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# Foot worn inertial sensors for gait assessment and rehabilitation based on motorized shoes

K. Aminian, *Member, IEEE,* B. Mariani, A. Paraschiv-Ionescu, C. Hoskovec, C. Büla, J. Penders, C. Tacconi and F. Marcellini

***Abstract*****—Fall prevention in elderly subjects is often based on training and rehabilitation programs that include mostly traditional balance and strength exercises. By applying such conventional interventions to improve gait performance and decrease fall risk, some important factors are neglected such as the dynamics of the gait and the motor learning processes. The EU project "Self Mobility Improvement in the eLderly by counteractING falls" (SMILING project) aimed to improve age-related gait and balance performance by using unpredicted external perturbations during walking through motorized shoes that change insole inclination at each stance. This paper describes the shoe-worn inertial module and the gait analysis method needed to control in real-time the shoe insole inclination during training, as well as gait spatio-temporal parameters obtained during long distance walking before and after the 8-week training program that assessed the efficacy of training with these motorized shoes.**

## I. Introduction

Gait characteristics such as stride velocity and gait variability during simple and dual task conditions have been used for fall risk assessment in elderly persons. A number of studies have shown that miniature body-worn inertial sensors can be used for estimation of important spatio-temporal gait parameters and their variability [1]. The advantages of these wearable technologies compared to traditional "gait lab" approaches are mainly their practical usefulness outside a laboratory, where longer walking distance in a natural setting can be performed. Nevertheless, the sensor configuration, the total weight of the system and the power consumption should be minimal while the physical integration of the sensors, memory and conditioning electronics with garments and attachment tools should be improved. Most current studies monitor gait "off-line", using recorded kinematic signals and dedicated algorithms. On-line gait phase detection has been addressed for the control of drop-foot stimulator using accelerometers [2], but such real-time applications remain rare, and lack implementation in wearable solutions, or testing in real conditions, or for rehabilitation purpose. We previously proposed and validated a gait analysis system based on double pendulum model with four gyroscopes on the lower limbs (one uni-axial gyroscope on each shank and thigh) [3]. The system can be reduced to two gyroscopes on shanks by predicting the signal of thigh sensors [4]. However, this model was 2D and required the knowledge of both thigh and shank length.

Fall prevention in elderly subjects is often based on training and rehabilitation programs that include mostly traditional balance and strength exercises. By applying such conventional interventions to improve gait performance and decrease fall risk, some important factors are neglected such as the dynamics of the gait and the motor learning processes. The EU project "Self Mobility Improvement in the eLderly by counteractING falls" (SMILING project: http://www.smilingproject.eu/) aimed to improve age-related gait and balance performance by using unpredicted external perturbations during walking through motorized shoes that change insole inclination at each stance. This paper describes a 3D method for gait analysis using the foot orientation and trajectory during each cycle based on two inertial modules (S-sense) worn on each foot. By real-time detection of gait phases, the modules can also control a motorized shoes designed for a new gait and balance rehabilitation program in elderly persons. Using data transmitted by the modules during long distance walking periods, a dedicated algorithm provides relevant gait parameters for outcome evaluation of the rehabilitation program.

## II. Methods

### A. Shoe-worn inertial module

A wireless inertial sensor module referred as ''S-sense'' has been designed which integrating microcontroller, radio transmitter, memory, three-axis accelerometer (ADXL, Analog Device), three-axis gyroscope (ADXRS, Analog Device) and batteries [5]. S-sense module is small

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K. Aminian is with the Ecole Polytechnique Fédérale de Lausanne, 1015 Lausanne, Switzeralnd, (phone: +4121 693 26 17; fax: +4121 693 69 15; e-mail: Kamiar. aminian@ epfl.ch
B. Mariani, A. Paraschiv-Ionescu, are with the Ecole Polytechnique Fédérale de Lausanne, Lausanne 1015.
C. Hoskovec, C. Büla are with the Service of Geriatric Medicine, CHUV&CUTR Sylvana, Epalinges, Switzerland.
J. Penders is with Holst Centre/IMEC, High Tech Campus 31, Eindhoven, The Netherlands.
Carlo Tacconi is with the Department of Electronics, Computer Science and Systems of the University of Bologna, Italy.
F. Marcellini is with INRCA, Center of Psycho-social Aspects of Aging, Ancona, Italy.

