Step counting for slow and intermittent ambulation based on a smartwatch accelerometer

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ABSTRACT
The ambulatory monitoring of human movement can provide valuable information regarding the degree of functional ability and general level of activity of individuals. Since walking is a basic every day movement and an important element to introduce into one's daily routine, automatic step detection or step counting is very important in developing ambulatory monitoring systems. This paper is concerned with the development and the preliminary validation of a step counter (SC) that is especially designed for conditions of slow and intermittent ambulation. The SC was based on processing the accelerometer data measured by a Gear 2 smartwatch using a custom wearable app, named ADAM, running on the Gear 2. A dataset of 8 users, for a total of 80 trials, was used to tune ADAM. Finally, ADAM was compared with the native SC running in the Gear 2 smartwatch, and with the SC implemented in a waist-worn pedometer (Geonaute ONSTEP 400) (dataset of 8 users, for a total of 80 trials). The three SCs performed quite similarly in conditions of normal walking over long paths (1-3% of mean absolute relative error); ADAM outperformed the two other SCs in conditions of slow and intermittent ambulation; the error incurred by ADAM was limited to 5%, significantly lower than errors of 20-30% incurred by the two other SCs.

CCS Concepts
• **Human-centered computing → Ubiquitous and mobile computing**
• **Applied computing → Consumer health**

Keywords
step counting; accelerometer; smartwatch; pedometer; ambulation.

1. INTRODUCTION
Ageing of the population, especially in industrialized countries, and the concurrent increase of the number of people who spend a large part of their daily time in home, motivate the development of ambulatory monitoring systems that are capable to evaluate the level of physical activity, even in conditions of restrained mobility [1]. Because of the importance of walking for a healthy lifestyle, step detection and counting is thus one of the key problems for the understanding of the complex relationship between health and physical activity [2].

A large number of devices and applications have been developed for physical activity monitoring [3-5]. Accelerometry is the technology of choice for wearable devices to measure and assess physical activity. A pedometer – the device used for recording the number of steps taken – counts each step by detecting the motion of the person's arm or hip and it is considered a valid option for assessing physical activity in research and practice [6]. Differently from past switch-based devices, the recent pedometers are actually based on MEMS accelerometers whose data are processed by a dedicated algorithm that allows an accurate detection of steps. There are several factors that can limit the accuracy of pedometers, including placement site, intensity of walking, counting errors due to non-ambulatory activities [7-9]. The most common placement site of pedometers is the waist: devices are attached to the waistband or belt by means of a clip. Measuring the acceleration in all directions in the three-dimensional space relieves the wearer from the need to accurately position the device relative to an anatomical reference frame, which is important in the presence of body fat and clothing [7, 9]. User comfort and acceptability are generally high, since the freedom of movement is not restricted and donning-doffing is easy and convenient. Whereas counting errors due to non-ambulatory activities may not be critical to their performance, waist-worn pedometers are grossly inaccurate when the walking speed is low [1, 10].

Recent technological advances, in particular the development of mobile devices (namely, smartphones) that are endowed with inertial sensors, have motivated further research in the field. The problem with smartphone-based pedometers is that the mobile device is not necessarily taken in the same location at all times, and in the same position relative to the body (e.g., trouser pocket and bags) [11]. In contrast with waist-worn pedometers, smartphone-based pedometers are also more sensitive to the influence of non-ambulatory activities, although interesting results have been recently reported as for the recognition of activity and the estimation of spatial-temporal parameters of gait [12, 13]. Moreover, movements of the upper arm when the smartphone is carried in the hand are not necessarily correlated with walking, and can thus generate a lot of false positives. An interesting avenue of research concerns the creation of signal processing methods that can help reduce the sensitivity of step-counting algorithms to the issue of placement and non-ambulatory activities [11, 14, 15]. However, in a similar fashion to waist-worn pedometers, smartphone-based pedometers suffer from accuracy

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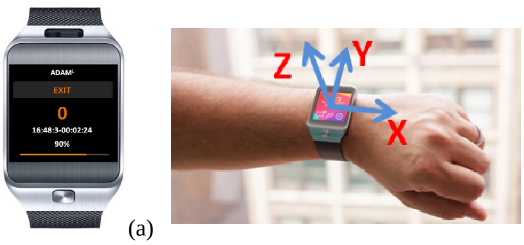
degradations when the walking speed is slow. In the attempt to improve the performance of smartphone-based pedometers, embedded MEMS gyroscopes have also been considered as an alternative to accelerometers [16].

