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A Smartwatch Step Counter for Slow and Intermittent Ambulation

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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 everyday movement, 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) designed to operate also in conditions of slow and intermittent ambulation. The SC was based on processing the accelerometer data measured by a Gear 2 smartwatch running a custom wearable app, named ADAM. A data set of eight users, for a total of 80 trials, was used to tune ADAM. Finally, ADAM was compared with two different commercial SCs: the native SC running on the Gear 2 smart watch and a waist-worn SC, the Geonaute ONSTEP 400. A second data set of eight additional users for a total of 80 trials was used for the assessment study. 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%, which is significantly lower than errors of 20%–30% incurred by the two other SCs.

INDEX TERMS Accelerometer, elderly, inertial sensor, pedometer, smartwatch, step counting, walking, wrist.

I. INTRODUCTION

Ageing of the population and the concurrent increase of the number of people who spend a large part of their daily time at home, motivates the development of ambulatory monitoring systems that are capable to evaluate the level of physical activity in conditions of restrained mobility [1]. Because of the importance of walking for a healthy lifestyle, step detection and counting is believed to convey valuable information about the complex relationships existing between health and physical activity [2].

A large number of devices and applications have been developed for the purpose of physical activity monitoring [3]–[5]. Accelerometry is the technology of choice for wearable devices to measure and assess physical activity, with several applications documented, including gait and balance quality evaluation for fall risk assessment [6], [7], sleep assessment [8], fall detection and prevention [9]. Albeit the importance of a reliable strategy for activity assessment in free living conditions for the elderly is widely recognized, the available technological solutions are not generally ready for deployment: there is not enough evidence to support the assumption that those solutions, validated by testing on young adults data, can be used without proper consideration that elderly people move differently from younger people. Age related changes in gait patterns and characteristics such as speed or duration of walking episodes are known [10] and have been observed to affect inertial sensor data processing [11], [12]. Thus, dedicated strategies have to be designed and developed with the specific aim of an effective activity monitor for the elderly. In this paper, we moved a first step in this direction, by carrying out experimental tests in which young volunteers were asked to walk, with different styles and speeds, including slow and intermittent ambulation, so as to stress the capabilities of the novel step detection and counting method we propose. The method was implemented in a smart watch; its performances were compared with the ones given by the native app running in the device, and by a commercially available waist-worn step counter (SC).

A. WEARABLE TECHNOLOGY FOR STEP COUNTING

An SC – the device used for recording the number of walked steps – 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 [13], [14].

Differently from past switch-based devices, modern SCs are based on Micro-Electro Mechanical Systems (MEMS) accelerometers. There are several factors that can limit the accuracy of SCs, including placement site, intensity of walking, counting errors due to non-ambulatory activities [15]–[17]. The most common placement site of SCs 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 in relation to an anatomical reference frame, which can be influenced by body fat and clothing [15], [17]. 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 SCs are grossly inaccurate when the walking speed is low [1], [18].

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 SCs is that the mobile devices are 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) [19]. In contrast with waist-worn SCs, smartphone-based SCs are also more sensitive to the influence of non-ambulatory activities, albeit interesting results have been recently reported as for the recognition of activity and the estimation of spatio-temporal parameters of gait [20], [21]. Moreover, movements of the upper arm when the smartphone is carried in the hand are not necessarily correlated with walking. 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 [19], [22], [23]. Anyway, in a similar fashion to waist-worn SCs, smartphone-based SCs suffer from accuracy degradations when the walking speed is slow. In the attempt to improve the performance of smartphone-based SCs, embedded MEMS gyroscopes have also been considered as an alternative to accelerometers [24].

B. SMARTWATCH TECHNOLOGY FOR STEP COUNTING

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 SCs. Lack of interest or motivation in using them is highly predictive of later refusal. In this regard, a new generation of mobile devices may ease a change of habits. 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 devoted 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 [25]–[27]. 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). All these data can be used for longitudinal monitoring of health status and for quantimetric self-tracking, as advocated by the Quantified Self movement [22], [28]–[31].