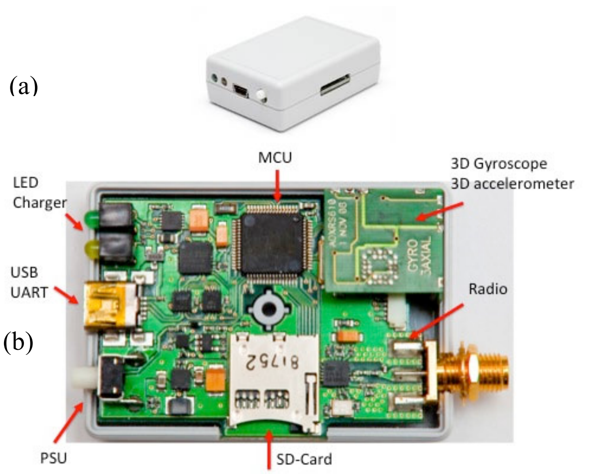


Fig. 1. S-sense module (a) composed of seven blocks (b): microcontroller (MCU), radio transmission, memory (SD-card), inertial sensors (3D accelerometer, 3D gyroscope), serial mode (USB/UART switch) and a power supply (PSU)

(57x41x19.5 mm3) and low power (18.5mA at 3.6V) and can be fixed easily on different type of shoes. It can record and transmit wirelessly kinematic signals with 12bit resolution at 200Hz during 24 hours (Fig. 1).

### B. *Embedded real-time walking phase detection*

Within each S-sense module, a walking phase detection algorithm (WPD) allows to detect swing and stance phase of gait in real-time. This information can be used as feedback for cueing and actuating device. WPD consists in a loop running at each new signal sample acquired during gait by the gyroscope mounted around pitch axis of the foot (Fig.2), and included in S-sense.

As illustrated in Fig.2, Mid-swing, Heel Strike and Toe off are noticeable by peak and valleys in the pitch angular velocity signal. These events were detected by adequate peak detection algorithms [6]. For real time detection of Stance/Swing phase, a state variable was first set to 1 for swing phase and 0 for stance phase. During Swing (state=1), if the algorithm detected heel-strike or reached the maximal swing duration, the state as well as the output variables were set to 0. In Stance (state=0), after minimal stance duration, if toe-off is detected then the output variable was set to 1 while state was also set to 1. In the case where the algorithm detects Midswing without detecting toe-off, the state was set to 1 but output variable was set to 0, because it means swing phase was detected too late for the actuators to respond before next stance phase. In conclusion, actuators were only triggered when output variable was equal to 1, i.e. when the beginning of swing phase (Toe off) was found. Although the detection of Mid-swing is not important for the output variable, it was a critical aspect that gives robustness to the algorithm by preventing false detection of Toe off at HeelStrike in the case where Toe off was not detected previously, because Toe off and Heel Strike features are quite similar.

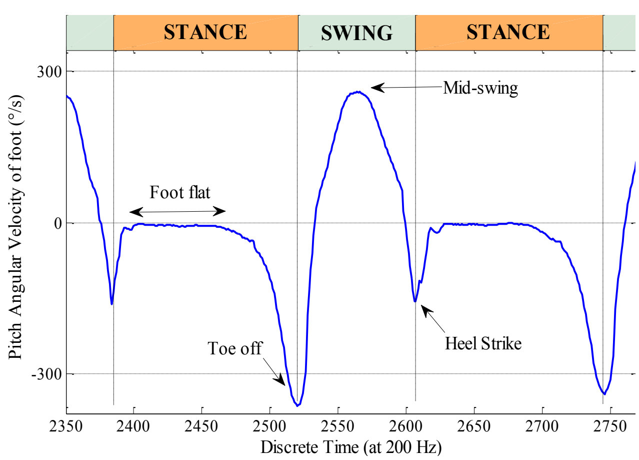


Fig. 2. Pitch angular velocity of foot during swing and stance phases

Algorithm was implemented in S-sense microcontroller. Its robustness was then evaluated in 5 healthy subjects wearing Smiling Shoes with S-sense and performing several gait trials at self-selected speed, including turns.

### C. *Application to neuro-rehabilitation*

Two S-sense modules were inserted in a pair of motorized shoes developed for gait training (Fig.3).

Each shoe comprises four individually controlled actuators, two on the heel and two in the forefoot, which can modify the sole inclination [7]. Using WPD algorithm, sole inclination was modified during each swing phase based on a chaotic algorithm [8]. This way, the motorized shoes generate unpredicted perturbation during the stance phase. The expected effect on the subject wearing the motorized shoes is to simulate neural plasticity that limits walking ability and therefore to enhance the flexibility of the motor control system, resulting in improved stability.

