

# Instrumented shoes for daily activity monitoring in healthy and at risk populations

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**So Long, And Thanks For All The Fish**

*(Douglas Adams)*





## *Abstract*

Daily activity reflects the health status of an individual. Ageing and disease drastically affect all dimensions of mobility, from the number of active bouts to their duration and intensity. Performing less activity leads to muscle deterioration and further weakness that could lead to increased fall risk. Gait performance is also affected by ageing and could be detrimental for daily mobility. Therefore, activity monitoring in older adults and at-risk persons is crucial to obtain relevant quantitative information about daily life performance. Activity evaluation has mainly been established through questionnaires or daily logs. These methods are simple but not sufficiently accurate and are prone to errors. With the advent of microelectromechanical systems (MEMS), the availability of wearable sensors has shifted activity analysis towards ambulatory monitoring. In particular, inertial measurement units consisting of accelerometers and gyroscopes have shown to be extremely relevant for characterizing human movement. However, monitoring daily activity requires comfortable and easy-to-use systems that are strategically placed on the body or integrated in clothing to avoid movement hindrance. Several research-based systems have employed multiple sensors placed at different locations, capable of recognizing activity types with high accuracy, but not comfortable for daily use. Single-sensor systems have also been used but revealed inaccuracies in activity recognition.

To this end, we propose an instrumented shoe system consisting of an inertial measurement unit and a pressure sensing insole with all the sensors placed at the shoe/foot level. By measuring the foot movement and loading, the recognition of locomotion and load bearing activities would be appropriate for activity classification. Furthermore, inertial measurement units placed on the foot can perform detailed gait analysis, providing the possibility of characterizing locomotion. The system and dedicated activity classification algorithms were first designed, tested and validated during the first part of the thesis. Their application to clinical rehabilitation of at-risk persons was demonstrated over the second part.

In the first part of the thesis, the designed instrumented shoes system was tested in standardized conditions with healthy elderly subjects performing a sequence of structured activities. An algorithm based on movement biomechanics was built to identify each activity, namely sitting, standing, level walking, stairs, ramps, and elevators. The rich array of sensors present in the system included a 3D accelerometer, 3D gyroscope, 8 force sensors, and a barometer allowing the algorithm to reach a high accuracy in classifying different activity types. The tuning parameters of the algorithm were shown to be robust to small changes, demonstrating the suitability of the algorithm to activity classification in older adults.

Next, the system was tested in daily life conditions on the same elderly participants. Using a wearable reference system, the concurrent validity of the instrumented shoes in classifying daily activity was shown. Additionally, daily gait metrics were obtained and compared to the literature. Further insight into the relationship between some gait parameters as well as a global activity metric, the activity “complexity”, was discussed. Participants positively rated their comfort while using the system.

Afterwards, the potential of analyzing postural transitions with the instrumented shoes system was presented. The transition duration, an important parameter of daily mobility evaluation, was calculated based on the insole and compared to reference force plate measurements in laboratory conditions, achieving low overall errors. An algorithm for transition detection was developed and tested, revealing high detection accuracy. The transition duration evaluated in real life conditions was somewhat different from trunk inertial measurement. Overall, the instrumented shoes were deemed usable for transition detection and duration estimation in daily life.

In the second part, the instrumented shoes and dedicated algorithms were used in clinical rehabilitation of post-surgery hip fracture patients, measured at baseline after surgery and follow-up two weeks later. Objective activity, load, gait, and complexity metrics were sensitive to recovery and were complementary to a standard clinical score.

The instrumented shoes were also employed in the rehabilitation assessment of stroke patients. Again, objective metrics revealed patient recovery and changed similarly to clinical test scores.

The thesis results highlighted the importance of accurate activity classification and contributed a rich set of objective metrics that could be used by clinicians to better assess rehabilitation outcomes and provide individualized and tailored treatment. The results also indicate that numerous other applications could benefit from the instrumented shoes in the future, including orthopedics, sports, and larger cohort studies of daily life monitoring in older adults.

