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Walking and running cadence estimation using a single trunk-fixed accelerometer for daily physical activities assessment*

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***Abstract*— Accurate assessment of the type, duration, and intensity of physical activity (PA) in daily life is considered very important because of the close relationship between PA level, health, and well-being. Therefore, the assessment of PA using lightweight wearable sensors has gained interest in recent years. In particular, the use of activity monitors could help to measure the health-related effects of specific PA interventions. Our study, named as *Run4Vit*, focuses on evaluating the acute and long-term effects of an eight-week running intervention on PA behaviour and vitality. To achieve this goal, we developed an algorithm to detect running and estimate instantaneous cadence using a single trunk-fixed accelerometer. Cadence was computed using time and frequency domain approaches. Validation was performed over a wide range of locomotion speeds using an open-source gait database. Across all subjects, the cadence estimation algorithms achieved a mean bias and precision of -0.01 ± 0.69 steps/min for the temporal method and 0.02 ± 1.33 steps/min for the frequency method. The running detection algorithm demonstrated very good performance, with an accuracy of 98% and a precision superior to 99%. These algorithms could be used to extract metrics related to the multiple dimensions of PA, and provide reliable outcome measures for the *Run4Vit* longitudinal running intervention program.**

***Clinical Relevance*—This work aims at validating a multi-dimensional physical activity (PA) classification algorithm for assessing the acute and long-term effects of eight weeks running intervention on PA behaviours and vitality.**

I. Introduction

Sedentary lifestyle is currently considered as a global pandemic [1], with major health-related issues such as cardiovascular disease and premature death [2]. Conversely, practicing regular physical activities (PA) has a wide range of health benefits including the reduction of cardiovascular disease, diabetes, cancer, obesity or depression among others [3]. Because of modern lifestyle (e.g. desk-bound work, television viewing), about two third of European adults do not reach the PA recommendations provided by WHO [4]. In this context, the use of activity monitors could help to measure the health-related effects of specific PA interventions, as well as to defined effective personalized interventions by providing relevant outcome measures.

Clinical-oriented analyses identified key PA assessment components as the activities' type, duration, and intensity [5]. Moreover, their temporal fluctuation, as well as, variance in day-to-day activities are of interest to characterize individuals' specific behavior and predict the trend of functional status [5]. Indeed, even when adults meet the weekly PA guidelines, sedentary postures for prolonged periods affect metabolic health, known as the *"Too much sitting"* issue [6, 7]. Thus, basic quantitative PA metrics such as the daily walking time, number of bouts, or the total sedentary time (e.g. sitting, standing, lying) may be useful to assess the overall PA behaviors and compare results across studies [8]. However, more advance analysis related to dynamics of PA time-series might be relevant for analyzing PA patterns in the context of sedentary behaviors and intervention outcomes [5, 9].

The methodology for classification of PA behavior into multiple 'states' representation as a multidimensional time-series (*barcode)* and quantification of temporal pattern have already been developed and validated for clinical applications such as old adults [9] or patients with chronic pain [5]. However, those algorithms have not been validated for heathy individual performing moderate-to-vigorous or vigorous PA (e.g. running). Furthermore, the intensity of each detected activity is based on the average locomotion cadence computed over the corresponding walking bout, ignoring inter-bout fluctuations.

The main objective of this study is to extend the algorithm proposed in [11] in order to extract walking and running instantaneous cadence (i.e. PA intensity) in daily life. To achieve this goal, two validations are necessary for; (1) the running detection method, and (2) the instantaneous cadence estimation algorithm over a wide range of locomotion speeds. Future work will consist of applying this analytical toolbox to a real-life longitudinal study. Indeed, this work falls within a more general framework named as *Run4Vit* study, which focuses on the relationship between *running* activity and *vitality* - acute and long-term effects of eight weeks running intervention. The outcomes of the current PA classification algorithms will allow us to quantitatively measure the effects of this running intervention on PA behaviors and vitality.