The reluctance to accept and to routinely use new technologies is an important issue for the development of wearable sensor systems, such as activity monitors and pedometers. Lack of interest or motivation in using them is highly predictive of later refusal. In this regard, a new generation of mobile devices may imply a change of attitude. The compliance with the use of a device worn at the wrist (namely, a smartwatch) would be generally high, which is one reason for the increasing interest attached to this technology: recent works involving long-term monitoring in large cohorts of users highlighted that using wrist-worn sensor devices can grant longer wear times [17] [18]. Moreover, smartwatches provide unprecedented opportunity for collection of large datasets of continuous measurement of physiological parameters (e.g., heart rate, galvanic skin resistance and temperature), and activity-related data (e.g., built-in accelerometer recordings), which can be used for longitudinal monitoring of health status and for quantimetric self-tracking, as advocated by the Quantified Self movement [14, 19-22].

The problem of reliability of measurements is often cited as a major obstacle for wider use of wearable health monitoring devices such as smartwatches. For instance, processing the accelerometer data for activity recognition provides a challenge because of the wrist gesticulation and variability in movement, compared with placement sites such as waist or ankle [23]. The wrist may move differently during the same activity, depending on what is in the hand and what the hand is holding or stabilizing. It is expected that these difficulties may affect step counting using a wrist-worn pedometer, although arm movements are generally well correlated with leg movements during steady walking.

In the case of intermittent ambulation activities, a critical issue affecting the accuracy of existing pedometers is the number of missed steps that may occur due to the irregular signal patterns from the built-in accelerometer, regardless of placement site. For instance, consider the problem of estimating a few steps interspersed with frequent stops and restarts. In this scenario, acceleration peaks correlated with steps are expected to be distributed irregularly both in amplitude and in time; hence, any predictive mechanism embedded in the algorithm of step counting is likely to perform poorly, due to the difficulty to specify and match template patterns describing the events occurring during any single step. Another element of difficulty is that data windowing itself would be a critical process in conditions of slow and intermittent walking (low time-resolution issue) [9]. A wristwatch pedometer that would search for the periods inherent in the cyclical nature of walking would require indeed long signal windows for extracting, e.g., the frequency-domain features needed for step identification.

The literature existing on the application of wrist-worn accelerometry to the problem of step counting is still scarce, and scattered, especially in conditions of slow and intermittent ambulation. Few patents were also surveyed [24, 25]. This paper is an initial attempt to fill the gap. Previous research on smartphone pedometry showed that frequency-domain or correlation approaches did not accrue substantial benefits compared with windowed peak detect (WPD) methods for step counting in conditions of normal walking [9]; on the other hand, WPD methods are easier to implement and present reduced computational loads. Therefore, we developed an adaptive WPD algorithm for wrist pedometer step counting using the built-in accelerometer of a commercial smartwatch. We compared the performance of the proposed algorithm, the native app running in the smartwatch for step counting, and a waist-worn commercial pedometer. The experimental tests included steady walking at several speeds, jogging, non-ambulatory activities, and intermittent and slow ambulation.



(a) (b)

Figure 1. (a) The Gear 2 smartwatch used for ADAM development; (b) The mobile reference frame aligned with the sensitivity axes of the embedded accelerometer.

2. EXPERIMENTAL SECTION

2.1 System Design and Implementation

The developed algorithm was implemented in a wearable app named ADAM (Advanced Daily Activity Monitor) running on a commercial Tizen smartwatch (Gear 2, Samsung Electronics Co., Ltd.), Fig. 1a. ADAM was written in HTML5 using the IDE Tizen SDK for Wearable (version 1.0.0). The smartwatch provided acceleration components a_x, a_y, a_z (normalized to the gravitational acceleration g, g = 9.81 m/s^2) relative to the mobile reference frame shown in Fig. 1b. The MP65M 6-axis chip manufactured by InvenSense, Inc., San Jose CA, USA serves as the inertial measurement unit within the smartwatch. The acceleration was measured by the embedded tri-axial accelerometer, internally sampled at the sampling frequency f_s = 25 Hz (sampling interval T_s = 40 ms). Additionally, a tri-axial gyroscope was available to measure the angular velocity at the rate of, approximately, one sample per second (feature not used in this work). Although it might be interesting to use the measured angular rate for step counting purposes, this sampling rate was believed too low for allowing any use in the present context..