The problem of the reliability of measurements is cited as a major obstacle to a wider use of wearable health monitoring devices such as smartwatches. Not dissimilarly from smartphones, processing the accelerometer data from smartwatches for activity recognition is challenging because of the wrist gesticulation and variability in movement, compared with other placement sites such as waist or ankle [32]. 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 SC, although arm movements are generally well correlated with leg movements during steady walking.

In the case of intermittent ambulation activities, a critical issue is the number of missed steps that may occur due to the irregular signal patterns from the built-in accelerometer, regardless of the 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) [19]. A wristwatch SC 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, [33], [34]. This paper is an initial attempt to fill the gap. Previous research on smartphone step counting showed that frequency-domain or correlation approaches did not accrue substantial benefits compared with windowed peak detection (WPD) methods for step counting in conditions of normal walking [19]; on the other hand, WPD methods are easier to implement and present reduced computational loads. Therefore, we developed an adaptive WPD algorithm for wristwatch-based 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 SC. Experimental tests included steady walking at several speeds, jogging, non-ambulatory activities, and intermittent and slow ambulation.

II. EXPERIMENTAL SECTION

A. SYSTEM DESIGN AND IMPLEMENTATION

The technological solution we propose and describe in this paper can be considered just as a module of a full suite of devices and algorithms of a multi-purpose Body Sensor Network (BSN) for monitoring and assessing (elderly) individuals involved in several of their daily-life activities, see Fig. 1. Within the framework of this platform, algorithms for fall risk assessment [30], gait and balance assessment [35], fall detection [36], activity recognition [32], [37] and gait alteration detection [38], [39] have been and currently being conceived and deployed.

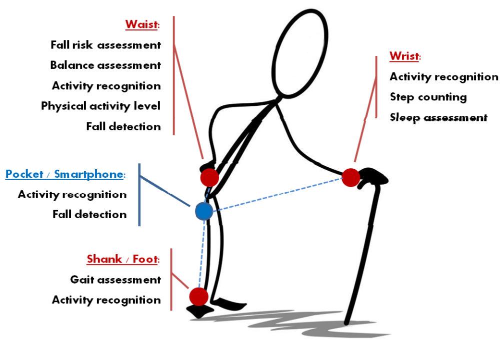

FIGURE 1. Multi-purpose BSN for monitoring and assessing (elderly) individuals in daily-life activities.

Given the scope of this paper, the development of a single sensor unit is targeted, aiming specifically at providing solutions to the problem of step counting. The smartwatch is thus just another node that was integrated in the BSN, with all sensor and processing resources needed to perform step counting.

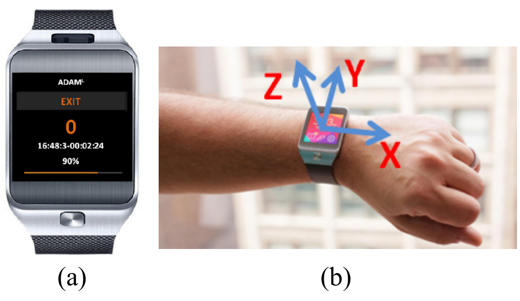

FIGURE 2. (a) The Gear 2 smartwatch used for ADAM development; (b) The mobile reference frame aligned with the sensitivity axes of the embedded accelerometer.

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. 2. 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 at the sampling frequency $f_s = 25$ Hz (sampling interval $T_s = 40$ ms), normalized to the gravitational acceleration g, $g = 9.81$ m/s^2, relative to the mobile reference frame shown in Fig. 1b. Additionally, a tri-axial gyroscope was available to measure the angular velocity. However acceleration data only were included in the SC algorithm.