***Keywords: physical behavior, activity classification, gait analysis, instrumented shoes, complexity, postural transition, older adults, hip fracture, stroke***

## *Résumé*

L'activité quotidienne reflète l'état de santé d'une personne. L'âge et les maladies affectent l'activité quotidienne dans toutes les dimensions, du nombre de périodes, leur durée et leur intensité. Être moins actif engendre une détérioration des muscles et provoque un affaiblissement qui peut augmenter le risque de chutes. La qualité de la marche est également affectée par l'âge et peut être nuisible à la mobilité quotidienne. En conséquence, le suivi de l'activité chez les sujets âgés est crucial pour obtenir des informations pertinentes concernant la mobilité quotidienne. L'évaluation de l'activité est généralement établie par des questionnaires ou un cahier de notes journalières. Ces méthodes sont simples mais pas suffisamment précises et peuvent contenir des erreurs. L'apparition de systèmes micro-électromécaniques (MEMS) et la disponibilité de capteurs embarqués a réorienté l'analyse de l'activité vers un suivi ambulatoire. En particulier, les capteurs inertiels constitués d'accéléromètres et de gyroscopes ont démontré une excellente capacité à analyser le mouvement humain. Cependant, les systèmes embarqués ou intégrés dans les habits doivent être confortables et faciles d'utilisation pour ne pas gêner le mouvement. Plusieurs systèmes utilisés en recherche sont basés sur une multitude de capteurs placés à différentes positions du corps, et sont capables de reconnaître le type d'activité avec une précision élevée. Néanmoins, ces systèmes ne sont pas agréables pour une utilisation quotidienne. Des systèmes à capteur unique ont été également utilisés mais leur précision quant à la classification du type d'activité était plus faible.

A cet effet, nous suggérons une chaussure instrumentée qui consiste d'un capteur inertiel et une semelle de pression avec les capteurs intégrés dans la chaussure ou sous le pied. La reconnaissance des différents types d'activité pourrait alors être effectuée à partir du mouvement global du pied et des forces agissant sous la plante du pied. De plus, les capteurs inertiels placés sur le pied peuvent effectuer une analyse précise de la marche, offrant ainsi la possibilité de caractériser la locomotion. Le système et l'algorithme de classification d'activité ont d'abord été conçus, testés et validés pendant la première partie de la thèse. Leur application en réhabilitation clinique avec des personnes à risque a été mise en évidence durant la deuxième partie.

Pendant la première partie de la thèse, le système conçu a été testé selon des conditions standardisées avec des sujets âgés sains effectuant une séquence d'activité structurée. Un algorithme basé sur la biomécanique du mouvement a été élaboré pour identifier chaque activité ou posture, notamment être assis, être debout, marche à plat, monter/descendre les escaliers, marcher en pente, et prendre l'ascenseur. Le grand nombre de capteurs incorporés dans le système soit un accéléromètre 3D, un gyroscope 3D, 8 capteurs

de force, et un baromètre a permis d'obtenir une précision élevée pour la classification des différents types d'activité. Les paramètres de réglage de l'algorithme ont démontré une bonne fiabilité face à des changements mineurs. L'algorithme est donc utilisable pour la classification du type d'activité chez les personnes âgées.

Par la suite, le système a été testé en situation réelle avec les mêmes participants. La validité des chaussures instrumentées pour classifier l'activité journalière a été démontrée en comparaison à un système de référence. Par ailleurs, des paramètres de marches ont été obtenus et comparés à la littérature. La relation entre les paramètres de marche et un indice global d'activité, la « complexité », a été évalué. Les participants à l'étude ont jugé l'utilisation du système confortable.

Le potentiel des chaussures instrumentés à analyser des transitions posturales a été présenté ensuite. La durée d'une transition, qui est un paramètre important dans l'évaluation de la mobilité quotidienne, a été calculée grâce aux signaux de la semelle et comparée en laboratoire à une plateforme de force. Le système produit des erreurs faibles. Un algorithme de détection des transitions en conditions réelles a été développé et présente une précision élevée. Globalement, les chaussures instrumentées ont démontré de bonnes performances pour la détection des transitions posturales et la mesure de leurs durées au quotidien.