2.2 Experimental Protocol

Two sets of experimental trials were performed, with the aim to build one dataset for tuning the parameters needed by the step counting algorithm (training dataset), and another dataset for assessing its performance (testing dataset). Two groups of healthy adult subjects participated in the experiments. All participants signed an informed consent before starting experimental sessions. Research procedures were in accordance with the Declaration of Helsinki. All subjects wore the Gear 2 smartwatch at the non-dominant hand wrist and a commercial pedometer (Geonaute ONSTEP 400), which was clipped to the waist belt at the right anterior iliac spine. During experimental sessions, subjects were free to wear their preferred shoes. Although the testing was not done in true naturalistic environments, we took care to minimize experimental biases, by asking subjects to move as naturally as they could. Moreover, they did not receive verbal or any other feedback information about their performance, only start and stop messages were issued to them. The subjects were instructed to walk at their preferred speed (free-selected speed), slower, or much slower, than normal and faster than normal, being free to interpret the speed at their own convenience. The set of activities considered for training ADAM and for testing ADAM, the Gear 2 and the Geonaute step counters (SCs), is given in Table 1. The experimenter observed the participants while performing activities and counted the number of steps walked in each trial, so as to compute the reference step count N_{ref} used for algorithm performance assessment.

Table 1. Activity types and description

Type	Description
Walk-turn-walk	Walk ten steps along a straight path, including a half-turn to walk ten steps in the opposite direction so as to return to the initial location (a rest of two seconds allowed before and after the half-turn). Repeat at four different speeds: slower than normal, normal (i.e., free-selected), faster than normal, jogging.
Slow and steady walk	Walk 500 steps at constant, slow speed (level walking); directional changes are allowed.
Variable-speed walk	Walk 500 steps at variable speed (level walking), with walking speed being freely changed (slower than normal, normal, faster than normal); directional changes and stops-starts are allowed.
Very slow walk	Walk 100 steps at very low speed (level walking), with minimal trunk and head oscillations; directional changes and stops-starts are allowed.
Jog	Jog 100 steps; directional changes and stops-starts are allowed.
Going up-and-down stairs	Climb a staircase of 11 steps (16-cm high), including a half-turn to the higher floor; walk downstairs along the same staircase, so as to return to the initial location.
In-home task	Subjects were asked to do a predefined sequence of actions in a structured room, walking at their own preferred speed (see figure 2): a) Take a box placed on the desk at point A and place it on the top of the shelf at point B (*d* = 7.8 m) b) Reach the coat rack at point C and pick up a bag (*d* = 3.6 m) c) Carry the bag on the top of a second shelf at point D using the smartwatch side arm (*d* = 8.4 m) d) Reach the shelf at point B and recoup the box (*d* = 7.2 m) e) Bring the box on the desk at point A (*d* = 7.8 m) f) Reach the shelf at point D and recoup the bag (*d* = 4.2 m) g) Carry the bag to the coat rack at point C using the left arm (*d* = 8.4 m) h) Reach the point A (*d* = 6.6 m) The distance walked in each section from a) to h) is denoted with *d*. Between each section, subjects were asked to rest for two seconds.

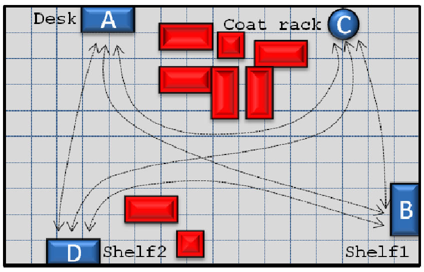


Figure 3. Room layout, with the furniture location for the *In-home task* activity. The red shapes are fixed obstacles to be avoided. The blue shapes are the target points. The grid size is 60 cm × 60 cm

The training dataset included the accelerometer data acquired from group 1-subjects asked to perform the *Walk-turn-walk* activity, with all variants indicated in Table 1. Eight subjects (5 males and 3 females) participated in the training phase. Age ranged from 28 to 55 years (38.5 ± 11.8 years) and height from 160 to 185 (172.8 ± 10.5 cm). The testing dataset included the accelerometer data acquired from group-2 subjects asked to perform all activities in Table 1. Eight subjects (3 males and 5 females) participated in the testing phase. Age ranged from 29 to 54 years (37.2 ± 9.7 years) and height from 158 to 187 (172.1 ± 9.5 cm).