B. 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). Although field tests involving elderly users are surely needed for a thorough validation of the proposed approach, just two groups of healthy adult subjects participated in the preliminary experimental phase reported in this paper. 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 on the non-dominant hand wrist and a commercial SC (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 truly naturalistic conditions, we took care of minimizing experimental biases, by asking subjects to move as naturally as they could. Moreover, they did not receive verbal or any other feedback information about the SC output, only start and stop messages were issued to them. The device initialization required a 2-s interval when the subject was asked to stand still in the so-called neutral standing posture, which allowed to recognize whether the smartwatch was worn on the left or right wrist. Because of the absence of elderly participants in the subject pool, particular care was devoted to the definition of the experimental study protocol, which also involved conditions of slow and intermittent ambulation typical of walking habits of elderly people. After initialization took place, 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. An activity named "In-home task" was also considered, figure 3. The full set of activities considered for training ADAM and for testing ADAM, the Gear 2 and the Geonaute SCs, is reported 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.

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).

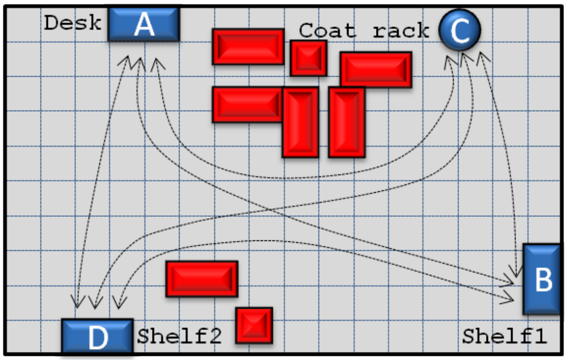

FIGURE 3. Room layout, with the furniture location for the In-home task activity. The red shapes are fixed obstacles to be avoided. The blue shapes are the target points. The grid size is 60 cm × 60 cm.

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 Fig. 3): 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.

C. THE STEP COUNTING ALGORITHM

A standard calibration procedure was employed to calibrate the built-in tri-axial accelerometer [40]. 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

$$A_m = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

was computed from the acceleration components. An 8-point moving average filter was applied to the acceleration magnitude, following 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}.

1) DYNAMIC THRESHOLDING

In accordance to previous studies, we hypothesized that local maxima of the acceleration magnitude correlated with foot contacts at the beginning of each gait step, provided that such peak values were high enough and were not determined by acceleration measurement noise [41]. Hence, each peak of A_{mL} whose value exceeded some threshold value λ_D *could* 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 in on-line conditions (i.e., dynamic thresholding) by time-shifting A_{mL} of $\tau_d = K_d T_s$ seconds and clipping its value to a prefixed minimum value (to reduce the effects of the device vibrating very rapidly or very slowly from a cause other than walking). The rationale behind this choice was explained, first, by analyzing the shortcomings of a popular means to compute λ_D [41]:

$$\lambda_D = \frac{max\,\{A_{mL}\}_{\tau_w} + min\,\{A_{mL}\}_{\tau_w}}{2}. \tag{2}$$

The adaptive threshold was computed as the arithmetic mean between the maximum and the minimum values of A_{mL} occurring in a signal window of length τ_w that extended from the current A_{mL} sample backwards, respectively: $max\,\{A_{mL}\}_{\tau_w}$ and $min\,\{A_{mL}\}_{\tau_w}$; the threshold was then clipped to a minimum value $A_{\min}$. The peak was searched in the time interval from the positive crossing time (rising time), i.e., when A_{mL} crossed λ_D with positive slope, to the negative crossing time (falling time), i.e., when A_{mL} crossed λ_D with negative slope. In the example reported in Fig. 4, λ_D was computed over different time windows according to (2), and clipped to $A_{\min}$ ($A_{\min} = 1.033\ g$). When A_{mL} exceeded the dynamic threshold λ_D, the SC state was set to *armed* (*notarmed* otherwise).

