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Abstract**Book**

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Track I

Wearable Sensors

Real-world speed estimation using single IMU: A conceptual framework

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Abstract- In this study an extensive technical review was performed to identify original algorithms for walking speed (WS) estimation using single IMU. Based on the review a conceptual framework was proposed highliting different stages for accurate assesment of WS from separate cadence and step length estimation. Original algorithms and their improved versions were implemented and tested on gait dataset including large range of WS. Time-domain algorithms allowed a better step demarcation while had more error that frequency-domain for cadence estimation. Machine learning provided better results than model based approach but may suffer from overtraining. The results showed high heterogeneity between algorithms and a significant decline in performance for low WS values. Considering the higher risk of disability in slow walkers, there is a need in clinic to improve WS performance. An interesting approach would be weighted average of WS estimated with various algorithms in order to take the best from each algorithms and potentially improve robustness.

Keywords-component; IMU; real-life; walking bouts; walking speed; single-sensor-based algorithms

1. 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 assessment of real-world WS may open new clinical perspectives, as for example early detection and prevention of functional decline, and/or as a 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. In order to be used in practice, in a large scale and during real-world 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, selected walking bouts (WB) for WS estimation and optimal monitoring duration.

Currently, many IMU-based algorithms allow estimation of WS, however a comparison of these algorithms in a large population with different range of WS is still missing. This is particularly important to take advantage of strength of different algorithms to improve the reliability of WS estimation. Starting from a comprehensive review of current state of the art regarding IMU-based WS algorithms, the objective of this study was to search for a possible conceptual framework needed for an accurate estimation of WS using single IMU. Original methods and the most relevant WS algorithms identified from this review were implemented and evaluated on extensive datasets to highlight there strength and limitation and to propose new perspective for real-world WS estimation.

2. MATERIAL AND METHODS

A broad technical literature review was conducted in order to identify the state of the art algorithms for WS estimation and related steps/cadence and stride length parameters. Then, original algorithms based on single IMU fixed on upper trunk (lower back, waist, chest) were identified and implemented (MathWorks, Matlab R2017b). In addition to the original published version, the algorithms were also implemented in improved versions, with the aim to increase performances in challenging conditions (e.g., pathological/slow gait, issues related to body sensor fixation) by adding more advanced techniques for IMU orientation estimation and calibration, adaptation of single-axis based algorithms (e.g. using either the vertical or anteroposterior acceleration). Additional improvement included feature enhancement by sharpening the weak steps-related peaks in acceleration signal during slow walking for better step detection and high resolution localization of temporal events using adapted time-frequency scales [2-4]. To date, the implemented algorithms were evaluated on a database including walking trials recorded in a clinical setting in a sample 100 community dwelling elderly people. During the walking trials each participant wore on sensor on lower back (L5) fixed with elastic belts. Performance assessment of L5-IMU algorithms (Median and Inter-Quartile-Range of error) was achieved using four sensors on shanks and tights with a validated algorithm extracting accurate gait parameters [5].

3. RESULTS

Conceptual framework for WS estimation

From a total of 2749 articles identified through the database search, 162 were included as description of a new method. By considering only single sensor configuration on trunk, we ended with 18 algorithms estimating spatial and 9 estimating temporal parameters. According to different methodologies, the WS estimation pipeline necessitates IMU data corresponding to each WB, and processing including various stages for: global frame calibration, preprocessing, detection of temporal features (step detection/demarcation), and stride length estimation, as illustrated in Figure 1.

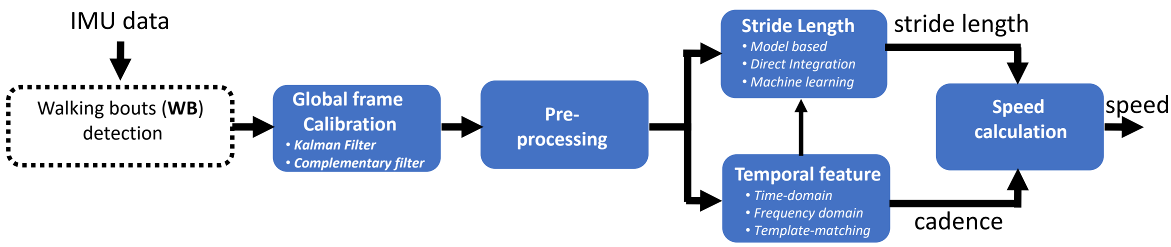

Figure 1. Processing stages in the pipeline for walking speed estimation.

