Experimental Evaluation of a Smartphone Based Step Length Estimation

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***Abstract*— Step Length (SL) is an essential parameter in the healthcare field to monitor the gait of patients affected by motor disorders such as Freezing of Gait (FoG), a motor block that provokes an interruption of the normal gait cycle. As a consequence spatio-temporal parameters of gait, in particular SL, are strongly altered before and during a FoG event. In this work we present a non-intrusive and non-invasive architecture applicable in this clinical scenario and we evaluate its reliability of SL estimation on 8 healthy subjects. We obtained mean errors of 7.77%, 6.99% and 6.44% for low, normal and high velocity respectively, which is a sufficient accuracy for FoG detection.**

I. INTRODUCTION

The monitoring of gait parameter during standard daily activities is an important issue for many applications related to healthcare. In particular, Step Length (SL) can be used to monitor motor symptoms in patients affected by neurological disorders. For example Parkinsonian patients can manifest Freezing of Gait (FoG), which is a common and highly distressing gait disorder ranging between 21% and 27% of patients in the early stages and $60-80\%$ in the later stages [20]. It is defined as a 'brief, episodic absence or marked reduction of forward progression of the feet despite having the intention to walk' [3]. FoG has a high impact on patients' quality of life because of its connection with falls and of social implications that this sudden block can bring in patient's daily living. Furthermore standard pharmacological treatments do not have significant effects on FoG reduction. A promising and non-invasive approach to alleviate FoG seems to be the rehabilitation therapy, in particular the use of rhythmic sensory cues, which are 'temporal or spatial external stimuli associated with the initiation and ongoing facilitation of gait' [13]. However cues should be contextual to FoG events in order to be comfortable and effective during daily activities. In fact a number of FoG detection systems have been proposed in the literature and some of them are also able to provide rhythmic cues after FoG detection[2], [8]. For what concerns the hardware, these architectures are usually composed of inertial sensors network that communicates measured data, such as acceleration or angular velocity, to a computing unit attached to the patient or nearby. Instead about the software, the major part of such systems conducts FoG detection using frequency analysis of lower limbs acceleration, which leads to the definition of a freeze index [12], or using statistical classification approaches [8]. In recent works we tried to improve the hardware employing a more acceptable and usable architecture [16], [17], that performs FoG detection using the only smartphone. In this work we want to use the same architecture to estimate SL, because it is an important gait parameter that can be used to detect FoG. In fact several clinical researches showed how time instances preceding FoG are characterized by a disruption of the standard trend of spatiotemporal parameters of gait [15]. In particular in [14] authors found a strong increase in step cadence, decrease in SL, linear velocity and angular excursion of legs joints. Before applying SL estimation to FoG detection, we have evaluated the error of our architecture on healthy subjects' SL estimation, in order to investigate the feasibility of a smartphone based SL estimation.

This approach has been preliminary presented in [10]. The results were encouraging but we found a polarization of the estimation error. The contribution of this paper is twofold: we improved the estimation algorithm by means of a correction factor customized for each patient; we evaluated the algorithm with a new and wider set of experiments (where subjects walked at three different velocities instead of two). The results show a reduction of the estimation error and no polarization. The paper is organized as follows. In section II we will summarize previous works in the literature that address the question of SL estimation through inertial sensors. In section III we will explain the hardware and software of our architecture for SL estimation. Section IV describes the experimental set up to validate the proposed methodology and section V reports the results. Finally in section VI we draw conclusions.

II. RELATED WORKS

Recently inertial sensors were widely applied for gait analysis in an out-laboratory context, given their low cost and being wearable. However since they do not provide direct measurement of gait parameters such as SL, estimation methods must be introduced. The inverted pendulum model of human gait introduced by Zijlstra et al. [23] highlights a relation between vertical (VT) change of body center of mass and SL, described by the following equation:

$$sl = 2\sqrt{2lh - h^2} \tag{1}$$

where l is the length of subject's leg, while h is the difference between maximum and minimum height reached

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by body center of mass during gait cycle and it can be computed through double integration of VT acceleration measured approximately at L3-L4 (considered a good approximation of body center of mass). A refinement of this model was described by Gonzalez et al. [4], in which the human gait cycle is modeled with the inverted pendulum introduced in [23] during the swing phase and with a second pendulum of unknown radius during the double-stance phase. The contribution of the second pendulum is set as a quantity proportional to foot length. Some works described empirical approaches to SL estimation, but all of them need complex and accurate calibration procedure across different subjects and several walking tests in order to obtain optimal value for parameters [5]. For example in [6] the author found an empirical linear relation between SL and step frequency. Moore et al. [11] used a geometric formula to estimate SL from angular velocity of the shank. They mounted an inertial measurement unit on the shank and a wearable computer on the waist. Their architecture needs a complex and long calibration process and the methodology gives best results for short steps.