In the example, it is noted that the step annotated as P4 was not detected when $\tau_w = 1$ s, yielding a false negative in the

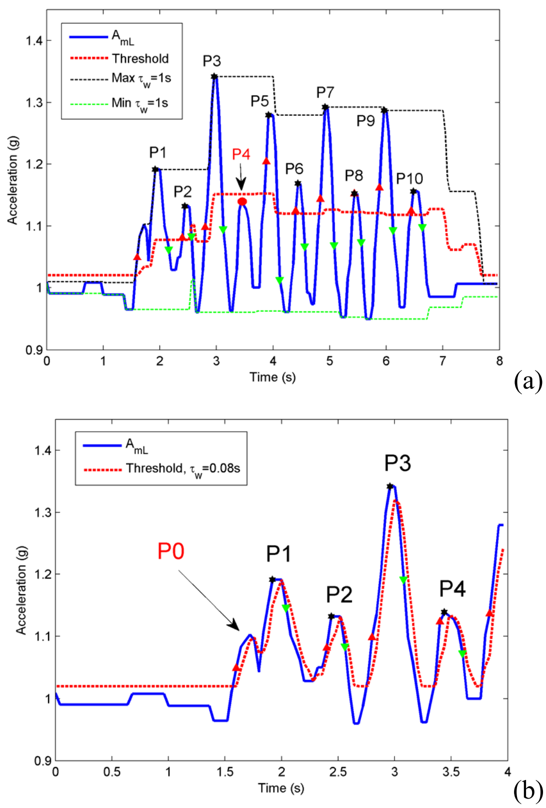

FIGURE 4. The time functions of A_{mL} (blue) and λ_D (red) are reported for a representative walking bout from activity Walk-turn-walk. (a) $\tau_W = 1$ s; (b) $\tau_W = 0.08$ s. Red and green triangular markers indicate the samples within which the dynamic threshold is crossed in rising and falling directions, respectively.

step detection process (Fig. 4a). This behavior was quite typical, especially when the peak values of A_{mL} differed markedly during consecutive steps, namely when left and right steps were not symmetric. Slight asymmetries are typical even of healthy gait as highlighted by analyzing data from waist-worn sensors [42] 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) would further exacerbate the problem. In the effort to make the dynamic threshold adapting faster to the signal shape, τ_w could be reduced, as in Fig. 4b, where $\tau_w = 0.08$ s. The peak at P4 was correctly detected, however we observe a false positive occurring in the case of the peak at P0. It is also noted that reducing the window's length τ_w, the time function of the dynamic threshold λ_D tended to a delayed replica of A_{mL}. Let us suppose that the time window was narrowed down to the point when $\tau_w = T_s$, in which case the dynamic threshold turned 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 were irregular. In our WPD implementation, our proposal was to design the dynamic threshold using a deliberate time-shift of A_{mL} by $K_d > 1$ samples, in the effort to avoid proliferation of false positives, whilst retaining

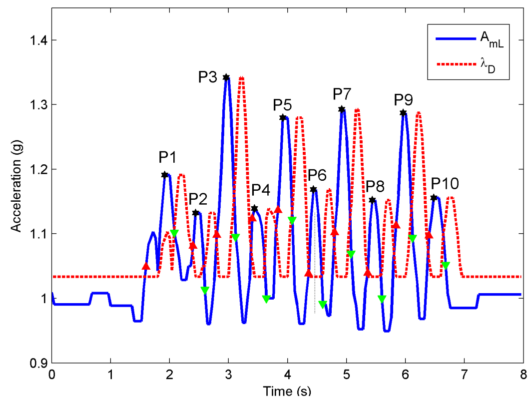

FIGURE 5. The time functions of A_{mL} (blue) and λ_D (red) are reported for the same walking bout from activity Walk-turn-walk in Fig. 4.

good adaptation properties. Hence, λ_D was computed as the clipped (to $A_{\min}$) and time-shifted (by $\tau_d = K_d T_s$ seconds) replica of A_{mL}. We hypothesize that this approach may ensure fast adaptation to any change of the underlying signal shape. Fig. 5 shows the results for the same example as in Fig. 4: λ_D was computed by delaying A_{mL} by four samples, and the result was then clipped to $A_{\min}$.

In this particular example, the peak at P4 was correctly detected, without introducing false positives in the step detection process. However, successful peak identification did 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 were computed. The step time, expressed in seconds, was computed as the difference between successive occurrences of the A_{mL} peaks that were identified by dynamic thresholding. The cadence, expressed in Hz, was computed by inverting the average step time, which was estimated from a specified number of step times. Finally, the Root Mean Square of A_{mH} ($\mathrm{RMS_H}$) was calculated in a window of length τ_s extending backward from the current sample of A_{mH}.