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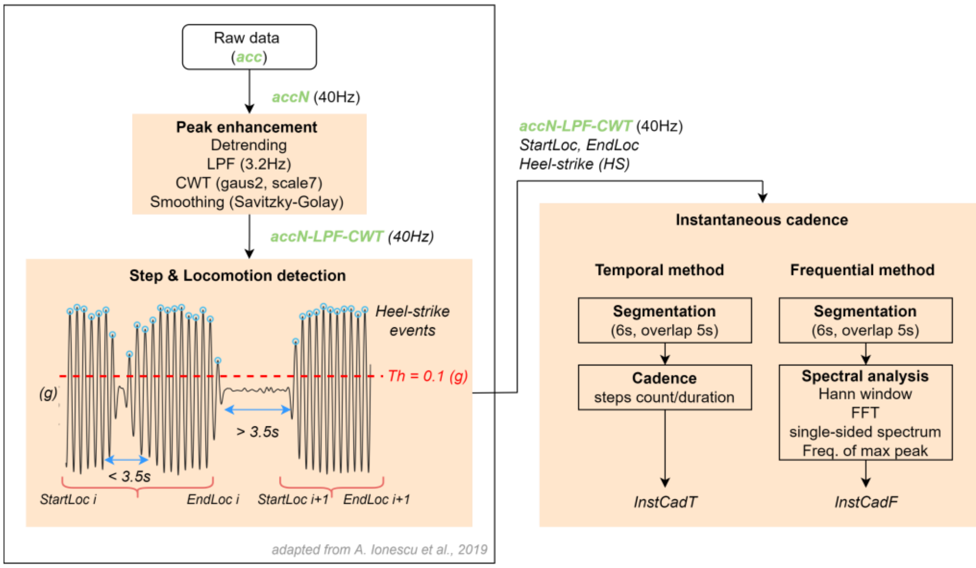

Figure 1. Flowchart of processing stages

II. MATERIALS AND METHODS

A. Database

1) MAREA database

To validate the algorithms, we used the open-source *"Movement Analysis in Real-world Environments using Accelerometers"* (MAREA) gait database [10]. 11 healthy subjects (age: 33 ± 7 y/o) participated in the study that was approved by the Ethical Review Board of Lund, Sweden. Each subject was equipped with a 3-axes accelerometer (Shimmer Research, Dublin, Ireland) fixed on the trunk, as well as instrumented insoles used as gold standards. We tested the performance of the algorithms using the two following protocols: (1) *treadmill incremental test,* where the test starts at 4km/h, then the speed is increased by 0.4km/h every minute until 8km/h; (2) *indoor walk & run*, in which subjects walk and run for 3min each at self-selected speed. The *treadmill incremental test* offers a large range of walking and running speeds, while the *indoor walk & run* presents a walk-to-run transition in a natural environment.

2) Run4Vit database

Then, we tested the validated algorithm to a subset of data from the *Run4Vit* project that was approved by the Ethic commission of the University of Salzburg, Austria. 28 healthy sedentary females (age: 23 ± 3 y/o) recorded their daily PA (~12 hours/day) for 6 days, at pre- and post-intervention, using a single trunk sensor (ECGMove4, *Movisens*®). The intervention consists of running three times per week (~30 min/session) during eight consecutive weeks.

B. Trunk sensor algorithms

1) Locomotion & step detection

Locomotion periods and heel-strike (HS) events were extracted using an adapted version of the algorithms proposed in [11], as shown in the Fig. 1. The acceleration norm, used to be unresponsive to sensor orientation and placement, is first down sampled to 40 Hz. Then, a peak enhancement filtering method is applied using: (1) low-pass and detrending filters. A cutoff frequency of 3.2 Hz was selected to remove high frequency noise while allowing the detection of high step cadence up to ~ 195 steps/min; (2) continuous wavelet transform (*CWT*); and (3) Savitzky-Golay smoothing filter. The *CWT* and smoothing filter were applied to heighten steps-related peaks, making the algorithm robust to artefacts in impaired gait. The scale of the *CWT*, which determines how much the wavelet is stretched or compressed, is a critical parameter for the step detection and cadence estimation. Several *CWT* scale values (from 5 to 10) were tested to find the appropriate wavelet fitting for both walking and running frequency components. Then, from the signal obtained after peak enhancement, *accN-LPF-CWT,* all the peaks with an amplitude above a fixed threshold (*Th=0.1 (g)*) are selected as potential HS events. Finally, the start and end of the locomotion periods (*StartLoc* and *EndLoc*), as well as the HS events, are selected using the criteria defined in [11].

2) Instantaneous cadence estimation

Two methods were implemented to compute the cadence from a single trunk sensor: (1) a time-domain approach based on peak detection corresponding to HS events, and (2) a frequency-domain method based on Fast Fourier Transform (*FFT*).

In the temporal domain, the processed accelerometer signal is segmented using 6s sliding windows with 5s overlap to obtain an estimate each second. Then, the cadence was calculated on each 6s window based on N_{steps} and D_w as:

$$InstCad_T = \frac{N_{steps}}{D_w} \quad (1)$$

In the frequency domain, *accN-LPF-CWT* is segmented into 6s windows (with 5s overlap to obtain one cadence estimate per second). The 6s window length was chosen as an optimum for both, robust features extraction and tracking of instantaneous cadence every second. Then, spectral analysis using *FFT* (Hann window) is computed, and the $InstCad_F$ is defined as the frequency of the maximum peak in the power spectrum.

