Step Detection and Parameterization for Gait Assessment Using a Single Waist-Worn Accelerometer

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***Abstract*—One of the major reasons why the elderly lose their ability to live independently at home is the decline in gait performance. A measure to assess gait performance using accelerometers is step counting. The main problem with most step detection algorithms is the loss of accuracy at low speeds (<0.8 m/s) which limits their use in frail elderly populations. In this paper, a step detection algorithm was developed and validated using data from 10 healthy adults and 21 institutionalized seniors, predominantly frail older adults. Data were recorded using a single waist-worn triaxial accelerometer as each of the subjects performed one 10 meter walk trial. The algorithm demonstrated high mean sensitivity (99±1%) for gait speeds between 0.2-1.5 m/s. False positives were evaluated with a series of motion activities performed by one subject. These activities simulate acceleration patterns similar to those generated near the body's center of mass while walking in terms of amplitud signal and periodicity. Cycling was the activity which led to a higher number of false positives. By applying template matching, we reduced by 73% the number of false positives in the cycling activity and eliminated all false positives in the rest of activities. Using K-means clustering, we obtained two different characteristic step patterns, one for normal and one for frail walking, where particular gait events related to limb impacts and muscle flexions were recognized. The proposed system can help to identify seniors at high risk of functional decline and monitor the progress of patients undergoing exercise therapy interventions.**

***Index Terms*—triaxial accelerometer, step detection, gait analysis, elderly people, body's center of mass**

TYPICALLY the elderly lose their ability to live independently because of decline in functional mobility, frailty, or dementia; and many require long-term care, which can include hospitalization, community care, and home nursing [1]. Consequences of age-associated functional decline represent a substantial socioeconomic hurdle for the community, especially in developed countries where the number of dependent older people is forecast to quadruple by 2050 [1].

Home-based programs targeting underlying impairments in functional mobility can reduce the progression of functional decline among the elderly [2]. A primary factor in evaluating functional mobility is the assessment of gait performance [3]. Main outcome measures of such an assessment include number of steps [4] and parameters derived from step detection, like cadence or step duration [5].

Among the existing technologies for gait analysis, triaxial accelerometers have been presented as a portable and reliable alternative [6]–[11]. They can be used in clinical settings and to record long-term acceleration data in free-living environments for higher ecological validity. Accelerometers are also useful to monitor patients in rehabilitation therapy [12] and as fall detectors [13]–[15].

However, the performance of accelerometry-based algorithms for step detection at low walking speeds is still deficient. This is a great limitation since the populations who could benefit most from step detection applications for medical diagnosis and monitoring of ambulatory ability are the frail elderly or patients with gait impairment walking at low speeds. In particular, in elderly persons with frailty syndrome usual gait speeds are $\leq$ 0.75-0.8 m/s [16], [17].

The only studies that used accelerometers for step detection and reported good results at low gait speeds (as low as 0.1 m/s), used multiple sensors or placed the sensor on the ankle [18]–[20]. Using multiple acceleration sensors allows complex activity detection, but it is highly likely that this will increase costs and will reduce wearer compliance. Placing accelerometers in multiple locations can become cumbersome for the wearer, especially in long-term monitoring applications. [21], [22]. With a single sensor, most studies adopt waist placement because of the limited obtrusiveness of the sensor and because the waist is close to the center of mass (CoM) of the human body, and so the accelerations measured at this location can better represent the major human motion [23]. Among studies using single waist-worn accelerometers [24]–[33], the results of the detection in frail elderly populations or for low gait speeds (<0.8 m/s) was considerably poor (minimum relative error = 19.1%) [32], [33]. Only one study [34] using data from older adults reported acceptable results for slow paces, with a mean absolute percentage error equal to 4.3±1.1%. However, the seniors who participated in this study where relatively young and authors did not provide numeric values for the walking speed.

In general, weaknesses found in previous studies comprise the following.

1) Inadequate database: Dijkstra [34], Marschollek [33] and Storti [32], included in their studies a reasonable minimum amount of data from elderly persons. The remaining authors, either only included a few young subjects in their studies [26], [27], [29]–[31] or a low number of gait-impaired patients [24], [25], [31].

2) Lack of information about detection accuracy: Zijlstra [27] was the only author who reported detailed information about the accuracy of the algorithm relative to different walking speeds but he restricted his study to healthy subjects.

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Although Marschollek et al. did not report information about walking speed, they shown results of the relative errors in the number of steps detected in elderly persons. The errors ranged from 28.1% to 62.1%, depending on the algorithm they used. The more customized the algorithms were to specific walking patterns, the worse they performed on different samples.

3) Inadequate validation method: With the exception of Dijkstra [34] and González [30], all authors used the same database as training and validation set, which may lead to an overestimation of algorithm accuracy, especially with small databases.

4) Inability of recognizing specific gait events: Only three authors [27], [28], [30] developed algorithms to recognize each heel strike and validated it by comparison with a reference value, in contrast to other authors who simply detected a series of maxima or minima in the acceleration signal without verifying to which gait event these peaks corresponded to.

The aim of this research is, by using a single waist-worn accelerometer – the actibelt®, to improve the step detection in elderly subjects walking at low speeds, and therefore at risk of functional decline. A further aim is to investigate the potential of such a device to assess gait ability in seniors based on differences between healthy and frail walking patterns.