2) STEP VALIDATION

The step validation was intended as a set of algorithmic prescriptions used to reduce the rate of wrong detections incurred by the step-counting process. In particular simple heuristics were implemented, which helped improving performance by enforcing reasonable constraints of walking [43]. Throughout the various stages of the step validation process, the SC status was determined based on the values of two parameters: the total number of steps counted since the beginning of the current counting process (N_{step}), and the number of peaks that were recognized as valid, up to the current time ($Cont_{step}$) since last stop. A block scheme of the proposed algorithm is reported in figure 6.

The set of rules and the related parameters as implemented in the block scheme are illustrated in Table 2 and briefly explained in the following. In particular, on a sample-by-sample basis, Rule #1 was applied to avoid false

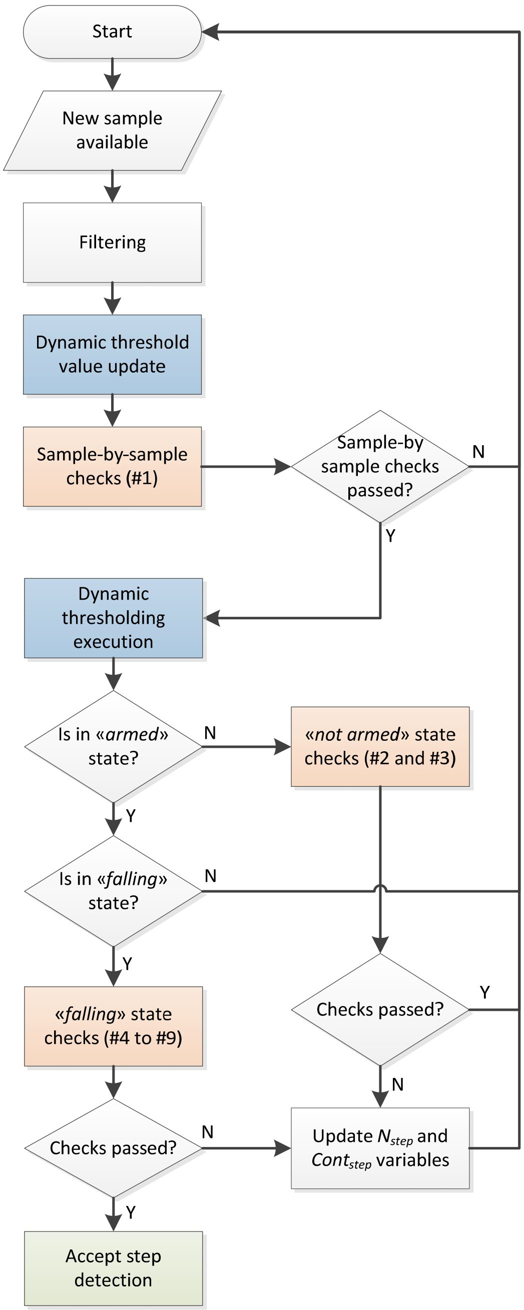

FIGURE 6. **Block diagram showing the algorithm of step validation in action. Blocks colored in blue refer to dynamic thresholding, blocks colored in orange refer to different stages of the step validation procedure. The numbers reported within the orange blocks correspond to the IDs of the rules described in Table 2.**

positives that were likely to occur due to arm swinging during the last step before a walk stop: $A_{x,min}$, $A_{y,min}$, $A_{z,min}$, $A_{z,max}$ were the values of thresholds applied to single acceleration data channels, tuned to discard signals that were not compatible with the walking-related arm swing. A second group of rules (#2 and #3) was applied in the case when dynamic thresholding indicated an ''armed'' condition, i.e. the threshold was crossed upwards, but it was not yet crossed in the opposite direction. Rule #2 reset the $Cont_{step}$ value to zero in