Pendant la deuxième partie de la thèse, les chaussures instrumentées et les algorithmes dédiés ont été utilisés dans une étude clinique de réhabilitation post-opératoire chez des personnes âgées ayant souffert d'une fracture de hanche. Ces personnes ont été évaluées en deux fois : un à deux jours postopératoire et deux semaines suivant la première mesure. Les paramètres objectifs d'activité, de force plantaire, de marche, et de complexité se sont améliorés conjointement à la récupération, elle-même attestée par des scores cliniques.

Les chaussures instrumentées ont aussi été utilisées pour le suivi de la réhabilitation de personnes ayant souffert d'un accident vasculaire cérébral, évalués à l'admission au centre hospitalier et avant la sortie. Dans cette étude, les paramètres objectifs ont aussi évolué avec la récupération d'une manière comparable et complémentaire aux scores cliniques.

Les résultats de cette thèse ont mis en évidence l'importance de classifier l'activité précisément et proposent un ensemble riche des paramètres objectifs utilisables par les cliniciens afin de mieux évaluer les programmes de réhabilitation et proposer des traitements adaptés à chaque individu. Les résultats indiquent aussi la possibilité d'utiliser le système dans d'autres applications comme en orthopédie, en sport, ou même pour des études de cohorte chez les personnes âgées.

***Mots clés: activité quotidienne, classification, analyse de la marche, chaussure instrumentée, complexité, transition posturale, personnes âgées, fracture de hanche, accident cérébral vasculaire***

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# Chapter 1

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## *Introduction*

### **1 What is physical activity?**

One of the earliest technical definitions was proposed by Caspersen et al. [1], stating that “Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure”, and that “the energy expenditure can be measured in kilocalories”. This definition tightly links physical activity to metabolic equivalent of task (or METs) and as such does not fully cover activity aspects, especially activity dynamics and time series. Recently, the term *physical behavior* was suggested as an “umbrella term which includes the behavior of a person in terms of body postures, movements, and/or daily activities in his/her own environment” [2]. Another noteworthy definition is that of Activities of Daily Living or ADL, which describes the habitual activities that individuals perform, in their everyday life, such as taking care of themselves and their environment, dressing, brushing teeth, and cleaning [3].

This overview focuses on the measurement of physical behavior and its implications on health in healthy and at-risk populations. The components of daily behavior as well as measurement techniques are exemplified in Figure 1-1. In this thesis, two aspects of physical behavior are studied: monitoring of physical activity in terms of basic activities, locomotion periods, and postures, as well as characterizing gait parameters and postural transitions. *Physical activity* and *daily activity* are used interchangeably throughout the thesis, and are mainly characterized by frequency, intensity, time, and type. These four dimensions are usually referred to as the FITT principle [4]:

- **F**requency: quantified as number of occurrences of the activity in a specific timespan (e.g. day or week)
- **I**ntensity: can be related to the energy expenditure of each activity, but also to other parameters such as movement speed or amplitude
- **T**ime: duration of each occurrence of the activity (commonly referred to as activity bout)

- Type: such as sitting, standing, walking, climbing up or down stairs, walking up and down slopes, picking up objects and lying down

Changes in-between activity types usually result from a transition, the most important being sitting to standing and vice versa. These transitions allow the passage from sedentary state to locomotion, and their inclusion in activity characterization is thus relevant. In this context, it is important to define sedentary behavior: from a metabolic perspective, sedentary is any behavior during which less than 1.5 MET are expended. In terms of posture, this mainly corresponds to lying and sitting [5]. An additional dimension that can be constructed from the FITT principle is the daily activity pattern or distribution, often described as the percentage of time spent in each activity/posture, but more importantly as the activity time series; i.e. the succession of activities and transitions between the different states. These characteristics form the basis of what is sought by activity monitoring systems and algorithms.