I. Gait Analysis Principles

Walking is a complex task involving nervous, somatosensory and musculoskeletal systems. The contribution of each body segment is determined by gait speed. Normal walking speed primarily involves the lower extremities, with the arms and trunk providing stability and balance [35].

The gait cycle is comprised of a complete stride, or equivalently a sequence of two steps. A step is defined as the interval between two consecutive heel strikes and is the elementary periodic signal measurable with the accelerometer near the CoM during walking. A step is characterized by the following phases and events (Fig. 1).

a) Initial contact or heel strike: The initial contact (IC) occurs in the first 0-2% period of the gait cycle when the foot first contacts the ground [36]. At this instant, the vertical component of the ground reaction force (GRF), the main contributor of the forces acting on the CoM, reaches a maximum of 120-150% of the body weight (BW) [37], [38]. During running, these forces can reach up to 500% of BW [39]. The position of the ankle joint at this instant determines the force response and therefore the way this IC is manifested in the actibelt® acceleration signal.

b) Loading response: The loading response is a bipedal phase which occupies about 10% of the gait cycle [40], from the IC to toe off of the opposite leg. During the loading response, the foot comes into full contact with the floor; the knee flexes slightly, absorbing some power in order to reduce the IC on the floor; and the body weight is transferred onto the stance limb [40]. A smooth transfer guarantees the stability of the upper body [41]. It is in the loading response phase that a running step can be distinguished from a walking step. If there is no bipedal stance, the person no longer walks but runs [42]. In the actibelt® acceleration signal during running, the acceleration in the vertical direction crosses the 0g line (g: the gravitational acceleration, 9.81 m/s^2) twice: once when the body accelerates upwards along the positive direction of the vertical axis propelled by the calf muscle; and again when it descends in free fall for a very short time, right before reaching the ground.

c) Single Limb Support: During this phase (10-50%), the body is supported by one single leg and the forces drop on average to about 60-80% of the BW. [36]. The body begins to move from force absorption of impact – mid stance (10-30%)– to force propulsion forward – terminal stance (30-50%) [35].

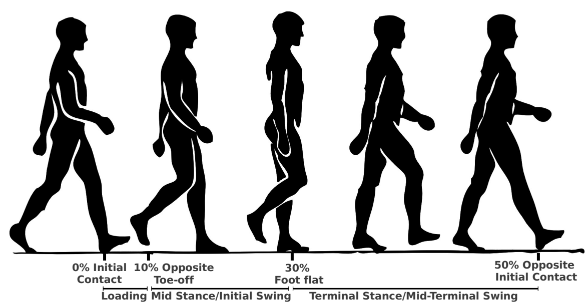


Fig. 1: Important phases for the detection of steps using the actibelt® sensor. Image adapted from [43]

II. Methods

A. Subjects

In total, 31 subjects were recruited for this study, of which 10 were adults with a mean age of 37.3±18.5 years (range 22 to 64 years) and 21 were institutionalized seniors with a mean age of 82.2±6.3 years (range 67 to 90 years). Adults were recruited among relatives and university students, and seniors were recruited at nursing homes. The local ethics committee approved the study and all subjects signed the informed consent prior to participation. Acceleration and video data were collected as each of the subjects performed one 10 meter walk trial. Furthermore, one female (30 years old) was filmed while wearing the sensor and as she performed a series of motion activities with a similar acceleration pattern to that originated while walking.

Subjects were classified as frail walkers if their walking speed, measured over 10 meters, was under 0.75 m/s. We chose a speed equal to 0.75 m/s as decision threshold for frailty based on the cut-off point suggested in the scale developed by Fried et al. [16]. According to this criterion, all seniors, except a 67 year-old senior with mean walking speed higher than 0.75 m/s, and one adult with mean walking speed equal to 0.66 m/s, were classified as frail walkers. We further categorized frail walkers as *mildly frail* (not needing a walking aid and able to complete daily tasks independently), *moderately frail* (needing a walking aid and dependent on specific services to complete daily tasks), and *severely frail* (needing a walking aid; incapable of transferring themselves and completing daily tasks).

B. Equipment

1) Acceleration Sensor: Data was collected using the actibelt® [44] sensor shown in Figure 2a. The actibelt® is a triaxial accelerometer (ADXL 345 BCCZ Analog Devices) placed inside a belt buckle that can be worn on a normal belt or on an elastic belt strapped around the waist. The design is unobtrusive and ensures that the accelerometer is located close to the subject's center of mass. The dimensions of the actibelt® sensor are: 67x10x40 mm (LxWx H); the weight is 34 gm. The acceleration sensor measures up to $\pm$ 6 g (g = 9.81 m/s/s) with a resolution of 0.0024g and sample frequency $f_s = 100$ Hz.

The power supply is provided by a rechargeable LiPo battery that lasts approximately one month and can be recharged via USB in 2 hours. The data is stored in an internal flash memory with a capacity of 512 MB, allowing uninterrupted recording for about 10 days. The acceleration signal recorded by the accelerometer is comprised of static gravity and dynamic acceleration components relative to the trunk along the vertical, mediolateral and anteroposterior directions. In anatomical position (see Fig. 2b), the orientation of the accelerometer is the following: positive X values correspond to up acceleration, positive Y values correspond to left acceleration and positive Z values correspond to anterior acceleration.

(a) (b)

Fig. 2: Images of (a) actibelt® sensor and (b) axis directions. Image (b) adapted from [45].

