Real-world speed estimation using single trunk IMU: methodological challenges for impaired gait patterns*

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***Abstract*— Walking speed (WS) is recognized as an important dimension of functional health and a candidate endpoint for clinical trials. To be adopted as a powerful outcome measure in clinical assessment, WS should be estimated pervasively and accurately in the real-life context. Although current state of the art points to possible solutions, e.g., by using pairing of wearable sensors with dedicated algorithms, the accuracy and robustness of existing algorithms in challenging situations should be carefully considered. This study highlights the main methodological issues for WS estimation using single inertial sensor fixed on trunk (chest/low back) and data recorded in** a **sample of stroke patients with impaired mobility.**

I. Introduction

There is a growing consensus that walking speed (WS) can be considered as a 6th vital sign since it is used as a predictor and outcome measure across multiple diagnoses [1]. The risk of mobility disability is increasing for WS less than 1.0 m/s in elderly population with changes of 0.04 to 0.06 m/s being clinically important [2]. Therefore, a reliable monitoring of real-world WS in clinical assessment may open new perspectives, e.g., early detection and prevention of functional decline, and/or as clinical outcome for more personalized treatments/interventions. Today advances in wearable technology based on inertial measurement units (IMU) associated with appropriate algorithms are leading the transition from punctual laboratory-based to pervasive real-world assessment of WS. To be used in practice, in a large scale and during daily-life condition, a single device (e.g. placed at the trunk) paired with a dedicated algorithm offers a satisfactory solution to deal with patient comfort and compliance. However, many issues challenge the reliability of WS estimation algorithms such as: movement artefacts, misalignment with the referential, abnormal gait pattern particularly present in slow walkers and/or neurological diseases, the lack of information about walking context and consensus about selection of walking bouts (WB) for WS estimation. This paper presents work from an ongoing study, with the objectives to: (1) establish a conceptual framework for WS estimation using real-world like recorded IMU data, by identifying the main processing stages and the associated methodological aspects; (2) devise and/or improve existing algorithms and compare their performances on data recorded in a sample of mobility-impaired patients; (3) understand the limitations of current state of the art algorithms and the potential developments/improvements necessary for the reliable assessment of real-world WS as a clinical outcome.

II. Methodology

A. Data

Data used for algorithm(s) evaluation/development were collected in a sample of 11 mobility-impaired stroke patients (7 females and 4 males), suffering from hemiplegia due to an ischemic or hemorrhagic stroke. Seven out of eleven patients were able to walk independently but four needed assistance (cane or walking frame). Each patient was equipped with a set of four IMU (shanks, chest, and low back) and performed daily-life like activities in a rehabilitation center, as instructed by the physician, for approximately 30 min, depending on the patient's fitness condition. The objective was to include a set of basic activities of daily living performed in a semi-structured protocol to better correspond to real-life situation (i.e., activities were suggested in such a way that flexibility was given on when and how to be performed). Each IMU device (Physilog4®, GaitUp, CH) included 3D accelerometer, 3D gyroscope, and barometer with adjustable ranges, battery, memory, and microcontroller. The sampling frequency was set at 200Hz. IMU devices on chest and low back were independently used for development and validation of algorithms, whereas the devices on shanks were used as reference system. The study was approved by the local ethical committee.

B. Processing stages in the pipeline for WS estimation

Fig. 1 illustrates the main processing stages and methodological considerations for estimation of WS of each detected WB in real life context.

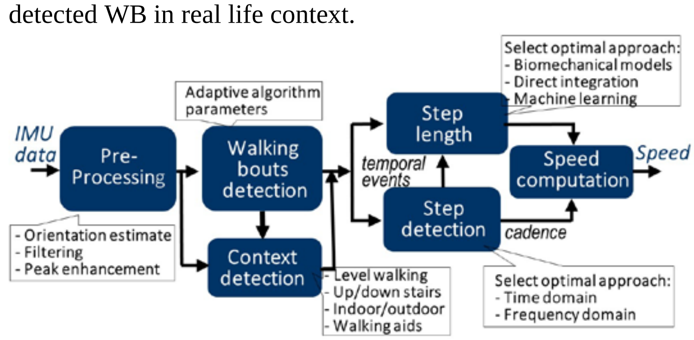

Figure 1. Processing stages for walking speed estimation

A. Preprocessing

The main challenges of processing data recorded with body-fixed IMU in populations with impaired mobility in daily-life context is the poor quality of sensor signals due to intrinsic causes (slow and impaired gait pattern with various