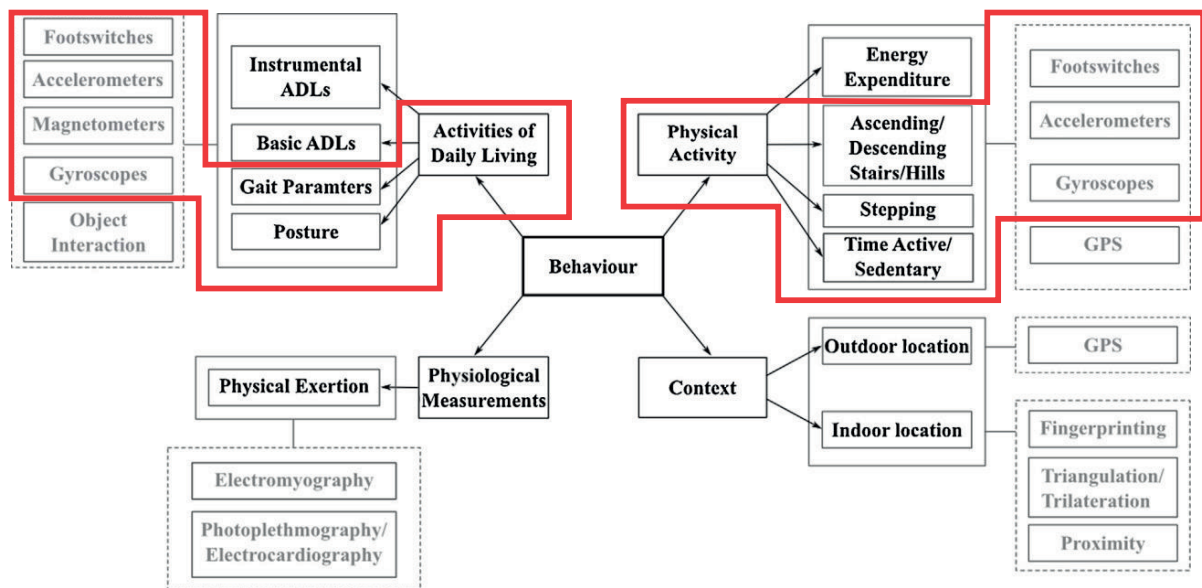


Figure 1-1 - Overview of physical behavior. Red rectangles indicate topics relevant to the thesis. Adapted from © Lowe et al. [6]

## 2 Why is it important to measure daily activity?

The World Health Organization has specific recommendations for adults (aged 18-64) and older adults (aged 65 or older) suggesting either 150min weekly of moderate activity or 75min of higher intensity

activity, or any combination leading to a sufficient total activity time<sup>1,2</sup>. However, more than half the U.S. population and especially older adults, for example, do not reach these activity levels [7]. This proportion is similar in adolescents [8]. This is a rather negative outlook, since increased activity levels are linked to lower risks of chronic diseases and mobility problems [9]. This is highly marked in older adults since chronic diseases and injuries cause a substantial burden on healthcare systems.

Approximately 35-40 % of community dwelling, healthy older adults aged 65 or more experience at least one fall every year, and the fall incidence rate increases with age [10]. Fear of falling is manifestly prevalent within this population of older adults with up to 65 % in some populations, leading in many cases to a significant decline in activity levels [11] (although to a certain extent, a minimum avoidance of some activities can be beneficial in fall prevention, especially activities that carry inherent fall risk). Thus, increased activity avoidance can lead to a reduced quality of life (QOL). This is depicted by the spiral of frailty, Figure 1-2, a chain of events leading to more detrimental effects on daily mobility and health [12]. As people age, their activity performance declines, causing an increased risk of falling. This in turn leads to activity avoidance and increased fear of falling. This results in muscle weakness which leads back to further decline in mobility. In contrast, certain activities accompanied by well suited exercise programs have shown potential in maintaining balance, strength, endurance, bone density; and functional ability; which in turn can lead to a better QOL and reduce the risk of falling [13].