2) High Speed Video Camera: A high speed camera (Go Pro HERO3), configured to record at 100 Hz with the highest resolution (1280x960 pixels), was used as the gold standard for acceleration data annotation. Synchronization of camera and accelerometer was accomplished by filming a tap on the sensor and subsequently matching the peak acceleration value in the anteroposterior acceleration signal with the frame that displays the instant of the impact.

C. Data Collection Protocol

1) 10 meter walk data: Standardized 10 meter walk tests were performed by the healthy adults and seniors described in the previous section. At the beginning of each test, an experimenter verified that the accelerometer was oriented correctly, firmly fastened around the waist, and centered at the middle of the mediolateral axis. The test consisted of walking a minimum distance of 10 meters at self-selected normal speed along a straight path. Participants started to walk approximately 1 meter before the start line and stopped around 1 meter after the end line to minimize the effect of acceleration and deceleration. Additional lines were marked on the floor to track the speed, with a maximum separation of 3 meters between lines. The experimenter walked slightly behind the test subjects in order to influence their walking speed as little as possible, holding the high speed camera attached to a metal rod at ground level to record the contacts of the foot with the ground. The camera lens was perpendicularly aligned to the anteroposterior plane. Participants were allowed to use a walking frame or crutches, or grasp somebody's arm for support. Each participant completed one walking trial. The data collection process was done at two different points in time, approximately three weeks apart from each other.

2) Walking-like data: In order to test for false positives, repetitions of nine different movements were recorded: 1-2) moving the heel up-and-down while sitting and also while standing, 3-5) doing sit-ups, push-ups and a standing toe-touch, 6-8) shaking the sensor up-down, backward-forward and left-right, and 9) cycling. All of them were performed by the same subject, a 30 year-old female, and repeated continuously with a frequency comprised between 1.5 Hz and 2.6 Hz – the limits of the average human step frequency [46]. We call these movements walking-like movements because their acceleration pattern is similar to the pattern generated while walking in terms of signal amplitude and periodicity (tested by visual inspection of the raw data). The duration of each walking-like record was approximately 15 seconds, except for cycling when it was 30 seconds.

D. Data Sets

Two analysis were performed using the 10 meter walk data. The first analysis consists of an exploratory analysis which was performed to gain understanding on how the gait acceleration pattern changes according to the subject's walking ability and, thereby, determine an optimal methodology for robust step detection. For the exploratory analysis, we used the data procured at the first time point of the data collection. The second analysis comprises the algorithm development and step parameterization, and makes use of the entire data set (the exploratory data and the data collected at the second time point) divided in training and validation part. Subjects included in each analysis are detailed below.

1) Data subset for exploratory analysis: This subset consists of a group of 5 healthy adults (4 females, 1 male) in the age range of 26-40 years, 3 *mild frail* females (74-80 years old), 1 *moderate frail* female (85 years old), and 2 *severe frail* seniors (1 female, 1 male; 84 and 89 years old respectively).

2) Training and validation data sets: For the final analysis the entire data set (n=31) was used. Data of adults and seniors were divided randomly into a training part (n=15, 22-90 years old) and a validation part (n=16, 21-90 years old) for testing and evaluation of the algorithm. Table I reports basic descriptive statistics of the data employed in this analysis.

E. Data Annotation

The instants of the initial contacts for a series of 10 consecutive steps were identified in the acceleration data using the gold standard (video camera). Ten was the maximum number

TABLE I: Gender of participants (f stands for female and m for male), mean (SD) age and mean (SD) walking speed.

			Gender f:m	Mean Age ± SD (yrs)	Mean Speed ± SD (m/s)
Training	Adults	non-frail	3:2	35.2±17.6	1.30±0.19
	Seniors	non-frail	0:1	67	0.96
		mild	4:1	83.0±5.9	0.63±0.21
		moderate	2:0	80.3±4.2	0.41±0.04
		severe	2:0	86.0±2.8	0.42±0.23
Validation	Adults	non-frail	2:2	33.8±19.7	1.23±0.33
		mild	1:0	62	0.66
	Seniors	mild	4:0	82.0±6.7	0.50±0.12
		moderate	4:0	79.5±6.6	0.34±0.19
		severe	3:1	87.0±2.0	0.34±0.15

of consecutive steps that could be annotated correctly for all participants. Initial contacts of some steps were not possible to identify from the video image due to poor illumination or interpose of walking frames in the way between the camera and the subject's heel.

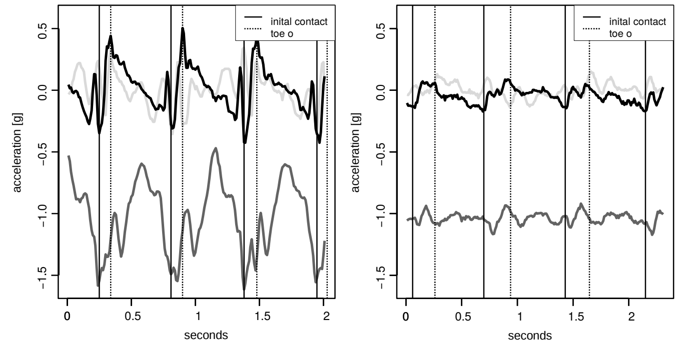
The time needed to walk the distance between two specific lines on the floor was extracted from the video recordings. With this information, the average gait speed was calculated. Although we can not exactly quantify the accuracy of the gait speed estimated from the video data using the tracking marks on the floor, we know that, in average, the maximum error we can make in the annotation of the data is ±3 frames (equal to ±0.03 seconds). Therefore, we can assume that the potential deviations from the real gait speed do not impose a big impact in the final results.