The systems described above are wearable and low cost, but they used inertial sensor and processing units to extract information. In an ambient assisted living context, the users of these systems are elderly people, that do not usually have a background of technical or engineering education. It is highly probable that this kind of users will not feel confident with such technology, which is probably unknown for them. We tried to overcome this problem having particular attention to user's needs during the design of our architecture. Moreover the major part of the works described above evaluated SL error estimation over the entire distance covered in each trial, while we will do error estimation on single steps, comparing our methodology with a stereophotogrammetric system.

III. MATERIALS AND METHODS

This section describes the hardware and software of our system for SL estimation; its major advantage and novelty lie in reaching the objective of SL estimation using only the smartphone accelerometer.

A. Hardware

We used a smartphone as sensing and processing unit because its high penetration into society made it very acceptable for the user. Acceptability is an important issue for medical devices, since patients do not want to be labeled as ill [21]. Furthermore smartphones have large touch-screens with the possibility to build user friendly interfaces as needed. In particular we used an iPhone 4 with its onboard triaxial accelerometer, but the software was developed also for the Android platform. The smartphone was fixed through an elastic belt and an appropriate socket at the level of L3-L4. The belt and the socket guaranteed the alignment of the accelerometer axes with the antero-posterior (AP), medio-lateral and VT axes of the subject. Fig. 1 shows the accelerometer reference frame and the laboratory reference frame.

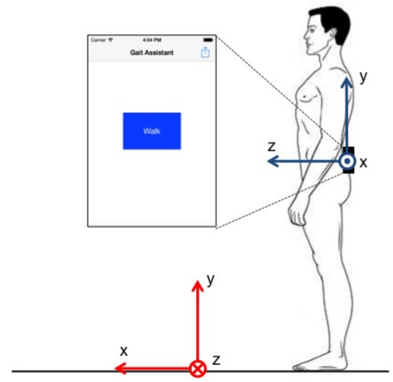

Fig. 1. The system used for SL estimation: smartphone placement and accelerometer reference frame (blue), laboratory reference frame (red).

B. Software

The algorithm used in this study for SL estimate was implemented on the smartphone for the sensing part and on Matlab for the processing part, since in this research phase we are investigating the possibility of a reliable SL estimate through the smartphone accelerometer. In fig. 2 we reported the algorithm flowchart.

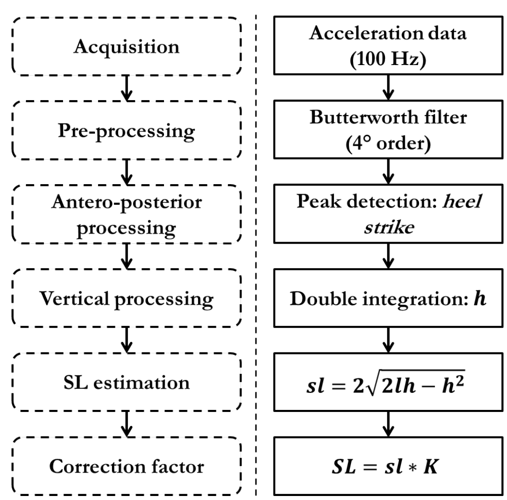

Fig. 2. Block scheme of the SL estimation algorithm

The first step is the acquisition of acceleration signal at a frequency of 100 Hz, hence we built an application to carry out this function through the onboard accelerometer. The application saved all acquired data on a text file. As proposed by Zijlstra and Hop [24] acceleration data were low pass filtered by a 4th order Butterworth filter with a cut off frequency of 20 Hz. The third step was heel strike (HS) detection on the AP signal. According to [24], the signal was filtered at 2 Hz in order to obtain the principal component of the subject's gait and here we searched the zero-crossing from positive to negative. Finally HSs were selected as the last peaks in the 20 Hz filtered AP signal before each zero-crossing. Fig. 3 shows the shape of AP acceleration and peaks selected as HS.

