attach the system on the body.
- This method is concurrently validated for consecutive strides during slow, normal, and fast overground walking conditions. The validation used reference spatial gait parameters provided by a kinematic system (used as gold standard).
- Compared to previous studies, the proposed method improves the accuracy, precision and RMS of the estimation of SLs and SVs during slow, normal, and fast overground walking conditions in young and healthy people.

The proposed method paves the way for an objective quantification of spatial gait parameters in routine clinical practice. This opens new perspectives for use in clinical contexts to deal with abnormal gait (e.g., gait of patients with Parkinson's disease).

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