2.3 The Step Counting Algorithm

A standard calibration procedure was employed to calibrate the built-in tri-axial accelerometer [24]. The computed values of offset and scale factor along the three sensitivity axes were used to compensate for calibration errors before processing the accelerometer measurements by ADAM.

The acceleration magnitude

$$A_m = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

was computed from the acceleration components. An 8-point moving average filter was applied to the acceleration magnitude, followed by a 3-point moving median filter, in the combined effort to remove the high-frequency noise and mitigate the effects of outlying measurements. If the absolute difference between the current sample and the previous sample at the output of the moving median filter was less than a small threshold (λ_M), the current sample was clipped to the previous sample, yielding A_{mL}. A high-pass filtered version of A_{mL} was obtained, namely A_{mH}, by subtracting an 8-point moving averaged version of A_{mL} from A_{mL} itself. On a separate conditioning line, the acceleration components a_x, a_y, a_z were filtered using a 16-point moving average filter, yielding a_{xL}, a_{yL}, a_{zL}.

2.3.1 Dynamic Thresholding

In accordance to previous studies, we hypothesize that local maxima of the acceleration magnitude correlate with foot contacts at the beginning of each gait step, provided that such peak values are high enough and are not determined by acceleration measurement noise [25]. Hence, each peak of A_{mL} whose value exceeds some threshold value λ_D *can* increase the step count by one unit, depending on the outcome of the step validation procedure described in the following. We propose to determine the threshold value on line (dynamic thresholding) by clipping A_{mL} to a minimum value (to reduce the effects of the pedometer vibrating very rapidly or very slowly from a cause other than walking), before being time-shifted by $\tau_d = K_d T_s$ units of time. The rationale for this choice is explained, first, by analyzing the shortcomings of a popular means to compute λ_D [25]:

$$\lambda_D = \frac{max\{A_{mL}\}_{\tau_w} + min\{A_{mL}\}_{\tau_w}}{2}. \quad (2)$$

The adaptive threshold is computed as the arithmetic mean between the maximum and the minimum values of A_{mL}. These values are evaluated using a signal window of length τ_w extending from the current sample of A_{mL} backwards; the threshold is then clipped to a minimum value A_{min}. The peak is searched in the time interval from the positive crossing time (rising time), i.e., when A_{mL} crosses λ_D with positive slope to the negative crossing time, to the negative crossing time (falling time) i.e., when A_{mL} crosses λ_D with negative slope. In the example reported in Fig. 3, λ_D is computed over different time windows according to (2), and clipped to A_{min} (A_{min} = 1.033 *g*). In the time window over which

A_{mL} exeeds (or not) the dynamic threshold λ_D the step counter state is: armed (not armed).

In the example, it is noted that the step annotated as P4 is not detected when τ_w = 1 s, yielding a false negative in the step detection process (Fig. 3a). This behavior is quite typical, especially when the peak values of A_{mL} differ markedly during consecutive steps, namely when left and right steps are not symmetric. Slight asymmetries are typical even of healthy gait as highlighted by analyzing data from waist-worn sensors [26] and they are likely to exist as far as the motion of the upper arm is considered; intermittent ambulation (e.g., frequent stops and starts, abrupt directional changes) thus further exacerbates the problem. In the effort to make the dynamic threshold adapting faster to the signal shape, τ_w can be reduced, as in Fig. 3b, where τ_w = 0.08 s. The peak at P4 is correctly detected, however we observe a false positive occurring in the case of the peak at P0. It is also noted that the time function of the dynamic threshold λ_D tends to a delayed replica of A_{mL} as long as the window's length τ_w is reduced. Let us suppose that the time window is narrowed down to the point when $\tau_w = T_s$, in which case the dynamic threshold turns out to be A_{mL} delayed by one sample. Following the reasoning above, the algorithm would become highly responsive, with the consequence that several false positives might arise, especially when the (wrist) acceleration patterns are irregular. In our WPD implementation, we propose to design the dynamic threshold using a deliberate time-shift of A_{mL} by $K_d > 1$ samples,