TABLE 2. **Step validation rules.**

Rule ID	Description	SC state
1	Suspend thresholding if $Cont_{step} \geq 2\ St_{min}$, or the step counter is armed or one of the following four conditions is satisfied: $a_{xL} \geq A_{x,\ min}$ $a_{yL} \leq A_{y,\ min}$ $a_{zL} \geq A_{z,\ min}$ $a_{zL} \leq A_{z,\ max}$	Sample by sample
2	If the time elapsed from last valid step (*ElapsedTimeFromLastStep*) exceeds Tst_{max}, then $Cont_{step} = 0$	Not armed
3	If the following conditions are satisfied: 1. $RMS_H \geq StRMS$ 2. $ElapsedTimeFromLastStep \geq Tst_{max}$ 3. $Cont_{step} \geq St_{min}$ 4. $N_{step} > 0$ then $N_{step} = N_{step} - 1$, and $Cont_{step} = 0$	Not armed
4	Wait updating N_{step} until $Cont_{step} \geq St_{min}$	Falling
5	If step time $\leq Tst_{min}$ or step time $\geq Tst_{max}$, then $Cont_{step} = 0$	Falling
6	If cadence $\geq Stf_{max}$, then $Cont_{step} = 0$ (cadence is computed from the last St_{min} steps)	Falling
7	If $max(A_{mL}) \geq Acc_{max}$, then $Cont_{step} = 0$	Falling
8	If $max(A_{mL}) \leq Acc_{min}$, then $Cont_{step} = 0$	Falling
9	If A_{mL} exceeds λ_D for a time less than ΔT, then $Cont_{step} = 0$	Falling

case of long time intervals elapsed from the last valid step, based on the threshold Tst_{max}. Rule #3 detected sudden stops of walking and was designed to reject false positives related to arm swinging occurring in the course of the last step before a walk stop. In order to detect such conditiona joint check was carried on the RMS_H of the signal by means of the St_{RMS} threshold, on the time elapsed from the last step (threshold Tst_{max} as in Rule #2), on the value of $Cont_{step}$ (this had to be greater than its minimum value St_{min}) and on the value of N_{step}.

Rules from #4 to #9 acted at the time instant of step detection, which occurred when the dynamic threshold was crossed downwards (''falling'' state, see figure 7). Depending on the outcome of rules from #4 to #9, we were in the position to accept the step or not. Rule #4 was related to the assumption that a steady walking activity required at least some consecutive steps to occur [41]. In particular, the update of the N_{step} value was inhibited until $Cont_{step}$ value reached the threshold value St_{min}. Rules #5 and #6 coded 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 [43]. These rules were driven by the parameters Tst_{max}, Tst_{min} (maximum and minimum step time), Stf_{max} (maximum cadence), Acc_{max} (maximum value of A_{mL}), Acc_{min} (minimum value of A_{mL}) and ΔT (minimum duration of a step-related acceleration burst).

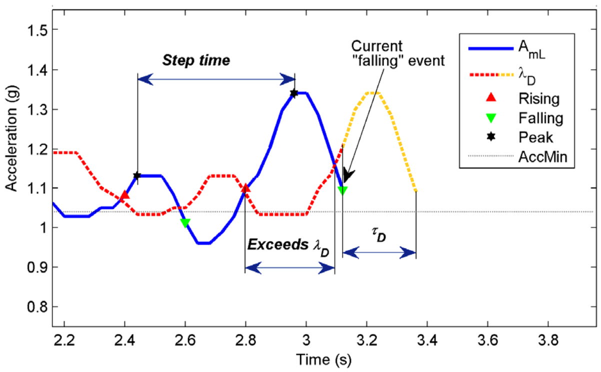

FIGURE 7. Schematic description of parameters used in the step validation rules that were applied in the "falling" state (green marker). In particular, rules #5 and #6 of Table 2 were applied to stride time and cadence evaluated starting from peaks (black markers), rules #7 and #8 referred to the amplitude of the signal (Acc_{min}, black dashed line), Acc_{max} is not reported (2.5 g). Rule #9 was applied to the time interval in which A_{mL} exceeded the dynamic threshold λ_D (red dashed line). In orange, the dynamic threshold that will be applied to the K_d samples of the A_{mL} signal following the current sample.