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characteristics), contextual factors (environment, usage of various walking gaits) and incorrect on-body sensor fixation. The conditioning of accelerometer signals, subsequently used for speed estimation, basically includes IMU *orientation estimation and alignment* with the global frame and, appropriate *filtering and step-related peak/feature enhancement* in acceleration data. An efficient category of algorithms for orientation estimation offering good performances with low computational cost is the complementary filters (CF) [3]. The basic idea of CF is to eliminate the unreliable frequencies for each sensor and then combines their output to get a better estimate throughout the entire bandwidth. Due to inaccuracies of magnetometers for in-door environments, orientation filters are generally implemented for 6D-IMU (3D accelerometers, gyroscopes), therefore additional techniques, such as principal component analysis, are necessary to align the IMU signals with the direction of body movement [4]. The preprocessing of raw IMU signals also includes appropriate techniques to enhance the steps-related features, often buried in noise and movement artefacts specific to impaired gait patterns. As example, a combination of detrending, zero-phase distortion low pass filter (FIR, n=120 coefficients, $Fc \approx 3.2$ Hz), Savitzky-Golay filter, and continuous wavelet transform (`cwt`, scale 10, gauss2) was necessary to effectively process the trunk acceleration signals recorded in children with cerebral palsy (CP) [5]. Usually, different filters are applied to raw IMU signals, according to the requirements of the methods for parameter extraction in the subsequent stages in Fig. 1.

B. Walking bouts (WB) detection

Accuracy of WB detection is essential since the errors at this stage will be propagated to the subsequent stages/parameters. We aimed to further validate the algorithm we devised in [5], and to address the limitations using new signal processing approaches. Although the algorithm appeared robust, with good performances in CP and elderly population, there are two critical aspects that may negatively affect performances in more heterogeneous and mobility impaired subjects. A first issue is the effectiveness of the filtering/peak enhancement procedure, since a direct 'strong' processing might attenuate/remove useful features, or the opposite, highlight unwanted ones. For the gait of study population (slow, spastic, walking aids) the optimal processing of trunk acceleration norm (*accN*) was a succession of several smoothing and enhancement stages as follows: the *accN* processed as in [5] (*accN–orig*) was further processed with: `cwt` (scale 10, gauss2) and three consecutive mild Gaussian-weighted moving average filters over a window length corresponding to about 0.25 seconds (`smoothdata`, Matlab 2017b), to obtain *accN* enhanced (*accN-enh).* A second limitation of algorithm [5] is the fixed amplitude-based threshold used to select the potential step-related peaks in acceleration signal. This issue was addressed by devising a data-adaptive threshold approach, described in Fig. 2. Basically, the procedure includes detection of walking periods using the Hilbert transform and adaptive smoothed envelope [6] of *accN-enh* signal (Fig. 2a,b), followed by detection and statistical description of peak amplitudes in *accN-enh* during all detected walking periods (Fig. 2c,d). The threshold was selected as the 5th percentile of peak amplitude distribution (i.e., the value over which 95% of the peaks may be found).