Global Frame calibration: To be independent of sensor location, measurements should be expressed in global frame (GF) by computing IMU orientation in GF over the time. We found two main categories of algorithms to estimate IMU orientation based both on strapdown integration using both acceleration and angular velocity signals: *Kalman filter* (KF) and *complementary filter* (CF) [6]. KF requires a number of sensitive input parameters to determine how sensor signals are weighted during the filtering process. 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. The gradient descent based orientation filter [7] and the explicit complementary filter [8] offered efficient performance with low computational cost. Due to inaccuracies of magnetometers for azimuth estimation, additional techniques were necessary, such as principal component analysis to align the IMU signals with direction of body movement.

Preprocessing: basic preprocessing included low pass filtering and detrending. In the case of slow and/or pathological gait, an effective and reliable estimation of gait parameters in subsequent stages required more advances techniques to enhance the features of interest in the IMU data, as for example those related to the step events.

Temporal features (step detection and demarcation): step-related events allows identification and demarcation of steps, necessary for estimation of gait parameters, such as cadence, step duration, symmetry, and step-by-step variability and further WS. According to literature, step detection/demarcation algorithms can be classified as *time-domain* [3], *frequency-domain* [9] and *template-matching* [10]. Peak and zero-crossing detection of preprocessed acceleration signals were 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 template-matching methods a template was generated which represent a typical step/gait cycle. Then, a template mathematical tool (cross-correlation, dynamic time warping) was used to scan the IMU signals and a true step was recognized when there was a match between the signal and the template.

Stride length: Stride or step length estimation is the more challenging stage for WS estimation. We found different methods for step length estimation that can be grouped into three main approaches: *model based* , *direct integration* and *machine learning* [11-12]. Model based approach used *Biomechanical* or *Empirical* modeling. Biomechanical models were based on the geometrical approximation of the body segment trajectory during walking (e.g. inverted pendulum), and the relationship of step length with anthropometric data like height, length of lower limbs, foot size and waist circumference. Empirical models did not require subject's anthropometric data, instead they were based on linear/nonlinear relationships between step length and other measured parameters like cadence or body acceleration. Both models included tunable parameters for each individual, to be fixed prior to data collection for training and optimization procedures. Direct integration was the straightforward way to estimate the stride length by double integration of the forward acceleration expressed in GF. The main difficulty with this approach was to assure a good estimation of the forward acceleration, and to remove the accumulated integration drift using appropriate techniques. Machine learning utilized supervised learning to train a statistical model relating measurements of walking kinematics with stride length. In practice, a set of features including parameters extracted from IMU sensor data, and eventually subject anthropometric data, were used with learning rule. This approach necessitated a 'training sets', i.e., data collected in a sample of subjects, whith the hypothesis that larger training datasets yield a more accurate capture of the true relationship between the measured features and step/stride length. The train model was then applied to unseen new data for step/stride length estimation.

Algorithms implementation and validation

Temporal features. From the literature review 4 algorithms targeting temporal parameter estimation such as cadence were improved (see Materials and Methods) and were implemented with the 9 original ones. The performance of these algorithms which used time-domain or frequency domain approach showed similar median error with lower interquartile range (IQR) in favor of frequency domain class (Table 1).

Table 1. Range of error (Median and IQR) for cadence estimated every second by implemented algorithms

Cadence per second (steps/min)	Number of algorithms	Median (range)	IQR (range)
Time domain	11 (8 original)	[1.3 – 2.9]	[1.6 – 5.4]
Frequency domain	2 (1 original)	[1.4 – 1.8]	[2.0 – 2.5]

The error for cadence estimation decreased when speed decreased with highest error for walking less than 1m/s (Figure 2). This tendency was much more pronounced for time domain approach.