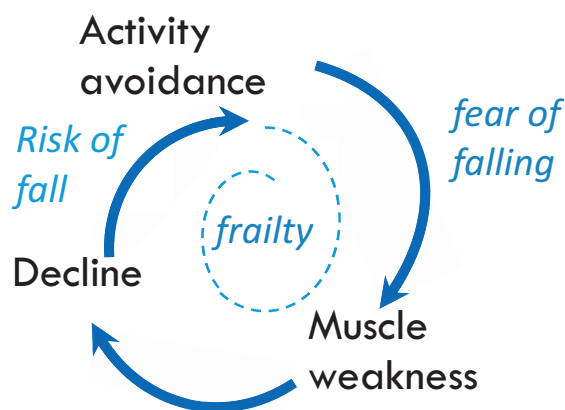


Figure 1-2 - Spiral of frailty

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<sup>1</sup> [http://www.who.int/dietphysicalactivity/factsheet\\_olderadults/en/](http://www.who.int/dietphysicalactivity/factsheet_olderadults/en/) (accessed 26.05.2016)

<sup>2</sup> <http://www.who.int/dietphysicalactivity/physical-activity-recommendations-18-64years.pdf?ua=1> (accessed 26.05.2016)

Consequently, data on daily activity are of crucial interest to the medical community in both healthy and diseased persons, with an emphasis on older adults and populations at risk of mobility impairments. Since older adults spend most of their time in sedentary behavior, it is more relevant to measure sedentary time rather than energy expenditure (which could be more suitable to highly active persons, e.g. athletes). Continuous activity monitoring could allow the prediction of functional decline by looking at the evolution of sedentary and active time. Having accurate daily activity profiles could help clinicians improve recommendations as well as rehabilitation programs and strategically tailor these to each individual's needs [14]. Through activity monitoring, clinicians could give precise and timely feedback to change the sedentary behavior of older persons. In clinical practice, activity monitoring could help evaluate a rehabilitation intervention in longitudinal studies and could have an impact on recovery strategies. To further elaborate on activity monitoring possibilities in daily life, different techniques are presented in the next section.

### **3 Overview of daily activity monitoring techniques**

Daily activity assessment falls under one of two main categories: self-report or objective measurements [15]. Self-report is mostly subjective and is based on questionnaires or diaries/logs, whereas objective measures rely on relevant features assessed through sensors and monitoring devices, as well as direct observation. In the following, direct observation is treated as a separate category because it rarely resorts to sensors.

#### **3.1 Self-report**

Questionnaires administered by clinicians and daily logs filled by individuals are relatively easy and inexpensive, therefore they can be commonly used for population-wide activity assessment [16]. They require no material other than pen and paper (or a computer device for electronic questionnaires), take a short time to administer, and require little post-processing [17]. They can additionally inform about the environmental factors affecting activity [17]. However, their reliability is quite limited because of poor individual recall of activities performed over a past week or month [18]. This is particularly problematic with some populations including children, older adults, and persons with dementia [15]. Questionnaires and logs are also prone to underestimation of sedentary bouts and overestimation of higher intensity activity. Their use for long-term physical behavior assessment is therefore questionable especially in diseased populations.

## **3.2 Direct observation**

Direct observation has the advantage of being by itself a ground-truth measurement, since the activity observed is the true activity. It could also rely on technology in the form of specifically dedicated logging software [19]. Important questions arise from using direct observation such as when to monitor, for how long, in what environment, etc... It is arguably impossible to monitor continuously through direct observation, since the presence of an observer can affect the behavior of monitored persons. From a logistical point of view, there would be unsurmountable difficulties and time constraints for logging and post-processing [16]. This limits the use of direct observation to short bouts of activity in a constrained environment such as the lab or the clinic.