III. Exploratory Analysis: Walking Acceleration Patterns

As explained in the gait analysis section, the initial contact (IC) of the foot with the ground marks the beginning of a step. In the actibelt® acceleration signal, this translates into an acceleration peak in the vertical axis at every contact of the foot with the ground, as shown in Fig. 3a.

In healthy adults, the peaks caused by the initial contacts in the vertical axis reached maximum negative values of around -1.4 g for slow walking and -2.2 g for fast walking. This means a maximum net acceleration change of 1.2 g (from -1 g to -2.2 g, where -1 g corresponds to the value measured when no other forces than the gravity force act on the body), a value which is consistent with the results from previous studies using force plates [38], [47]. In the elderly group, the amplitude of the minima turned out much lower and noisier (Fig. 3b), making difficult to pinpoint the IC peaks in the vertical axis. These changes in the amplitude were associated with the reduction in gait speed and the flat-footed landing, usually caused by a decreased ankle plantarflexion in older walkers [48].

To determine whether the mediolateral or the anteroposterior accelerations could yield more reliable results in the identification of steps, independently of the subject's age or the ability to walk, we examined the main acceleration frequency components (0-5 Hz [49]) of the average step for each subject and axes, and searched for a common step pattern. In the mediolateral axis, we found that the pattern of the average step was very idiosyncratic for each individual, which confirmed the results from an earlier study [27]. Conversely,



(a) (b)

Fig. 3: Acceleration near the body's CoM of (a) a healthy young male and (b) an elderly woman walking at normal self-selected speed. Black line corresponds to accelerations in the anteroposterior direction, dark grey line to accelerations in the vertical direction, and light grey line to accelerations in the mediolateral direction.

in the anteroposterior axis, the average step exhibited an ascending-descending acceleration pattern consistent for all individuals and more prominent than in any other axis. Still, the normalized peak to peak acceleration amplitude in the group of healthy adults was in average more than twice as high as in the frail group; and the variability, measured as the average of the standard deviation of the steps, increased up to three times as much with age.

The results of the exploratory data analysis evidenced: 1) the existence of different step patterns for healthy adults and for seniors, and 2) that the signal with a more consistent patternt in all subjects was the signal recorded along the anteroposterior axis.

IV. Step Parameterization

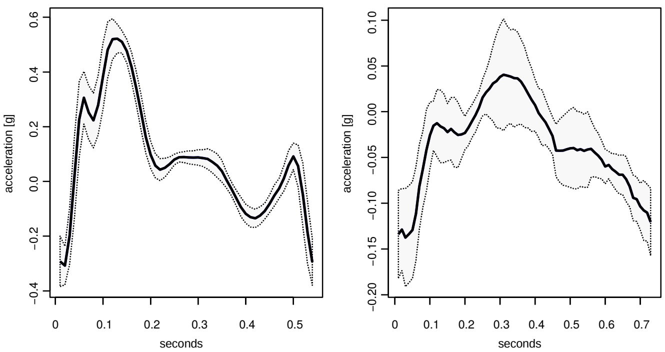
We define step parameterization as the process of identifying and defining the parameters necessary for a relevant description of the step pattern. Since the exploratory analysis suggested the existence of at least two different walking patterns, we first classified the patterns into two categories or into what we called two different "Characteristic Step Graphs" and, second, we defined the parameters for each of them. The parameterization was calculated using the data from the training set.

A. Characteristic Step Graph

The Characteristic Step Graph (CSG) is defined as an standard representation of a step pattern characteristic of individuals with similar walking ability. In our study, step pattern refers to the pattern of the actibelt® acceleration signal along the anteroposterior axis during a step cycle.

We calculated two different CSG's by grouping the average steps of all subjects into two categories as follows:

1) Calculation of Average Step Graph: The Average Step Graph (ASG) represents the person's average step and displays the average and standard deviation of each acceleration sample in a step interval for a series of ten single steps along the vertical, anteroposterior and mediolateral axis (see Fig. 4).



(a) (b)

Fig. 4: Comparison of the average acceleration pattern (solid black line) and standard deviation (dotted black line) in the anteroposterior axis for (a) a healthy young individual and (b) a frail senior, walking at normal self-selected speed.

2) Normalization of the ASG: To make all the steps comparable to each other, they were normalized in time and amplitude. Time normalization was done via linear interpolation to adjust the step lengths to the median value of all the step durations in the training data. The amplitude was normalized in between -1 and 1 dividing by the maximum absolute value.

3) K-means clustering: By applying K-means [50] clustering (with k=2) over the normalized ASG arrays, the average steps were grouped into two clusters: A and B. The clusters formed thereby rely only on the characteristics of the average step patterns. Frail seniors were classified in group A and all non-frail subjects, except one, were assigned to the group B. In view of these results, the Characteristic Step Graphs for frail and for normal walking (Fig. 5) were chosen as the A and B cluster means, respectively.

B. Parametric Description

Five main fiducial points were identified in the anteroposterior direction of the normalized ASG, each of them associated with a particular gait event. We validated them by inspecting the acceleration data and the video recordings in slow motion in parallel.