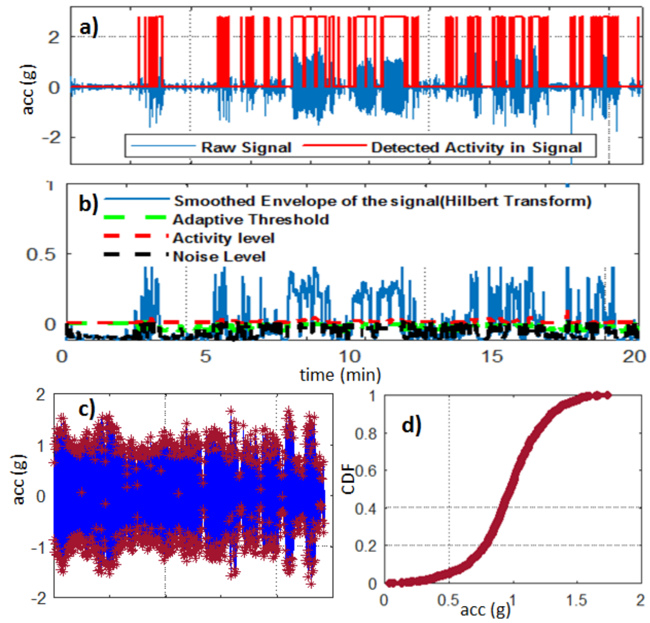

Figure 2. Estimation of data-adaptive threshold for WB detection algorithm: a-b) detection of walking-related 'activity' periods in *accN_enh* signal using the Hilbert transform and smoothing; c) merged detected WB and detected peaks (local minima/maxima); d) CDF of absolute values of peak amplitudes.

C. Step detection (SD)

Within a detected WB, identification and demarcation of steps allow estimation of gait parameters, such as cadence, step duration, symmetry, step-by-step variability and finally WS. The main step detection/demarcation algorithms can be classified as *time-domain* and *frequency-domain*. Peak and zero-crossing detection of preprocessed acceleration signals are the main time-domain techniques allowing both step detection and demarcation. Frequency-domain methods instead, based on Fourier or wavelet transform, did not allow step demarcation, but only an *estimation* of the number of steps (cadence) by identifying the periods inherent in the cyclic nature of walking. In this study we compared both original and proposed improvements of few promising algorithms in each category, specifically algorithm [5] based on *peak detection*, [7] using *zero-crossing*, [8] using *morphological filter* and peak detection, [9] using a frequency-based approach, and 'MaxL' using a maximum likelihood estimation approach.

D. Step length (SL)

SL estimation is the most challenging stage for WS estimation. There are three main approaches: model based, direct integration and machine learning [10],[11]. Model based approach uses biomechanical or empirical modeling of SL. *Biomechanical models* are based on geometrical approximation of the body segment trajectory during walking (e.g. inverted pendulum, vertical displacement of CoM obtained by double integration of vertical acceleration signal), and the relationship of SL with anthropometric data [12, 13]. *Empirical models* did not require acceleration integration and anthropometric data, instead they are based on linear/nonlinear relationships between SL and other measured parameters like cadence or body acceleration [14]. These models include tunable parameters for each individual. *Direct integration* is the straightforward way to estimate SL by double integration of forward acceleration in the global frame. The main difficulty with this approach is to assure good estimation of forward acceleration, and to remove the accumulated integration drift using appropriate techniques. *Machine learning* utilizes supervised learning to train a statistical model relating measurements of walking kinematics with SL. In this preliminary study we evaluated algorithms described in [12, 13] using original and improved detrending approach to remove integration drift (high pass filter end empirical mode decomposition (EMD) [15], respectively), and the algorithm described in [14].

E. Walking context – detection of up/down stairs

Information about daily-life walking context, e.g., ability to walk up/down stairs, may be useful for clinical assessment (subject's functional ability), and for a more reliable interpretation of estimated gait parameters by separating WB on flat from up/down stairs. Therefore, we aimed to investigate if the signal recorded by the barometric pressure sensor could provide reliable information. The main limitations of this type of sensor are: 1) high sensitivity to ambient fluctuations, decreasing drastically the signal to noise ratio and, 2) slow response time, making difficult to identify temporal events that mark a level change in the signal, since classical processing techniques such as signal differentiation are not appropriate [16]. These issues were addressed with an effective signal processing as follows. First, the barometric pressure signal converted in altitude (alt) [16], was detrended and low-pass filtered using a Savitzky-Golay filter. This allowed to obtain a smoothed altitude signal (*alt-smooth*), where high frequency noise caused by body movements and weather fluctuations were removed, while keeping steeper changes due to variations in altitude level. Subsequently, the instants where the mean value of *alt-smooth* signal changed significantly (t_i, $i=1,M$) were identified (`findchangepts`, Matlab 2017) and the difference at adjacent instants t_i was used to identify walking up-/down stairs or elevator using simple decision rules. If the type of activity was detected as walking, and the level of *alt-smooth* signal between instants t_i and t_{i+1} decreased with at least 2.5m (standard floor-to-floor height), it was assumed walking downstairs. Otherwise, if *alt-smooth* signal between t_i and t_{i+1} increased with at least 2.5m, it was assumed walking upstairs. When activity was detected as non-locomotion (e.g. standing) a similar reasoning was used to detect taking elevator down/up.