To estimate SL we must consider also the VT component

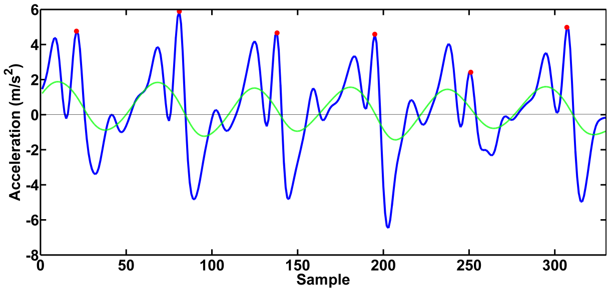

Fig. 3. 20 hz filtered AP acceleration of the smartphone (blue) with HS time instants (red dots) and 2 hz filtered AP acceleration.

of the acceleration. In fact, initial conditions for linear velocity must be known to obtain SL from double integration of acceleration signal of AP direction, but unluckily we can not assume any valid hypothesis on the value of AP velocity at HS. Instead for the VT velocity, we can assume that its value at the HS is close to zero, as confirmed by previous studies [7], [22]. The fourth step performs the double integration of VT acceleration to find the height change of body centre of mass during a step (parameter h in the flowchart).

Hence our algorithm uses both the AP and VT components of acceleration for SL estimation. The AP one is used to find the HS time instants, e. g. the extremes of integration. The VT one is used to calculate the height change of centre of mass during the gait cycle. Unlike the algorithm proposed by Lan et al. [7], we decided to use the AP component to detect HS because in the literature there is quite good agreement about the location of HS in the AP acceleration signal, while for the VT component there are different opinions [1], [7].

Finally, SL was evaluated according to the formula (1) of the inverted pendulum model. This formula underestimate SL, hence a corrective factor K is applied. Since in our previous work [9] we found a polarization of estimation error, we customized the correction factor on each subject. We used the least square method to find the optimum value of K for each subject, minimizing the following function:

$$\varphi(K) = \sum_{i=1}^{N} \|(y_i - K sl_i)\|^2$$

where N are the total number of steps of the given subject across all the trials, y_i are the true SL, measured from the stereophotogrammetric system, and sl_i are the SL computed from the inverted pendulum model (1).

IV. TESTS

The reliability of our method for SL computation was evaluated by comparison with a stereophotogrammetric system (gold standard for gait analysis) composed of six infrared cameras, which acquires the position of reflective markers in the laboratory reference frame (fig. 1) at 100 Hz sample frequency. Eight healthy subjects (5 males), aged between 22 and 30 years, took part in the tests. The tests were designed in agreement to the Helsinki protocol and were approved by the local ethics committee; all the subjects signed the informed consent. Each subject performed 9 walking trials, 3 at their normal speed, 3 at higher speed and 3 at lower speed. Nine reflective markers were placed on pelvis and feet. The pelvis was identified by three markers: two over the left and right anterior superior iliac spines and the third on the middle point between the posterior superior iliac spines. Each foot was identified by three markers placed on: heel, first and fifth metatarsal head. Markers' position is shown in fig. 4.

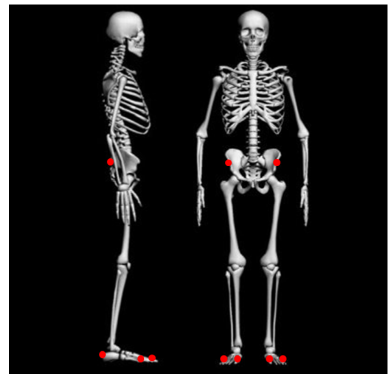

Fig. 4. Markers' placement during tests.

During each trial subjects were asked to walk forth and back along a straight platform (about 10 meters) inside the visual field of infrared cameras. Simultaneous acceleration signal was acquired from the smartphone placed at subject's lower back. Each trial started with the execution of a jump, which we used to synchronize smartphone data with stereophotogrammetric data and hence to ensure we would compare SL estimation (from the smartphone) and SL measure (from the gold standard) of the same step.