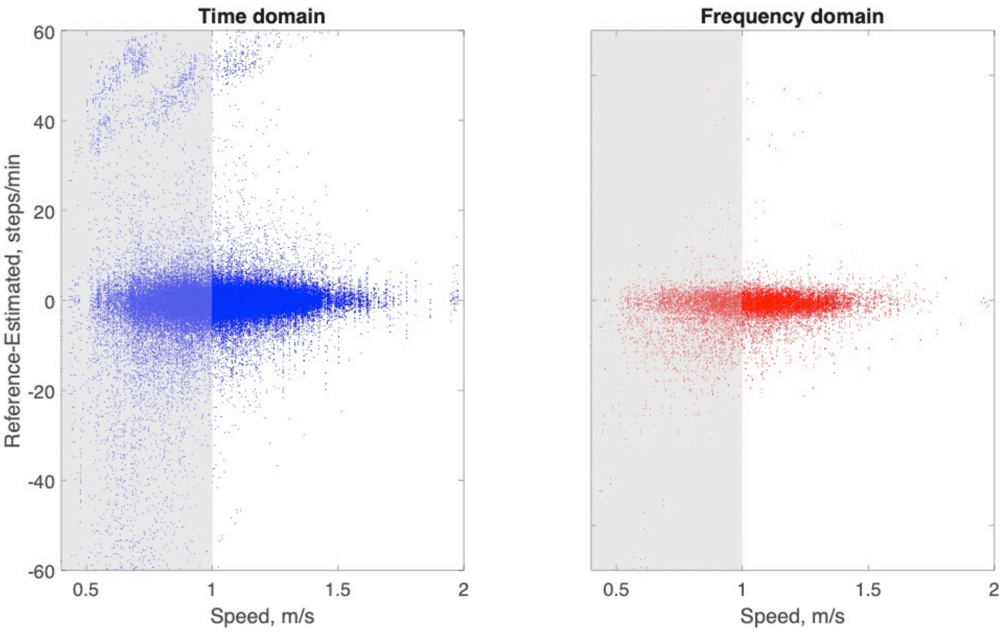

Figure 2. Cadence error estimated every second vs. actual walking speed. Grey zone shows speed lower than 1m/s.

Stride length. The review provided 18 algorithms for stride/step length estimation, where 11 were improved. All these algorithms were classified into three categories (Model based, Direct integration, Machine learning*)* and their performance compared to each other (Table 2).

Table 2. Range of error (Median and IQR) for stride length estimated every second by implemented algorithms

Stride length per second (cm)	Number of algorithms	Median (range)	IQR (range)
Machine learning	8 (8 original)	[8 – 16]	[11 – 17]
Biomechanical models	14 (6 original)	[10 – 36]	[13 – 45]
Direct integration	7 (4 original)	[12 – 34]	[16 – 53]

4. DISCUSSION

Preliminary evaluation of state of the art algorithms for WS estimation using single IMU fixed on lower back reveled the existence of different stages to reach an accurate estimation of WS. These stages were used to propose a conceptual framework for WS estimation in real-world conditions. In general, acceleration and angular velocity signals were used for GF calibration while further stages of processing were mainly based on acceleration. This framework allowed identifying missing stages and new possibilities for improvement. Relevant and original algorithms from the review process were identified and if necessary improved and tested on a large gait dataset. The results illustrates high heterogeneity and a significant decline in performance for estimating low WS values.

Considering that persons at risk of disability are prone to walk less that 1m/s, there is a real need in clinic to improve WS performance for slow walkers. WS is based on the two main parameters: cadence and stride/step length and high accuracy in both parameters are needed. Time-domain allows a better time resolution and step demarcation while has more error in cadence estimation than frequency-domain for slow WS. A mixed approach would be to apply first frequency-domain and fine-tune with time-domain. Direct integration of step length is sensitive to sensor orientation and GF calibration while model-based approach needs personal calibration of step length. Machine learning provides best results reaching a precision of 11cm (minimum IQR in Table 2) but it may suffer from overtraining and therefore higher error in unseen dataset. Considering the straight and drawback of each algorithm, an interesting approach would be weighted average of WS estimated with various algorithms in order to obtain 'hybrid approaches' take the best from each algorithms and potentially improve robustness by error compensation. Additional measurements in different diseased population as well as in lab validation using standard equipment (optical motion capture and forceplate) are necessary to have a more extensive evaluations are therefore a reliable outcome measure in clinical practice.

5. ACKNOWLEDGEMENT

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