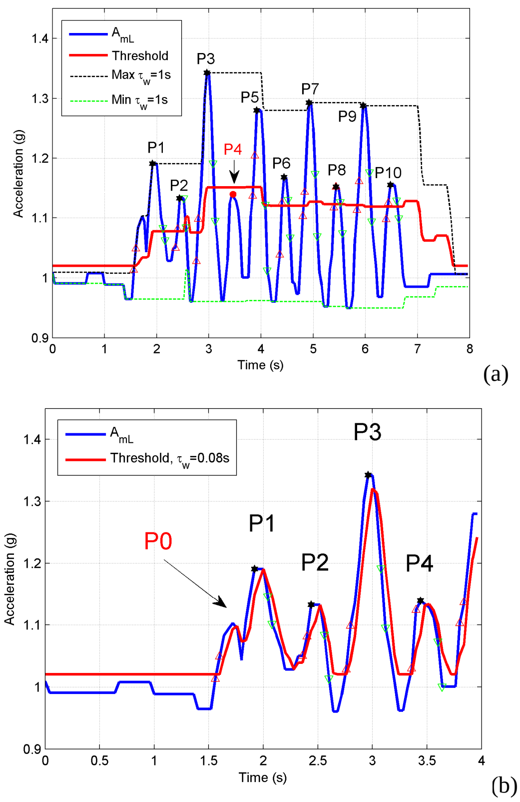


Figure 3. The time functions of A_{mL} (blue) and λ_D (red) are reported for a representative walking bout from activity *Walk-turn-walk*. (a) τ_w = 1 s; (b) τ_w = 0.08 s. Red and green triangular markers indicate the samples within which the dynamic threshold is crossed in rising and falling directions, respectively.

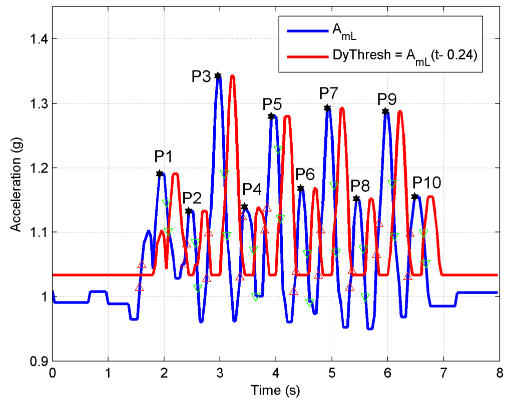


Figure 4. The time functions of A_{mL} (blue) and λ_D (red) are reported for the same walking bout from activity *Walk-turn-walk* in Fig. 3.

in the effort to avoid proliferation of false positives, whilst retaining good adaptation properties. Hence, λ_D is computed as the clipped (to $A_{\min}$) and time-shifted (by $\tau_d = K_d T_s$ units of time) replica of A_{mL}. We hypothesize that this approach may ensure fast adaptation to any change of the underlying signal shape. Figure 4 shows the results for the same example as in Fig. 3: λ_D is computed by delaying A_{mL} by four samples, and the result is then clipped to $A_{\min}$.

In this particular example, the peak at P4 is correctly detected, without introducing false positives in the step detection process. However, successful peak identification does not imply that the step count be increased necessarily by one unit; the detected step-related event must be further validated for achieving better robustness to false positives. In preparation for the step validation phase, the following quantities are computed. The step time, expressed in seconds, is computed as the difference between successive occurrences of A_{mL}-peaks that are identified by dynamic thresholding. The cadence, expressed in Hz, is computed by inverting the average step time, which is estimated from a specified number of step times. Finally, the Root Mean Square of A_{mH} (RMS_H) is calculated in a window of length τ_s extending from the current sample of A_{mH} backwards over the window τ_s.

2.3.2 Step Validation

The proposed procedure of step validation runs a set of rules that are applied at the time when a peak is detected and on a sample-by-sample basis. The SC status is determined by two values: the total number of steps counted so far (N_{step}) and the current number of consecutive peaks that are recognized as steps (ContStep).

The set of rules and the related parameters is illustrated in Table 2. Rule #1 is related to the assumption that a steady walking activity requires at least some consecutive steps to occur [25]. Rule #2 to rule #6 code the intuitive notion that a gait step cannot have abnormal durations (neither too long nor too short), and must be characterized by a significant acceleration footprint [27]. Rule #7 can detect sudden stops of walking (no additional steps have been counted in a given time interval). Rule #8 helps detecting situations when the wristwatch orientation in the three-dimensional space is likely to be inconsistent with the forearm orientation of a walker. Rule #9 helps detecting false positives that are likely to occur due to arm swinging during the last step before a walk stop.