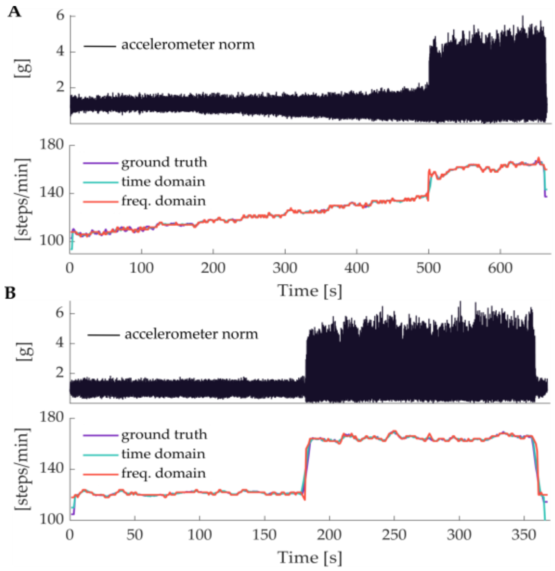

Figure 2. Instantaneous cadence estimation; (A) treadmill incremental test, and (B) indoor walk & run protocol. The top black curves represent the accelerometer norms measured by the trunk-mounted inertial sensor. The purple, blue and red lines correspond to the instantaneous cadence estimated by the reference system (ground truth), the time-domain and the frequency-domain trunk-sensor-based algorithms, respectively.

3) Walking vs running detection

Adults tend to spontaneously start running (walk-to-run transition) at a stride frequency around 140 steps/min [12], [13]. In order to consider inter-subjects' variability, we used 130 steps/min as a cadence threshold. Moreover, this threshold is a reasonable proxy of the absolutely-defined vigorous ambulatory intensity (metabolic equivalents) [14].

To improve the specificity of the running detection, this criterion was combined with a threshold on the amplitude of the acceleration norm empirically chosen based on observation ($Th_{amp} = 2.55\ g$).

C. *Validation and statistical analysis*

The performance of cadence estimation algorithms was assessed using the Bland-Altman analysis for each subject during the *treadmill incremental test.* In case of non-normally distributed errors (tested using the *Shapiro Wilk test*), median and inter quartile range (*IQR*) are used as bias and precision, respectively. Then, mean of the bias and precision across subjects were computed to estimate the overall performance obtained for the MAREA database. The significance level was set to $p < 0.05$. The performance of the running detection algorithm was assessed in terms of accuracy, precision, sensitivity and specificity using the *indoor walk & run* protocol.

III. RESULTS

A. *Filtering, CWT scale optimization*

In order to select the appropriate *CWT* scale parameter, we first visually checked the *accN-LPF-CWT* signals to ensure that the peak enhancement procedure is working properly. Secondly, we computed the rms errors between the estimated and the reference cadence for *CWT* scale values ranging from 5 to 10. The lowest average error across all subject was obtained for the scale parameter 7.

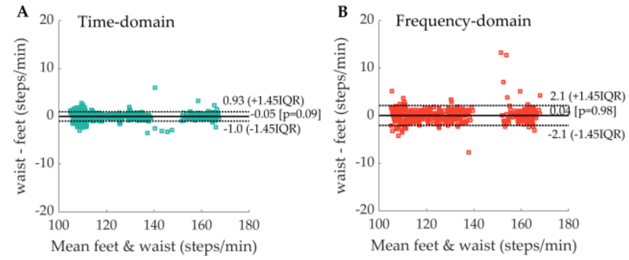

Figure 3. Bland-Altman analysis obtained for the treadmill incremental test for one subject; (A) time-domain method, (B) frequency-domain approach.

B. *Instantaneous cadence estimation*

Fig. 2 shows the acceleration norm, as well as the obtained instantaneous cadences of one subject in the two conditions (*treadmill incremental test* and *indoor walk & run*). The time and frequency-domain estimations (blue and red lines respectively) fit very well the ground-truth cadence measured from the instrumented insoles (purple line, Fig. 2). Bland-Altman analysis obtained for one subject during the *treadmill incremental test* is shown in the Fig. 3. As the computed errors were not normally distributed, we used the median and IQR statistical metrics for each subject (Fig. 3). The mean bias and precision (IQR) across all subjects for both the temporal method (-0.01 ± 0.69 steps/min) and the frequential method (0.02 ± 1.33 steps/min) revealed no systematic error (bias) and very precise estimations (< 1.5 steps/min).