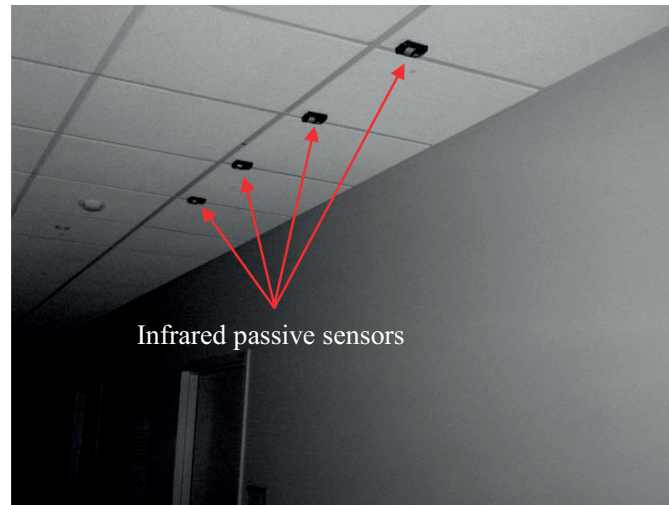
## **3.3 Technology-based monitoring**

Monitoring human activity through technology has expanded rapidly in recent years. Wearable and stationary sensors have been developed to allow direct measurement of movement, which in turn is translatable into activity profiles using the FITT principle.

### **3.3.1 Stationary home systems**

Monitoring daily activity at home through sensors at fixed locations is one application of the “smart home” concept. In terms of dedicated activity classification, video recording has been chiefly used. To reduce extensive and tedious post-processing, features from 2D images have been extracted and used as inputs for machine learning algorithms to separate subjects from the environment and identify movement patterns [20], [21]. Recently, developments in depth-sensitive through systems such as Kinect® have provided 3D alternatives to video-based activity classification [22].

Besides video monitoring, devices such as radio frequency identification chips (RFID), infrared, proximity, position, light, humidity, and temperature sensors are embedded at strategic locations inside the user’s home to measure daily movement [23], [24]. One example of such sensors is shown in Figure 1-3: passive infrared sensors attached to the ceiling measure gait speed in a corridor every time a subject passes through it [25].



*Figure 1-3 - An example of fixed at-home sensors for activity monitoring. The arrows indicate the locations of the passive infrared sensors, adapted from © Hagler et al. [25]*

The main issue with stationary home systems, especially when using video recording, is ethical: video is perceived as the most invasive activity monitoring technique [26]. Other issues of home monitoring include limitation to the indoors home environment, potential image/sensor obstruction, complicated setup, and high cost.

### **3.3.2 Wearable sensors**

Recent developments in microelectromechanical systems (MEMS) have led to the miniaturization of sensors, making it possible to use them for direct measurement of human body movements. Accelerometers and gyroscopes have been predominantly used, usually combined in an inertial measurement unit (IMU). Other sensors include magnetometers, GNSS (Global Navigation Satellite System), goniometers, ECG (electrocardiogram) electrodes, humidity, temperature, barometers, and plantar force/pressure sensors [27], [28]. Besides the suitable form-factor, wearable sensors have several advantages. They can be directly placed on the body or integrated into clothing, collect data continuously and autonomously (at a certain frequency) both indoors and outdoors, store data on internal memory or transmit in real-time [29]. They also provide a low-cost monitoring solution and can be found in several devices such as smartphones.

However, several issues are associated with using wearable sensors. These systems do not directly measure the activity itself, but rather kinematics such as acceleration/angular velocity, or GPS position. Consequently, algorithms are required to interpret such input data and classify/characterize activity



accordingly. The location of these sensors on the body is also a critical aspect. Both the interpretation and the location of the sensors' recordings will be further discussed in section 4. Autonomy is a limiting factor in wearable monitoring, owing to the use of compact batteries to power the different components thus limiting power supply. A tradeoff between autonomy and factors such as number or type of sensors, their sampling rates, the data recording mode (internal logging or transmitting to a receiver) is necessary and generally depends on the final application. Nevertheless, wearable sensors have been used to monitor daily activities for up to one week [30] using adequate combinations of sensor types and sampling rate.

In conclusion, wearable sensors are a viable solution for daily activity monitoring provided that classification algorithms are accurate in translating sensor data into activity classes. Wearable sensors offer a reasonable compromise between the excellent accuracy of direct observation and the intrusiveness of video monitoring, while providing additional advantages such as simple setup and small system size.