III. Results

A. Preprocessing

Fig. 3 illustrates an example of raw acceleration norm (a) corresponding to a WB, shown comparatively as processed with original version of algorithms [5], [7], [8] (left panel - b, d, f, respectively), and the contributed improved versions (right panel - c, e, g, respectively). The peaks, related to potential step events, as detected by each algorithm are marked with the black circles. Fig.3h shows the shank angular velocity signals (superposed left, right) and the heel strike events, used as reference for evaluation of trunk algorithm. The improved versions, principally based on *accN-enh* signal and adaptive peak detection, allowed to accurately extract the step-related features from the noisy raw acceleration data.

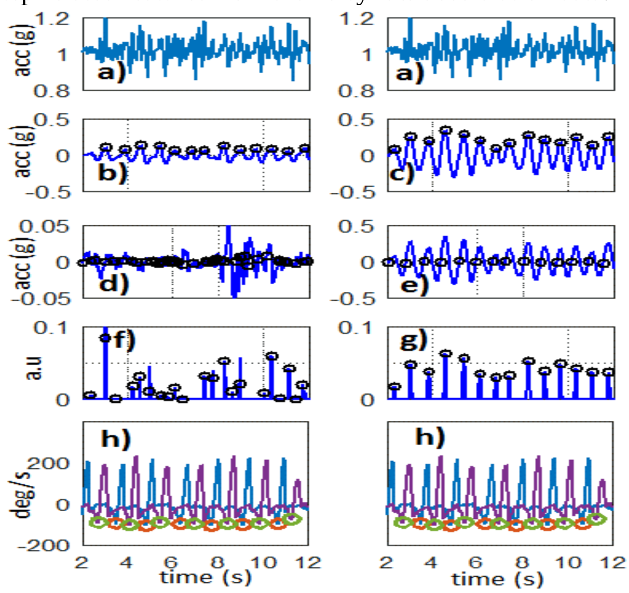

Figure 3 Illustrative example of raw and processed trunk acceleration norm according to original and improved versions of step detection algorithms.

B. Walking bouts detection

Performances of WB detection algorithm [5], applied to acceleration data recorded on chest or low back are shown in Table I. The improved version (*) allowed an increase of about 10% for specificity, accuracy and precision whereas sensitivity remained comparable.

TABLE I. Performance of WB Detection Algorithm

Method	***Sen*** (%)	***Spe*** (%)	***Acc*** (%)	***Pre*** (%)
[5] LB	98 (0.7)	85 (6.2)	81 (4.0)	73 (9.8)
[5]*LB	92 (1.0)	93 (5.6)	93 (2.0)	84 (10)
[5] Ch	98 (0.8)	82 (8.6)	87 (4.5)	70 (9.6)
[5]*Ch	91 (1.0)	91 (5.9)	91 (3.5)	81 (12)

LB: Low back Sensor; Ch: Chest Sensor; *improved versions; values as mean (SD)

C. Step detection

Table II contains the estimated errors of original and improved step detection/cadence estimation algorithms. The improved versions (*) allowed a significant reduction of error for algorithms [7] (44 to 61% on average) and [8] (12 % on average).

TABLE II. Performance of Step/ Detection (cadence) Algorithms

Method	***Absolute error*** (steps/min)		***Relative error*** (%)	
	LB	**Ch**	**LB**	**Ch**
[5]	-3 (13)	-3 (13)	15 (23)	15 (22)
[5]*	1 (13)	1 (13)	14 (15)	13(15)
[7]	-51 (31)	-39 (28)	74 (64)	57 (56)
[7]*	-3 (12)	-3 (11)	13 (18)	12 (17)
[8]	-16 (17)	-16 (17)	26 (36)	27 (35)
[8]*	-4 (12)	-4 (12)	14 (20)	14 (19)
[9]	-9 (18)	-11 (20)	19 (36)	23 (38)
MaxL	5 (32)	0 (24)	36 (38)	22 (38)

*improved versions; values as mean (SD) estimated from the ensemble of WB from all subjects.