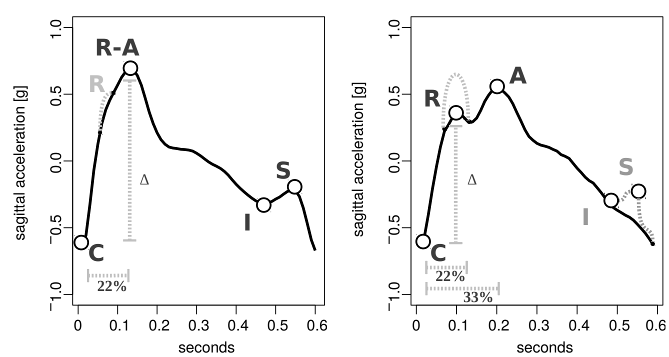
The **C** point (**Contact**) corresponds to the initial contact of the heel with the ground. In that moment, the ankle is dorsiflexed with toes pointing up and the foot begins to land on the middle to outside of the heel. As the foot continues landing, the ankle plantarflexes and, finally, the forefoot comes down.

In normal walking, when the heel of the right foot touches the ground, the ankle of the left foot begins to plantarflex immediately bringing the left heel off the ground, and by the time the right forefoot reaches the ground, the arch of the opposite foot recoils bringing the toes off. The same applies to the left foot. These actions push the body upwards and forwards bringing a peak on the anteroposterior acceleration, the **R-A** (**Rise** and **Advance**) peak.

The interval between the **C** point and the **R-A** peak corresponds to the double support phase, described in the gait theory as the period in which both feet are in contact with the ground. In our analysis, this phase occupies the 22% of the step time, or equivalently the 11% of the stride cycle for normal walking. This finding is in agreement with the results from the clinical literature [36].

In the elderly, the duration of the double stance is usually bigger. Winter [48] reported a difference of more than 6% with respect to young adults, indicating that the elderly adapt toward a safer and more stable gait pattern. We found that the average time spent in double stance by seniors was, in comparison with the healthy adults, of around 11% bigger. We saw that seniors tended to wait until the forefoot lands on the ground to start moving the rear foot forwards, what causes a drop in the forward acceleration followed again by an increase when the calf muscles of the rear foot begin to bring the heel off. This discontinuity in the loading response split the **R-A** peak in two, **R** and **A**. The **R** (**Rise**) point corresponds to the instant at which the forefoot of the stance leg comes down to the ground and the **A** (**Advance**) point marks the instant that immediately precedes the toe off. We observed that for a few seniors, the amplitude of the **R** peak, Δ, was higher than the one for the **A** peak. This is indicated in figure 5 with gray dotted lines. We also indicated in gray text the **R** peak found in the pattern of several young adults and that got filtered out when averaging all step patterns. This fine **R-A** separation found sometimes in the younger group is not related to any pathological gait pattern, since the loading response appeared totally normal and smooth, and the participants did not report any medical condition affecting the walking ability. This fluctuation is also not necessarily present in all the steps taken by a same individual.

The minimum and maximum difference in acceleration within the 22% first interval found in the training data was: $\min\Delta = 0.09$ [g] for a senior, and $\max\Delta = 1.05$ [g] for a young adult.



(a) (b)

Fig. 5: Parameterized Characteristic Step Graph for (a) normal walking (cluster B) and (b) for impaired walking (cluster A). In dotted lines possible variations of the pattern.

After the **R-A/A** instant, the acceleration begins to decrease until it reaches a point of **Inflection**, **I**, which marks the beginning of the mid-swing phase. In that moment, the hip is pulled forward by the concentric hip flexor and the knee extends rapidly. The end of this phase matches the end of the leg swinging towards a maximum extension, the so called **S** (**Swing**) peak in the step graph.

The possible variations on the mid-swing phase were depicted in gray in Fig. 5. The averaging of the step graphs smears out the **I** and **S** point. But, when inspecting each single pattern we observed that the **I** and **S** peaks were still present for a small group of seniors without reduced knee extension. The absence of **I-S** interval seemed to be closely related to the use of walking aid, especially a walking frame.

V. Step detection algorithm

The step detection algorithm was implemented in R language [51]. The raw data was processed in blocks of length equal to 1000 samples (empirically calculated as the optimal length [52]) and with an overlap of 200 samples.

The step detection algorithm is divided in three main parts: recognition of regions of interest, estimation of ICs and template matching.

A. Recognition of regions of interest

Walking implies the realization of a certain level of physical activity and to maintain an approximately upright standing posture. Using the capacity of the device as inclinometer and measuring the magnitude of the accelerations near the CoM, we can estimate which regions may contain walking segments. To identify these regions of interest, we first excluded from the analysis all intervals where the body orientation was considered not to be upright. Based on previous findings [14], we assumed an upright posture if the angle formed by the trunk with the anteroposterior axis (ϕ_B) is smaller than 45° (ignoring possible sensor tilt). Second, we excluded regions of low activity or motionless. The signal used to estimate the physical activity (PA) level while walking, g_n, was obtained by differentiation of the acceleration vector in the anteroposterior plane,

$$g_n = |v_{n+1} - v_n|. \tag{1}$$

Where $v_n = \sqrt{({a_n}^x)^2 + ({a_n}^z)^2}$, with ${a_n}^x$ and ${a_n}^y$ equal to the acceleration values along the vertical and anteroposterior axis respectively.