## **4 Activity classification from wearable sensors**

Analyzing physical behavior requires the knowledge at each specific window of observation of the activity, posture or transition taking place. The most common approach is through machine learning algorithms [31]. Sequentially, this requires a data preprocessing step (e.g. filtering, normalization, synchronization) followed by feature extraction. Features can be extracted in the time domain (e.g. statistical features such as mean, standard deviation, range), in the frequency domain (e.g. dominant frequency, wavelet coefficients), as well as from other methods (e.g. sensor inclination or area under the curve). They are calculated from signal windows that are usually of fixed length and can present overlaps. This approach is termed epoch-based feature extraction. Feature reduction and selection are then necessary to reduce the dimensionality of the problem and avoid redundancies. Finally, the classifier is trained on a data subset (e.g. a random 2/3 selection) and, to ensure the classifier generalizability, tested on the remaining unseen data. A variant of this technique in activity classification is to use cross-validation, typically by the "leave one out" method, where data is trained on all but one subject and tested on the remaining subject, before repeating the process for the entire sample size. The algorithm can then be used to classify new instances of activity that were not seen in training or testing phases. Several algorithms have been used to classify activity types including hidden Markov models [32], support vector machines [33], and neural networks [34]. These techniques require archetypal training data in order to be usable across populations.

Besides machine learning, expert-based algorithms exist, relying mainly on signal events or features that are representative of activity types, such techniques are referred to as event-driven [35]. A typical

expert-based classification scheme using a hierarchical binary decision tree is illustrated in Figure 1-4. The advantages of such methods include generalizability, simple implementation, and low number of features. Furthermore, using a fixed window size can drown activities that are much shorter than the window length [36], e.g. postural transitions. Event-driven techniques overcome this problem, provided that events are reliably detected.

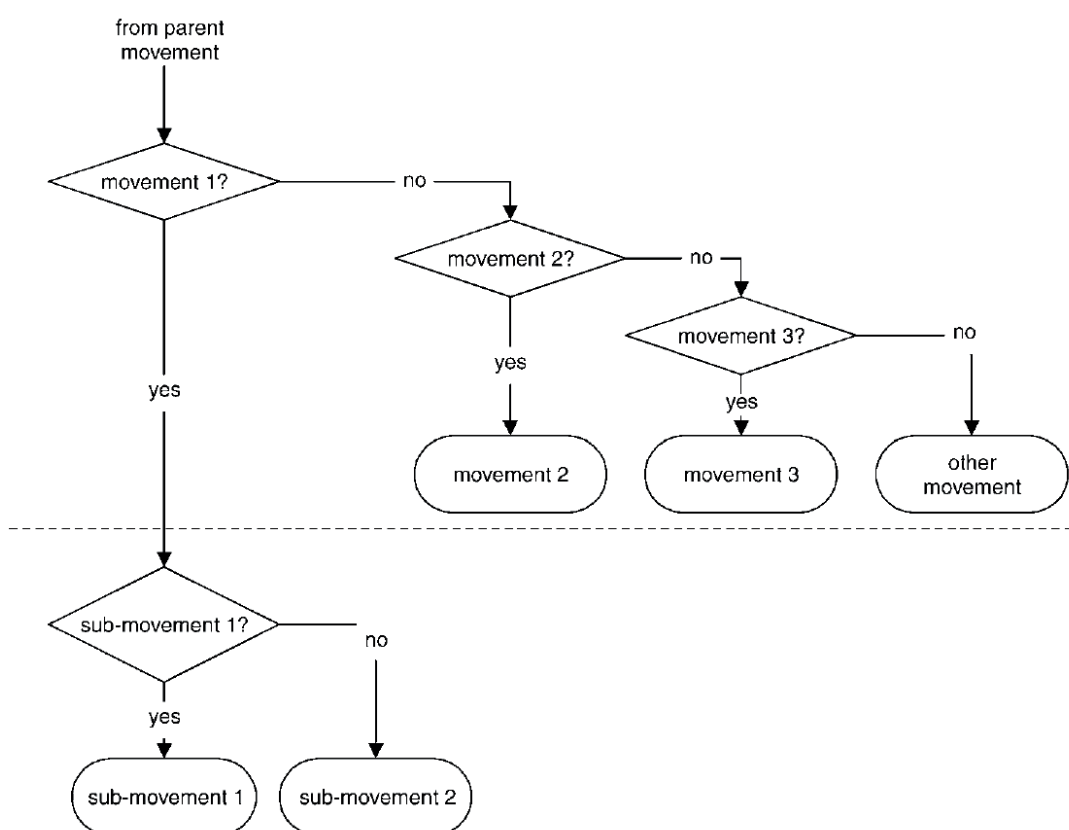


Figure 1-4 - Decision tree framework for activity classification based on expert-based features (© Mathie et al. [37])