TABLE 3. Input parameters of ADAM.

Processing	
λ_M, g	0.017
Dynamic thresholding	
K_d	4
A_{min}, g	1.033
Step validation	
St_{min}	6
Tst_{min}, s	0.30
Tst_{max}, s	1.50
Stf_{max}, Hz	3.00
$A_{x,min}$, g	0.25
$A_{y,min}$, g	0.15
$A_{z,min}$, g	-0.36
$A_{z,max}$, g	0.80
Acc_{max}, g	2.50
Acc_{min}, g	1.04
T, s	0.12
τ_s, s	3.00
St_{RMS}, g	0.08

D. ALGORITHM TRAINING

As explained in the Experimental Protocol section, two datasets (with different subjects involved in each) were considered for the purpose of training and testing the algorithm. In addition to the activities prescribed by the protocol in Table 1, we performed several other 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.

The training procedure was then implemented in two steps. First, the parameters, whose actual setting was verified to significantly affect the algorithm performance, namely λ_M, K_d, A_{min} and St_{min}, were identified. The remaining parameters were given default values that were found acceptable in the current scenario. In the second step, the parameters λ_M, K_d, A_{min} and St_{min} were tuned offline by implementing 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. Overall, the parameter setting we choose (Table 3) turned into 100% specificity, including analysis of data from sedentary activities and exercise breaks. 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. 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

E. METRIC OF PERFORMANCE

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

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

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

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

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.

III. RESULTS AND DISCUSSION

ADAM was trained using the CE-statistics generated from the training dataset. Table 3 shows the resulting setting of the input parameters needed by the algorithm. 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

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

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

some difficulties even during the activity *Very slow walk*. The explanation is that the factory calibration of the Geonaute SC was likely tailored to continuous walking at free selected walking speeds. The Samsung SC performed better than the Geonaute SC in our experiments, with the exception of the *Very slow walk* activity. The same comment concerning the factory calibration is pertinent to explain the behavior of the Samsung SC.

Limiting the statistical analysis to the trials in which 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. Due to an outlying subject performing the *Variable-speed walk* activity, 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.

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 step counters 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 St_{min} they have ($St_{min} = 10$, we believe). The approach we propose to dynamic thresholding allowed reducing St_{min} 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 commercial 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.*, who analyzed step counts using a custom smartphone algorithm and a commercial waist-band SC when two healthy subjects walked 500 consecutive steps, [44]. The custom smartphone algorithm outperformed the waist-band SC, showing performance comparable to ours (activities *Slow and steady walk* and *Variable-speed walk*). However, they taped together the smartphone and the waist-band SC 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 [45], [46]; however, serious concerns exist for its suitability when gait is pathologic, the gait speed is low, or both [47]. This same difficulty was recognized by Cheng *et al.*, in experiments involving COPD (Chronic Obstructive Pulmonary Disease) patients that performed the

Six Minutes Walking Test (6MWT), [44]; a discussion on the trend of state-of-the-art SCs to undercount steps in conditions of slow walking is also reported by Turner *et al.*, [48]. We verified the same behavior for 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.

It is noted that ADAM and the Samsung SCs 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 SC. In terms of power consumption, we verified that the time from full charge to complete discharge of the battery system is approximately 72 hours (low-power screen-off mode) and 5 hours (screen-on mode), irrespective of whether the Samsung SC runs alone or ADAM works in conjunction with it (the Samsung SC is a permanent application that cannot 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 too dissimilar from those of a smartphone.

IV. 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 SC running in the smartwatch or a waist-worn SC, 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 tested it yet. As for the wrist, the experimental results shown in the paper offer promise for a robust solution to the problem of step counting in the difficult conditions of slow and intermittent walking.

The availability of a step counter that can detect slow and intermittent walking allows to overcome the limitations of currently available commercial devices. As a consequence, the proposed ADAM app has the potential to improve the reliability of the objective quantification of mobility, physical activity level and fall risk in the elderly.

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