2.4 Metric of Performance

The Count Error (*CE*) was defined as follows (*i*-th activity, *j*-th subject):

$$CE(i,j) = N_{\text{step}}(i,j) - N_{\text{ref}}(i,j),\ i = 1, \dots, 10;\ j = 1, \dots, 8. \quad (3)$$

The Mean Absolute Relative Error (*MARE*) was also considered as performance metric:

$$MARE(i) = 100 \cdot \frac{1}{8} \sum_{j=1}^{8} \left| \frac{CE(i,j)}{N_{\text{ref}}(i,j)} \right|, \qquad i = 1, \dots, 10. \quad (4)$$

CE and *MARE* are the metrics to investigate the accuracy of the three SCs. Henceforth, the term *complete failure* will be used to denote when one method was 100% inaccurate, in the sense that it could not register any valid step in a particular activity.

3. RESULTS AND DISCUSSION

ADAM was trained using the *CE*-statistics generated from the training dataset to handcraft the setting of the input parameters needed by the algorithm, Table 3.

The parameters λ_M, K_d, $A_{\min}$ and StMin were tuned by performing a grid search for determining their optimal value. Empirically, we verified that they were important in determining the algorithm performance, especially the time delay K_d, which turned out to be the essential element of the proposed WPD method. Compared with the case when $K_d = 4$, a too small value tended to increase the detection sensitivity at the expense of the specificity; conversely, a too high value (say, $K_d > 8$) tended to improve the detection specificity, at the expense of the sensitivity.

The parameters TstMin (minimum step time), TstMax (maximum step time), StfMax (maximum cadence), AccMax (maximum value of A_{mL}), AccMin (minimum value of A_{mL}), StRMS (maximum value of RMS_H), and TimeOverT (minimum duration of a step-related acceleration burst) were used to implement simple heuristics that helped improving performance by enforcing reasonable constraints of walking [27]. All other parameters that were grouped under the category Step validation in Table 3 (i.e., A_xMin, A_yMin, A_zMin, A_zMax) helped essentially to improve the capability of rejecting the many false positives that could be collected during activities of daily living involving hand movements that were not necessarily related with walking (rule #8). We performed several tests with the subjects wearing the smartwatch; they were asked to freely perform sedentary activities (i.e., answering phone calls, drinking, typing a keyboard, gesticulating while speaking) and exercise breaks (i.e., outstretching the arms in different spatial orientations) – total recording time: 30 min per subject. By careful analysis of the accelerometer data recorded during these tests, we were able to choose a parameter setting that turned into 100% specificity. It goes without saying that the native Samsung SC accumulated several counts in the same situation where ADAM was not affected by false positives.

Table 4 reports the data concerning the complete failures of each SC. Not surprisingly, the Geonaute SC performed worse in conditions when the number of consecutive steps walked before any stop was not high enough for step validation (*Walk-turn-walk* and *In-home task*); moreover, it suffered from some difficulties even during the activity *Very slow walk*. The explanation is that the factory calibration of the Geonaute SC was for conditions of continuous walking at not-too-low speeds. The Samsung SC

Table 2. Step validation rules

Rule	Description	State
1	Wait updating N_{step} until ContStep ≥ **StMin**	Falling
2	If step time ≤ **TstMin** or step time ≥ **TstMax**, then ContStep = 0	Falling
3	If cadence ≥ **StfMax**, then ContStep = 0 (cadence is computed from the last StMin steps)	Falling
4	If A_{mL}-peak ≥ **AccMa**x, then ContStep = 0	Falling
5	If A_{mL}-peak ≤ **AccMin**, then ContStep = 0	Falling
6	If A_{mL} exceeds λ_D for a time less than **TimeOverT**, then ContStep = 0	Falling
7	If the time elapsed from last valid step (ElapsedTimeFromLastStep) exceeds **TstMax**, then ContStep = 0	Not armed
8	Suspend dynamic thresholding if ContStep ≥ 2 StMin, or the step counter is armed or one of the following four conditions is true: Workspace check: 1. a_{xL} ≥ **A_xMax** 2. a_{yL} ≤ **A_yMax** 3. a_{zL} ≥ **A_zMax** 4. a_{zL} ≤ **A_zMin**	Sample by sample
9	If the following conditions are true: 1. RMS_H ≥ **StRMS** 2. ElapsedTimeFromLastStep ≥ TstMax 3. ContStep ≥ StMin 4. $N_{\text{step}} > 0$ then $N_{\text{step}} = N_{\text{step}} - 1$, and ContStep = 0	Not armed

Table 3. Input parameters of ADAM.