C. *Walking vs running detection*

The Fig. 2B presents the cadence estimation, as well as the walk-to-run transition. On the 10 analyzed subjects' data, we observed a high inter-subject variability. Indeed, some start running at about 135 steps/min, while others around 145 steps/min. Consequently, a threshold on cadence only was not giving satisfactory results. However, the combination of thresholds on the amplitude of acceleration norm and cadence was an appropriate solution. Indeed, the mean and standard deviation (mean ± std) of the accuracy (98 ± 3.8%), precision (99.8 ± 0.4%), sensitivity (96.2 ± 7.6%) and specificity (99.8 ± 0.4%) computed across the 10 subjects of the MAREA database demonstrate good performance of the running detection algorithm. The amplitude threshold was empirically selected based on visual evaluation of the recorded signals. For all subjects, the running and walking periods were properly classified. However, the sensitivity is slightly lower, meaning that, for some subjects, the transition was not precisely detected, and some running gait were classified as walking.

D. *Run4Vit application*

Finally, we tested the validated algorithm on a subset of data from the *Run4Vit* study. The Fig. 4 shows an illustrative example of locomotion detection (walking and running) and instantaneous cadence estimation applied to a long term recording of one subject (~14 hours). This subject is quite active at the end of the day with several walking bouts, as well

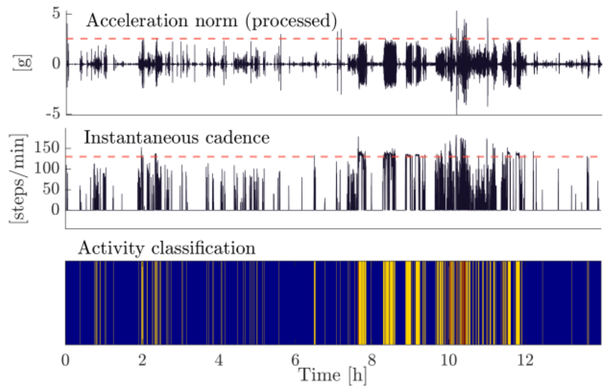

Figure 4. Application to the *Run4Vit* project, example of physical activity classification of one subject (~14h). The top plot represents the processed acceleration signal (*accN-LPF-CWT*). The middle plot shows the instantaneous cadence estimation using the time-domain method. The bottom plot corresponds to the activity classification with sedentary (blue), walking (yellow), and running (red) activities.

as, some running periods with a cadence greater than 140 steps/min. Based on a preliminary visual inspection, the algorithm works well for long term recording and challenging environment.

IV. Discussion

The single accelerometer-based algorithm for step/locomotion detection adapted from [11], and cadence estimation developed in this work demonstrated a good performance when applied to a large range of walking and running speeds (4 to 8 km/h). The running detection algorithm also demonstrated good results (accuracy and precision greater than 98 and 99% respectively) when applied to the MAREA database. Moreover, the algorithm is based on the norm of the accelerometer signal. Thus, functional calibration procedures do not need to be applied, making this algorithm very practical for real life monitoring.

The current version of the algorithm shows good performance for both time and frequency-domain cadence estimation (Fig. 2 and Fig. 3). On the one hand, the time-domain method, which is based on the heel-strike events, is more accurate for short periods of locomotion. However, the *CWT* scale and the peak detection threshold must be properly defined to obtain an accurate estimation. On the other hand, the frequency-domain method is less sensitive to outliers in the signal because it does not depend on an exact peak detection. However, the *FFT* is very computationally intensive, which can be a limitation when processing long recordings (~10 hours).

The main contribution of the current work is the validation of the algorithms for running detection and instantaneous cadence estimation, extending the scope from clinical (atypical gait patterns [11]) to sports applications. However, we are aware of certain limitations. First, the validation was performed with a limited number of subjects. Second, the step detection algorithm is robust to a wide range of gait patterns, provided that the *CWT* scale is chosen correctly. This is both the strength and weakness of the current method.

Finally, the validated algorithm, based on the time-domain cadence estimation, was successfully applied to a subset of long-term monitoring *Run4Vit* data (Fig. 4). The future work will consist of extending the *barcode* concept [5, 9] by including vigorous activities (e.g. running). Then, we will extract the classical daily PA features such as the locomotion (walking and running) and sedentary percent times; as well as, the *complexity metrics* aiming to capture the temporal fluctuations of the daily PA patterns. Those objective PA measures, combined with subjective evaluations based on questionnaires would help us understanding the effects of the eight weeks running intervention on PA behaviors, sleep quality and vitality.

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