The study followed a randomized cross-over design. Following a baseline evaluation that included gait, balance, and physical performance assessment (POMA), subjects (N=22) were randomized to a first 4-week period of training with the active (SMILING) shoes (N=11) or with inactive (i.e., DUMMY) shoes (N=11) of similar weight. The training program included walking exercises of increasing difficulty with addition over time of motor and cognitive dual-tasking. At the end of this first training period, all subjects underwent a similar assessment of gait, balance, and physical performance. After a one-week wash-out period, subjects switched to the other pair of shoes (i.e. SMILING to DUMMY and vice-versa), and completed an additional 4-week training period with similar gait training exercises of increasing difficulty. Once completed, a final gait, balance,

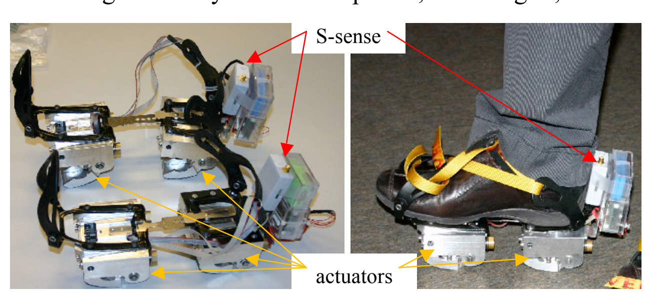


Fig. 3. Structure of the shoe with actuators controlled by the WPD of S-sense

and physical performance assessment was performed. The University of Lausanne ethical committee approved the protocol.

### D. *Gait analysis*

For each session, gait analysis was performed using a 6-Minute Walk Test (6MWT) [9] on each subject wearing S-sense modules on shoes. The 6MWT was preferred since it allows estimating gait variability over a long-distance. The walking course was 25m. The turnaround points were marked with a cone.

A gait analysis algorithm was designed to estimate spatio-temporal parameters based on the 3D kinematics of the both feet recorded by S-sense modules [10]. Among these parameters the following five parameters were considered in this study and were estimated for each cycle:

• Stride length (SL) was defined as the distance measured between two successive foot-flat positions of the foot.

• Foot clearance (FC) was defined as the maximal foot height during swing phase relative to the height at foot-flat.

• Stride velocity (SV) was considered as the mean value of foot velocity in forward direction during gait cycle.

• Turning Angle (TA) was defined as the relative change in foot heading (or azimuth), between the beginning and the end of gait cycle.

• Gait Cycle Time (GCT) was defined as the time between two successive heel-strike events.

The precision of the above parameters were estimated in a previous study by using optical motion capture as reference. We obtained a precision of 6.5% for Stride Length, 5.8% for Stride Velocity, 8.4% for Foot clearance and 6.1° for Turning Angle [10].

Gait variability was quantified by considering the stride-to-stride fluctuations in walking expressed by standard deviation (SD) of the gait parameters and its coefficient of variation (CV= SD/mean). Moreover, in order to illustrate the dynamic of gait variability and to quantify the 'complexity' of the gait pattern, we used Symbolic entropy (SEn) [11], [12]. Symbolic time-series analysis involves the transformation of the original time series into a symbolic sequence of few distinct values (e.g., binary sequences of 0 and 1) and the construction of words from the symbol series. After defining the word length ($l$ = 3) the Shannon entropy was calculated on the word frequency in the symbolic sequence [12]. These two parameters (i.e. CV and SEn) express different nature of gait variability. While lower CV or SD quantify a more regular stride-to stride walking patterns, a higher SEn characterize a more complex and improved walking dynamics.

In order to estimate the usefulness of gait parameters to compare gait pattern between young and elderly, ten young healthy volunteers (age 26.1±2.8 years), and ten fit elderly volunteers (age 71.6±4.6 years), took part in the study.

## III. Results

### A. *Walking phase detection*

A total of 778 cycles were recorded on 5 healthy subjects wearing Smiling Shoes with S-sense and performing several gait trials at self-selected speed, including turns. The signal from the pitch gyroscope and WPD output was recorded wirelessly in real-time. After a manual counting of the gait cycles was performed, we obtained a sensitivity of 93.6% with 728 successfully detected cycles, and a specificity of 100% (no false detection). Unsuccessful detection more likely occurred during gait initiation and during turns, where the pitch angular velocity pattern was altered.

### B. *Gait metrics in young and elderly*

Gait performances in elderly and young subjects were compared during a 6MWT. A total of 10,515 gait cycles were recorded among the 20 subjects. Turning Angle was used to separate periods of turn (every 25 meters) and straight walking for analysis. The other gait parameters and their variability were reported in Table 1 and Table 2.