The decision threshold for the PA levels was calculated empirically, as the minimum value of g_n among all walking segments in the training data set. Prior to calculation of this threshold, the signal g_n was smoothed with a Gaussian filter ($\frac{1}{\sigma} = 2.5$) of length $L = 400$ samples to guarantee that adjacent regions with similar PA level were merged together.

B. Estimation of Initial Contacts

The step detection is based on the detection of the greatest local minima in the anteroposterior axis, which corresponds to the instants of the initial contacts. These local minima are sometimes difficult to discriminate due to undesired fluctuations in the signal, usually produced by abdominal fat oscillations or by the hip extension. To remove these fluctuations, we applied a low pass Butterworth filter ($n = 4$) of cut-off frequency $f_c = 2$ Hz to the anteroposterior acceleration ${a_n}^z$. The cut-off frequency of the filter was calculated empirically using the training data. After that, we calculated the minima n_{min}

$$n_{min} = \{n \in 1, 2, \ldots, N \mid \tilde{a}^z_{n-1} - \tilde{a}^z_n > 0 \wedge \tilde{a}^z_{n+1} - \tilde{a}^z_n < 0\} \tag{2}$$

in the filtered signal $\tilde{a}^z_n$ by differentiation.

Each local minima marks off the interval I

$$I = [n_{min}, n_{min} + T_{min}) \tag{3}$$

where to search for the initial contacts in the anteroposterior axis a^z_n. The duration of the interval, T_{min} was chosen equal to 0.24 seconds, the inverse of the usual maximum step frequency during running [53]. In elderly people, the minimum step durations can reach values equal to 0.4 seconds when walking faster [54].

The first approximation of the initial contacts, $\hat{c}_i$, are the minima of the acceleration signal in the interval I along the anteroposterior axis, calculated again like in equation 2.

The next task is to verify whether each segment,

$$\hat{\mathbf{s}} = \{a^z_n \mid n \in [\hat{c}_i, \hat{c}_{i+1})\}, \tag{4}$$

between two consecutive estimations of the initial contacts fits in the parametric description of a step.

The first condition that the vector $\hat{\mathbf{s}}$ needs to fulfill to be considered as a step is to present a maximum of amplitude $\Delta \geq \min \Delta$, with $\min \Delta = 0.09$ [g], in the the first 22% of the interval. This maximum usually corresponds to the **R-A/A** point in normal walking and to the **R** point in impaired walking (Fig. 6). The **I** and **S** fiducial peaks were not considered for the step detection because they are not always present in the signal. The second condition is that the length of the vector $\hat{\mathbf{s}}$ in seconds should not be bigger than $T_{max} = 2$. T_{max} is considered an upper limit for the step duration and was estimated as approximately the double of the biggest step duration measured in the training data set (1.06 seconds).

The vectors that satisfy both conditions are the estimations of the real steps and they are denoted as $\mathbf{s}$.

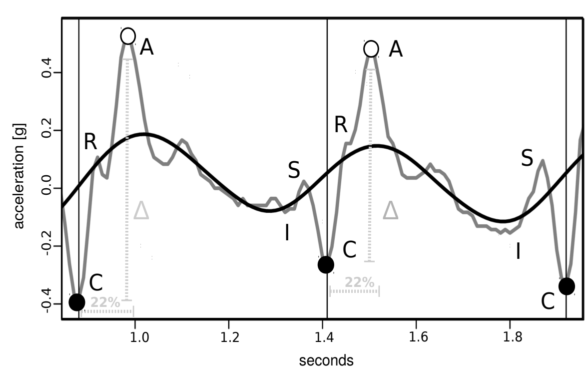


Fig. 6: Dots in black are the ICs detected using the algorithm. The grey line is the anteroposterior acceleration (g units) and the black line is the low-pass filtered version. Vertical lines correspond to the annotated ICs.

C. Template matching

One of the most challenging tasks in step detection under uncontrolled environment is the ability of the algorithm to distinguish between real steps and activities with similar acceleration patterns. In order to reduce the number of false positives, we measured the similarity of each of the signals previously estimated as true steps ($\mathbf{s}$) with a template ($\mathbf{t}$) and, depending on this value, we decided whether the signal $\mathbf{s}$ fits the shape of a standard step acceleration pattern or not. The normalized cross-correlation between both signals, defined as

$$\gamma_{\mathbf{s},\mathbf{t}} = \frac{1}{L}\sum_{j=1}^{L}\frac{(s_j-\mu_{\mathbf{s}})(t_j-\mu_{\mathbf{t}})}{\sqrt{\sigma_{\mathbf{s}}\sigma_{\mathbf{t}}}}, \tag{5}$$

was used as similarity measure. In the equation 5, the scalars μ and σ denote the average and the standard deviation, and L is the length of the template.

The Characteristic Step Graph for normal ($\mathbf{t_1}$) and for frail walking ($\mathbf{t_2}$) were used as templates. And the length of the step $\mathbf{s}$ was adjusted to the length of the template by linear interpolation.

The steps with a maximum normalized cross-correlation

$$\max(\gamma_{\mathbf{s},\mathbf{t_1}}, \gamma_{\mathbf{s},\mathbf{t_2}}) < 0.70 \tag{6}$$

were considered not to fit the standard. The value 0.70 corresponds to the lowest value of the normalized cross-correlation between the templates $\mathbf{t_1}$ and $\mathbf{t_2}$ and the steps annotated in the training data set.