Processing	
λ_M, g	0.017
Dynamic thresholding	
K_d	4.000
$A_{\min}$, g	1.033
Step validation	
StMin	6.000
TstMin, s	0.300
TstMax, s	1.500
StfMax, Hz	3.000
A_xMin, g	0.250
A_yMin, g	0.150
A_zMin, g	–0.360
A_zMax, g	0.800
AccMax, g	2.500
AccMin, g	1.040
TimeOverT, s	0.120
τ_s, s	3.000
StRMS, g	0.080

Table 4. Number of complete failures for each method.

Activity	ADAM	Samsung SC	Geonaute SC
Walk-turn-walk (slow)	0	3	8
Walk-turn-walk (normal)	0	3	8
Walk-turn-walk (fast)	0	6	8
Walk-turn-walk (jogging)	0	5	7
Slow and steady walk	0	0	0
Variable-speed walk	0	0	0
Very slow walk	0	4	2
Jog	0	0	0
Going up-and-down stairs	0	0	0
In-home task	0	0	5
Total	0/80	21/80	38/80

Table 5. Statistics of the performance metric *CE*.

Activity	ADAM				Gear SC				Geonaute SC			
	Mean	Max	Min	Std	Mean	Max	Min	Std	Mean	Max	Min	Std
Walk-turn-walk (slow)	0.7	4	–1	1.5	–3.0	–2	–4	1.0	NA	NA	NA	NA
Walk-turn-walk (normal)	0.6	3	–1	1.4	–1.8	1	–4	2.1	NA	NA	NA	NA
Walk-turn-walk (fast)	1.0	4	–2	2.0	–1.0	–1	–1	0.0	NA	NA	NA	NA
Walk-turn-walk (jogging)	2.7	7	–3	3.2	2.3	7	–7	8.1	4.0	4	4	0.0
Slow and steady walk	–4.9	3	–20	7.1	–4.5	0	–17	5.5	–4.8	3	–18	8.3
Variable-speed walk	–11.1	18	–84	30.9	–4.6	23	–50	20.8	4.4	36	–10	14.1
Very slow walk	–2.9	8	–17	7.1	–21.5	0	–76	36.4	–30.0	1	–82	38.5
Jog	0.0	5	–3	2.8	–5.5	15	–63	24.0	4.0	17	–4	6.4
Going up-and-down stairs	–0.1	3	–2	1.6	–1.3	1	–4	2.1	0.8	3	0	1.0
In-home task	–5.5	1	–26	9.0	–10.5	10	–42	19.0	–61.0	2	–103	55.6

performed better than the Geonaute SC in our experiments, but not for the activity *Very slow walk*. The same comment concerning the factory calibration is pertinent to explain the Samsung SC behavior.

Limiting the statistical analysis just to the trials when the methods did not undergo complete failure, Table 5 reports the *CE* statistics for each activity, averaged across subjects (mean value, standard deviation, minimum value, maximum value). The two commercial devices, particularly the Samsung SC, tended to undercount steps, especially when the walking conditions differed to some extent from those assumed for the factory calibration. Conversely, ADAM performed acceptably, although, due to an outlying subject performing the activity *Variable-speed walk*, namely one subject for which ADAM heavily undercounted steps, the mean error and the standard deviation were slightly greater than those achieved by the two other methods in the same conditions.

Finally, Table 6 reports the *MARE* values scored by the three SCs.

The three tested SCs performed similarly during the extended walks of *Slow and steady walk*, *Variable-speed walk* and during *Going up-and-down stairs*; conversely, ADAM outperformed the two other pedometers in all conditions when the movement was very slow (i.e., during *Very slow walk*) and more intermittent [*Walk-turn-walk* (except jogging) and *In-home task*]. *Walk-turn-walk (jogging)* was the only activity where the three methods performed poorly, although ADAM was better even in this case (no complete failures and lower MARE values).

The complete failures and the errors incurred by the three methods, and especially by the Geonaute SC, during the activity *Walk-turn-walk*, in all conditions of walking speed, can be partly explained as the consequence of the built-in assumption of registering a step only after that a certain number of consecutive steps have been observed. This assumption is common to all tested methods. In the absence of documented information about the behavior of the two commercial devices, we can only conjecture which value of the parameter StMin they have (StMin = 10, we believe). The approach we propose to dynamic thresholding allowed reducing StMin without substantial performance degradation, provided that the time delay K_d was suitably chosen.