Whereas relatively small, non significant-differences ($p$>0.05), between mean value of Stride Length and Stride Velocity were observed, Foot-clearance appeared to significantly discriminate performance between the two groups. During turns, Stride Length, Stride Velocity, and Foot clearance were significantly reduced in all subjects compared to period of straight walking ($p$<0.02 for all mean, SD, and CV of those parameters). Interestingly, the differences in mean gait parameters between Young and Elderly groups were larger during turns. In addition, mean and SD values obtained during straight walking were consistent with values found in the literature for samples of fit elderly and young healthy subjects [13].

### C. *Gait parameters before and after rehabilitation*

Overall, results over the entire trial showed that subjects significantly increased the distance walked during 6 MWT and the balance score (POMA). However, there was no significant differences when comparing training periods using SMILING vs DUMMY shoes. Trends were noticed in walking speed that constituted the study's primary outcome and approached the minimal clinically important difference

TABLE 1 Gait parameters in young and elderly groups.

| | GCT, s | SL, m | SV, m/s | FC, m |
|---|---|---|---|---|
| Elderly | 1.12±0.08 | 1.31±0.10 | 1.20±0.10 | 0.24±0.02 |
| Young | 1.15±0.07 | 1.34±0.12 | 1.19±0.11 | 0.27±0.02 |
| p-value | 0.6 | 0.7 | 0.9 | 0.02 |

Gait parameters of straight walking were averaged over 6MWT of young (10 subjects) and elderly (10 subjects) groups. Turning angle TA was used to extract straight walking periods

TABLE 2 Gait variability in young and elderly groups

| | CV(GCT) | CV(SL) | CV(SV) | CV(FC) | SEn(GCT) |
|---|---|---|---|---|---|
| Elderly | 3±0.92 | 5.7±2.6 | 7±2.8 | 4.4±1.9 | 1.49±0.41 |
| Young | 2.6±0.97 | 4±1.38 | 5.1±1.75 | 4±0.9 | 1.74±0.34 |
| p-value | 0.4 | 0.09 | 0.06 | 0.9 | 0.1 |

Gait variability in straight walking averaged over 6MWT of young (10 subjects) and elderly (10 subjects) groups in gait speed for the SMILING group. The minimal clinically important difference (MCID) is the amount of change that is clinically important to elderly subjects. Several studies have reported MCID for walking speed in an elderly population that range between 0.05m/s to 0.1 m/s [14]. The SMILING group participants increased their mean gait speed during the first period of 4 weeks by 0.05m/sec (from 1.48 to 1.53 m/s) while the DUMMY group kept same speed (1.39m/s).

## IV. Discussion

In this study we reported the development and evaluation of a wearable 6D inertial measurement system, S-sense for gait stimulation and monitoring. With S-sense, an algorithm was devised for real-time walking phase detection to control motorized shoes. It was possible to change the insole inclination at each stance in a chaotic way to better stimulate the motor learning process during walking. The outcome of this new neuro-rehabilitation technique was evaluated by gait metrics derived form wearable S-sense modules extracted during long distance walking.

The new shoe worn inertial system was able to provide main spatio-temporal gait parameters and to evaluate both variability and complex dynamic of these parameters. To our knowledge, this is the first time that gait parameters, such as foot horizontal turning angle and foot clearance were estimated outside a laboratory and during long distance walking. Actually, Turning angle is an important outcome to evaluate gait in Parkinson disease [4] and Foot-clearance which was the most discriminative parameters between our group of subjects could also be an important new gait parameters to estimate risk of fall in elderly [15].

Using 6MWT, we estimated walking variability and its dynamics. Though a certain amount of stride-to-stride variability allows adaptability to external perturbations (e.g. change in direction and speed, obstacle avoidance), high variability is usually associated with impaired motor function. As such, higher stride-to-stride variability with age was confirmed in this study by higher coefficient of variation (CV) in elderly subjects compared to healthy young subjects. When considering walking as a dynamic biological system, higher dynamic range and complex variability enable the organism to rapidly respond to internal and external perturbations. The non-linear gait variability metrics (i.e. SEn) in this study corroborated this aspect as we found that those metrics tend to decrease with age, implying a less complex and frailer behavior. This is in agreement with a well-known loss of complexity with aging [16].

The SMILING training program with motorized training shoes requires to adopt a new approach to improve neural plasticity in a natural way. While a certain positive trend in gait parameters was observed after this training program, much more measurements with higher sample size are needed before reaching final conclusions.

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