VI. Validation

We calculated Characteristic Step Graphs using the steps annotated with the gold standard in the validation data set, to cross-check the results obtained with the training part.

To validate the step detection algorithm, we calculated the sensitivity (S) and the Positive Predictive Value (PPV) regarding number of steps, and the average error ($\overline{E}$) for the detection of the IC instants. The sensitivity is defined as the number of steps correctly detected by the algorithm (true positives) divided by the total number of steps. The PPV represents the ratio of true positives to combined true and false positives. And the average error, $\overline{E}$, is an average of the difference between the real instant of the initial contact and the one detected by the algorithm,

$$\overline{E} := \frac{1}{n}\sum_{i=1}^{n}|c_i^{Alg} - c_i^{Gold}|, \tag{7}$$

where c_i^{Alg} are the initial contacts detected with the algorithm and c_i^{Gold} are the ones annotated with the gold standard for each step i.

To evaluate the walking-like data, we calculated the false positive rate (FPR). The FPR is defined as the average number of false positives (false steps) per minute.

VII. Results

A. CSG cross-check

All frail subjects in the training data (n=9, 77-90 years old) were correctly classified by the K-means algorithm (k=2) in in the group labeled as frail, whereas 83.3% of non-frail subjects (n=5, 4 adults in the range 22-36 years and one 67 year-old man) were assigned to the "normal" group. Only one 65 year-old healthy adult with speed = 1.01 m/s was assigned to the frail group. The confusion matrix for this classification is shown in Table II.

TABLE II: Confusion Matrix of the k-means (k=2) classification in frail/normal walking for the training set.

		predicted	
		frail	normal
actual	frail	9	0
	normal	1	5

The classification of the K-means algorithm using the validation data produced less accurate results that in the training set, with 5 misclassified frail subjects, as shown in Table IIIa. Among these five subjects, two presented the highest speed in the frail group (0.62 m/s and 0.66 m/s). The three remaining presented extreme to very low speeds (between 0.12 m/s and 0.36 m/s), which evidenced their condition as outliers. To confirm this assumption, we applied K-means clustering with k=3 and observed that three misclassified samples with lower gait speed were grouped together in a new cluster. Table IIIb shows the Confusion Matrix after the removal of outliers. The still misclassification of the two patterns corresponding to gait speeds in the range 0.6-0.7 m/s suggests that the average step graph may still present characteristics of a normal walking pattern at those speeds.

TABLE III: Confusion Matrix of the k-means classification in frail/normal walking for the validation set before (a) and after (b) the removal of outliers.

		predicted	
		frail	normal
actual	frail	7	5
	normal	0	4

(a) k=2

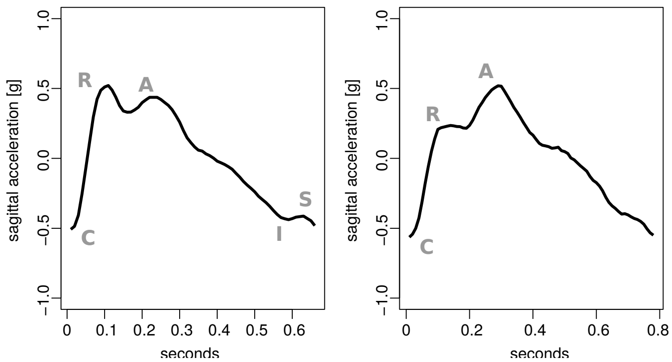
		predicted	
		frail	normal
actual	frail	7	2
	normal	0	4

(b) k=3

The cluster means of the validation data set produced almost identical Characteristic Step Graphs as the ones depicted in Fig. 5 for the training data set. The Average Step Graph of seniors who used a walking frame (Fig. 7b) in comparison with seniors who did not use one (Fig. 7a) revealed that, for the first group, the interval **I-S** tends to disappear and the amplitude of the **R** peak was in average smaller than the amplitude of the **A** peak.

B. Algorithm performance

The accuracy of the step detection algorithm depends on the walking speed. The spectrum of gait speeds in the validation



(a) (b)

Fig. 7: The Average Step Graph of seniors (a) without walking frame (n=10) and (b) with a walking frame (n=11).

data set ranged from 0.12 m/s, for the most functional impaired senior, to 1.47 m/s. We categorized the gait speeds in: *normal*, *slow*, *very slow* (Vslow), and *extremely slow* (Xslow) as defined in Table IV. The sensitivity was equal to 99.33% for speeds between 0.20-1.5 m/s and without the use of template matching. Overall, sensitivity was reduced by 27.03% when using template matching.

The minimum and maximum error in the IC detection was equal to 20 and 60 milliseconds respectively.

The sensitivity and average error of the algorithm are detailed in Table IV according to different speed intervals.

TABLE IV: Average error ($\overline{E}$) and Sensitivity with (S_t) and without (S) template matching

	Speed (m/s)	n	$S(\%)$	$\overline{E}$ (sec)	$S_t(\%)$
normal	$0.75 \le v < 1.50$	4	100	0.02	97.5
slow	$0.50 \le v < 0.75$	5	98.0	0.04	76.0
Vslow	$0.20 \le v < 0.50$	5	100	0.06	80.0
Xslow	$0.10 \le v < 0.20$	2	45.0	0.06	35.0

No false positives were found in the validation set, which means that the Positive Predictive Value (PPV) was equal to 100%. For the walking-like data, the false positive rate, with and without template matching, is presented in Table V.