TABLE I
NORMALIZED ESTIMATION ERRORS (ADIMENSIONAL)

Subject	Low Velocity (mean $\pm$ std)	Normal Velocity (mean $\pm$ std)	High Velocity (mean $\pm$ std)
1	$(8.75 \pm 6.01)\%$	$(7.32 \pm 5.51)\%$	$(5.26 \pm 4.51)\%$
2	$(12.44 \pm 9.04)\%$	$(6.96 \pm 4.41)\%$	$(8.77 \pm 7.74)\%$
3	$(8.09 \pm 5.38)\%$	$(5.19 \pm 2.94)\%$	$(6.67 \pm 4.90)\%$
4	$(6.77 \pm 5.17)\%$	$(8.04 \pm 6.23)\%$	$(8.25 \pm 6.67)\%$
5	$(6.15 \pm 4.49)\%$	$(6.92 \pm 3.12)\%$	$(4.95 \pm 2.97)\%$
6	$(7.05 \pm 5.00)\%$	$(5.92 \pm 3.95)\%$	$(3.92 \pm 3.02)\%$
7	$(5.77 \pm 3.81)\%$	$(7.75 \pm 5.54)\%$	$(7.68 \pm 5.79)\%$
8	$(7.18 \pm 5.53)\%$	$(7.80 \pm 5.65)\%$	$(6.05 \pm 4.93)\%$
Mean	$(7.77 \pm 5.55)\%$	$(6.99 \pm 4.67)\%$	$(6.44 \pm 5.07)\%$

V. RESULTS

We collected a total of 735 steps and the system was able to correctly detect 721 of them, hence the sensibility of the system in HS detection is 98.1%. Speed ranges were $0.60 - 1.13$ m/s for low, $1.01 - 1.61$ m/s for normal and $1.07 - 1.51$ m/s for high speed. We computed the estimation error according to the following formula:

$$e = \frac{\|(sl_g - sl_s)\|}{sl_g}$$

where sl_g is the gold standard SL and sl_s is the estimated SL. Both sl_g and sl_s were normalized over the leg length in order to make possible inter-subject comparison. Hence the resultant error is adimensional and percentage. We obtained an error of $(7.77 \pm 5.55)\%$ (mean $\pm$ standard deviation) for low velocity, $(6.99 \pm 4.67)\%$ for normal velocity and $(6.44 \pm 5.07)\%$ for high velocity. Table I shows estimation errors for each subject. In fig. 5 we reported a Bland-Altman plot built with all the 721 detected steps.

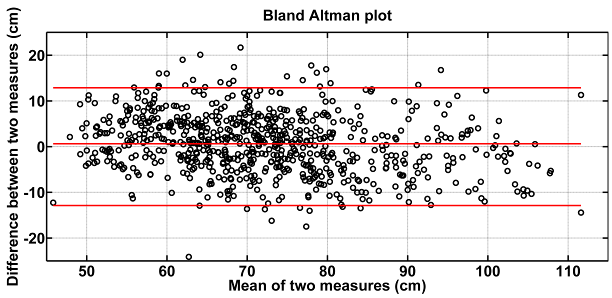

Fig. 5. Bland-Altman plot for all the detected steps.

The mean absolute error is about 1 cm, while the superior and inferior boundaries (mean $\pm$ 2$*$standard deviation) are under 15 cm of difference from the gold standard.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper we proposed a smartphone based SL estimation and tested its performance on 8 healthy subjects. After calibration of the correction factor K we reached mean errors of 7.77%, 6.99% and 6.44% for low, normal and high velocity respectively. We obtained a reduction of estimation error and no polarization with respect to our previous work [9] (10.63% for normal velocity and 11.01% for high velocity). The major part of previous works in the literature evaluated the error using the mean SL over the entire trial and not on each step [4], [22], [7], hence a direct comparison of the obtained error cannot be done. The SL estimate in [10] is less accurate, reporting an error of 15%, while in [11] authors obtained a mean error of 2.8%, this difference may be due to different factors: their calibration involves first the determination of an algorithm and then the optimization of 5 parameters in such algorithm; another reason may reside in the different sensor placement (shank).

As a next step we will apply the proposed system in FoG monitoring to improve the reliability of the application we previously used for FoG detection [18], [17]. Since previous works in the literature concerning FoG characterization [15], [14] reported a mean reduction of 71.89% in SL before a FoG episode, we can expect that our accuracy is sufficient for FoG detection or even prediction.

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