From inspecting the performance data reported in Tables 4-6, the Samsung SC outperformed the Geonaute SC; ADAM outperformed both during *Walk-turn-walk* (in all variants) and *In-home task*. Moreover, the two wrist-worn SCs tended to perform better than the waist-worn SC when the walking speed was slower than normal, with the preference to be given to ADAM. We can conclude that the two customer SCs were not probably designed to perform accurate step counting in those situations (slow and intermittent walking) where ADAM suited better. The data reported in Table 6 indicate MARE values incurred by ADAM lower than 5% during continuous walking across a range of speeds, which increased to 5%-18% when short walking bouts were considered. We consider the results of this paper in connection with the results reported by Cheng et al [28], who analyzed step counts using a custom smartphone algorithm and a commercial waist-band pedometer when two healthy subjects walked 500 consecutive steps. The custom smartphone algorithm outperformed the waist-band pedometer, showing performance comparable to ours (activities *Slow and steady walk* and *Variable-speed walk*). However, they taped together the smartphone and the waist-band pedometer and fixed them at the L3 level (lower trunk). In these conditions, trunk accelerometry is widely regarded as a feasible technique to accurately measure spatio-temporal parameters of gait, including step time and cadence [29], [30]; however, serious concerns exist for its suitability when gait is pathologic, the gait speed is low, or both [31]. Cheng et al recognized This same difficulty was recognized in [28], in experiments involving COPD (Chronic Obstructive Pulmonary Disease) patients that performed the Six Minutes Walking Test (6MWT); see also [32], for a discussion of the trend of state-of-the-art pedometers to undercount steps in conditions of slow walking. We verified the same behavior of either the Samsung or the Geonaute SC, which sometimes also completely failed to count at slow walking speeds. On the other hand, the undercount bias of ADAM was generally small. We consider therefore the ADAM error rate, particularly during the activity *Very slow walk*, a very promising result.

Table 6. Values of the performance metric MARE.

Activity	ADAM	Samsung SC	Geonaute SC
Walk-turn-walk (slow)	5	15	NA
Walk-turn-walk (normal)	6	11	NA
Walk-turn-walk (fast)	9	5	NA
Walk-turn-walk (jogging)	18	35	20
Slow and steady walk	1	1	1
Variable-speed walk	3	2	2
Very slow walk	5	21	30
Jog	2	12	5
Going up-and-down stairs	2	3	2
In-home task	6	17	61

It is noted that ADAM and the Samsung pedometer are two apps that run on the smartwatch, sharing the same raw accelerometer data. The ADAM step counting loop works at the rate of 25 samples per second; in the absence of any further information, we believe that the sampling rate is the same for the Samsung pedometer. In terms of power consumption, we verified that the time from full charge to complete discharge of the battery system is 72 hours (low-power screen-off mode) and 5 hours (screen-on mode), irrespective of whether the Samsung pedometer runs alone or ADAM works in conjunction with it (the Samsung pedometer is a permanent application that can never be aborted). The computational load of ADAM is therefore similar to that of the Samsung SC, and both apps drain only a limited amount of battery power, compared with the battery draining due to, e.g., the screen condition. Of course, any further consideration about the battery life must consider that smartwatches are devices that can be used for fulfilling many functions, including, e.g., telephony, e-mailing, Bluetooth connectivity, which all are known to be greedy of battery power. In this sense, the power requirements and the battery charging policies of a smartwatch would not be dissimilar from those of a smartphone.

4. Conclusions and Outlook

This paper was concerned with the development and the preliminary validation of a step counter that was designed for applications when ambulation can be slow and intermittent. The step counter was based on processing the accelerometer data measured by a commercial smartwatch using a custom wearable app (ADAM). Compared with either the native step counter running in the smartwatch or a waist-worn pedometer, ADAM exhibited similar accuracy levels in conditions of normal walking, and was superior in conditions of slow and intermittent ambulation. The WPD algorithm developed in this paper for step counting can be ported to any wrist-worn mobile device that embeds a tri-axial accelerometer to measure wrist acceleration. Our novel approach to dynamic thresholding might be useful even in the implementation of WPDs for step counting using other accelerometer placement sites, although we have not yet tested it. As for the wrist, the experimental results shown in the paper offer promise for a robust solution to the problem of step counting in difficult conditions of slow and intermittent walking.

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