D. *Step length/Speed*

WS estimation errors were assessed independently from errors in the previous processing blocs (Fig. 1), by using for SL estimation the temporal events from the reference system. Table III includes results obtained using the model-based SL estimation, and averaged WS computed for each WB as the ratio of estimated distance to duration. The errors decreased when the integration drift was removed with the signal adaptive EMD techniques. However, these errors were higher as compared to the previous processing stages/parameters, due principally to inaccuracies in the computational model (lack of accurate anthropometric data, disturbed signal as result of impaired gait, suboptimal drift removal).

TABLE III. PERFORMANCE OF SPEED ESTIMATION ALGORITHMS

Method	***Absolute error** (m/s)*	***Relative error (%)***
[12]	-0.001(0.19)	29(30)
[12]*	0.09 (0.15)	22(18)
[13]	-0.1(0.19)	40(35)
[13]*	-0.01 (0.16)	25(23)
[14]	-0.03(0.18)	28(22)

*improved versions; values as mean (SD) estimated from the ensemble of WB from all subjects.

E. *Walking context – detection of up/down stairs*

An illustrative example of up/down stairs detection using the barometer sensor is shown in Fig.4. It can be observed that the raw altitude signal, *alt*, (Fig.4a, blue) appears very noisy as a result of high sensitivity to body movements, especially walking due to air drag force that increases with movement speed. After detrending and smoothing, the *alt-smooth* signal (Fig.4a, red), allowed to identify a floor-to-floor change (according to observer's log-file the subject took downstairs for one floor, spent some time at this level, then took back the upstairs). The algorithm used *alt-smooth* signal to identify the time-instants of changes in altitude levels (Fig.4b), and to select those corresponding to up/down stairs based on direction and amount of change in altitude levels between successive time-instants (Fig.4c). It can be observed from Fig.4d (zoom-in) that the pattern of trunk acceleration signal appears less regular during this period.

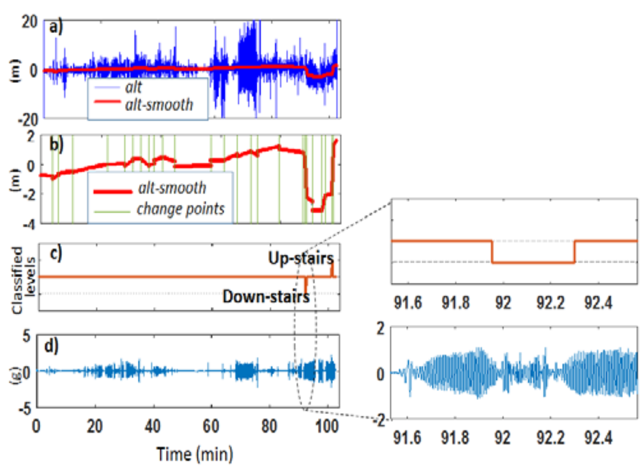

Figure 4: Detection walking on up/down stairs using barometer sensor: (a) barometric pressure signal converted in altitude before and after smoothing; (b) identification of change points in altitude level; (c) algorithm output providing direction (up/down) and duration of stair walking; (d) trunk acceleration indicating walking activity; the zoom-in on down-stair period shows changes in the pattern of acceleration signal.

IV. CONCLUSION

This preliminary study conducted on patients with mobility impairments and real-life like data indicated that performances of current single-sensor based algorithms are critical and various techniques are necessary to increase their robustness. The main sources of errors identified were heterogeneity of acceleration pattern due to various movement impairments (slow, compensatory strategies reflected in high acceleration peaks detected as false positive steps), and the lack of optimal SL estimation approach. Future work will therefore focus on further methodological developments and more extensive clinical validation.

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