Among all walking-like activities, cycling produced the higher number of false positives with a considerable high rate (FPR =96.0 steps/min). However, when applying template matching, the false step rate during cycling was reduced by 72.9%, and it reached zero for the rest of activities.

VIII. Discussion

The results of the exploratory data analysis have shown that the changes in the actibelt® signal during walking were consistent with the qualitative and quantitative description of the gait phases found in the clinical literature [36], [48], and with other previous studies using force plates [37], [38] and accelerometers [27], [30].

The axis with a more congruent step pattern for all subjects was the anteroposterior axis, and the minima in the signal along this direction corresponded to the heel strikes. An additional investigation would be required to determine whether

TABLE V: False step rate in walking-like movements with (FPR_t) and without (FPR) template matching

	Movement description	FPR [steps/min]	FPR_t [steps/min]
1	Sitting and moving heel up-and-down	0.0	0.0
2	On tiptoes and lowering back down	20.0	0.0
3	Sit-ups	0.0	0.0
4	Push-ups	0.0	0.0
5	Standing toe-touch	3.2	0.0
6	Shaking sensor up-down	0.0	0.0
7	Shaking sensor backward-forward	0.0	0.0
8	Shaking sensor left-right	0.0	0.0
9	Cycling	96.0	26.0

the use of combined data from multiple axis could improve the performance of the step detection.

The Characteristic Step Graph has been demonstrated to be a useful model to represent the general dynamics of the step pattern in adults and in the elderly, independently of inter- and intra-individual fluctuations in signal amplitude and step duration (fluctuations in amplitude and time are eliminated during the process of averaging and normalization of the step pattern, respectively). Some of the major limb movements and forces acting on the muscles during walking, like: the flexion of the foot, the knee extension, and the the maximum forces of the heel strike and the forefoot loading, were manifested in the Characteristic Step Graph. For a small group of individuals, we found considerable variations between their average step pattern and their corresponding Characteristic Step Graph. It should be further investigated to what extent these variations may result from the effect of the walking speed, walking aid, or from other factors related to aging, such as loss of strength and flexibility. Some gait movements, like for example the knee flexion, has been shown to be related to walking speed [55]. For that reason, it is essential that in the future, normal ranges for gait parameters are defined with reference to walking speed.

The performance of the algorithm presented in this study is superior if we compared it to the results from other studies using a single waist-worn accelerometer in frail seniors or seniors walking at low speeds. In particular, Storti [32] reported a relative error equal to 19.1% for speeds lower than 0.8 m/s, and Marschollek [33] obtained a minimum relative error of 28.1% on a group of mobility-impaired older people. Dijkstra et al. [34] reported a mean absolute percentage error in the detection of steps equal to 4.3±1.1%; however, the sample included in their study was comprised of young seniors (in average, 68.5±7.4 years old) and they did not specified numeric values for slow pace walking. In our study, we achieved a relative error equal to 10.0% for gait speeds less than 0.75 m/s without template matching, and a mean sensitivity equal to 99±1% for walking speeds comprised between 0.20–1.5 m/s. At speeds lower than 0.20 m/s, only 45% of the steps taken could be detected by our algorithm.

We obtained an average error in the detection of the initial contacts equal to 0.05 seconds for *low* speeds (<0.75 m/s) and 0.02 seconds for *normal* speeds (>0.75 m/s). We did not find reference values in frail senior populations to compare these results with. But, there exist studies in healthy individuals that reported maximum and minimum absolute errors in the detection of the initial contacts equal to 0.103 and 0.002 seconds respectively [27]. The differences in timing between the real heel strikes and those detected by our algorithm may be affected by the accuracy with which the video data was annotated. In the worst case, this difference was estimated to be equal to 0.03 seconds.

The utilization of template matching reduced false positives and also the sensitivity of the step counter. Given that this technique is very sensitive to changes in gait profile, possible approaches to increase the accuracy of the step detection are to employ different gait templates, such as templates derived from pathological gaits, or to use templates adapted to each person. However, these approaches would probably increase the processing time and computational load, or may require the use of supervised learning for each particular gait pattern. In controlled environments, like in clinical settings, when the measurements are restricted to walking activities, applying template matching may not present any advantage.

Despite including diverse step patterns and gait speeds in this study, each subject was only tested for one trial of self-selected normal speed. Further validations using bigger data sets, including several trials, different speeds, and ideally some pathological gaits, would be needed. It would be also important to assess the ecological validity of the step detector in uncontrolled environments, like in the community or at home, where walking is not limited to a straight walk and the effects of accelerations and decelerations during walking may affect the performance.

IX. Conclusion

Systems using a single 3D accelerometer are a promising technology for reliable long-term evaluation of physical functioning, and monitoring of exercise therapy or medication interventions. The placement of the sensor inside a buckle of a normal belt guarantees a limited obtrusiveness, and the fixed location near the center of mass of the body has been shown to provide reliable information to detect steps with a high sensitivity, even in frail seniors walking at relatively low speeds. Furthermore, we have shown that using a single waist-worn acceleration sensor is possible to distinguish in the acceleration signal some of the major forces responsible for the control of the gait. To the best of our knowledge, this is the first study that has identified fiducial points in acceleration step patterns with clinical significance for the gait assessment of older adults. The system presented in this paper could be useful to identify and monitor seniors at high risk of decline in gait performance, via step counting and analysis of their acceleration patterns.

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