A relevant consideration for activity classification through wearable sensors is sensor location [38]. Depending on the robustness of the algorithm used, classifiers may have varying results based on the sensor location [39]. Several researchers have resorted to multi-sensor systems with more than one body location (generally the shank, hip, and trunk) and showed that activity can be classified with high accuracy, exceeding 95%, using such configurations in structured protocols [40], [41]. Few studies have used multi-sensor configurations to validate activity classifiers in real life [42]–[46]. Accuracies exceeding 90%

for some activities were often reported. However, these systems are impractical for daily life monitoring because of their required number of sensors and setup complexity. Single sensor solutions have been also applied in daily life classification validation [47]–[49] again with a wide range of accuracies between 70–90%. Interestingly, studies comparing performances of algorithms validated in the lab and applied in real life conditions generally reported a substantial decrease in classification accuracy [46], [50], [51]. It is therefore essential to get data from real-life measurements rather than in-lab measurements to better train activity classification algorithms with more representative activities and postures than what could be achieved in structured protocols.

It is important to note, at this stage, that quality of the ground truth labels of the activity used in classification plays a big part in terms of accuracy. Most studies used video or direct observation, but some employed self-annotation and therefore the reliability of the ground truth is questionable. It has recently been suggested that a wearable system with high accuracy could be used as reference for concurrent validation, simplifying post-processing tasks related to video monitoring or direct labeling [52]. Several more recommendations for performing viable activity classification validations can be found in [52], [53].

In conclusion, it appears that single sensor locations could be valid for activity classification, but in addition to algorithm rules, the choice of location and number of sensors is crucial. In this thesis we selected the foot/shoe as the most suitable candidate location, based on assumptions detailed in Chapter 1, section 7, using a system that incorporates a number of sensors, all placed at the same location. An overview of instrumented shoes is presented in the following section.

## **4.1 Brief overview of instrumented shoe systems**

In recent years, a large number of studies have focused on the design of sensors placed at the shoe level or embedded in shoes/insoles. These studies are reviewed in Chapter 2. Instrumented shoes are systems that incorporate inertial sensors (accelerometers, gyroscopes) mainly placed on the shoes and/or plantar pressure sensors inserted between the foot and the shoe. Some research prototypes and commercial devices have integrated all the sensors in an insole to be simply inserted in the shoes. Systems with sensors integrated directly inside the shoes (i.e. encapsulated under the actual shoe insole) also exist. Instrumented shoe systems have been used for multiple applications such as activity classification, gait analysis, load monitoring, clinical mobility assessment, and feedback. These applications are also detailed in Chapter 2.

## **5 Applications of wearable sensors to real-life activity monitoring**

Studies reporting on activity profiling during daily life with wearable sensors in healthy adults are numerous. Sensors have been used to describe walking bouts and their distributions [54], other studies have focused on sedentary and active time measurements [55]–[59]. Populations of particular interest to this thesis are healthy and frail older adults as well as stroke patients. In healthy older adults, besides accelerometers placed on the thigh, most systems have only reported activity counts and/or step information [60]. There has been relatively few daily activity monitoring studies in frail older adults [61]. In a recent review it was shown that step count and locomotion bout analysis has been the predominant outcome of daily monitoring in stroke patients [62]. It was also evident that patients have less walking bouts at home compared to healthy adults [63]. Activity counts were used to determine active time in stroke patients, correlating well with physical capacity test scores [64]. Sedentary vs active time was assessed from an accelerometer placed at the ankle revealing that patients spent more than 93% of time in sedentary postures [65]. Monitoring of stroke patients using accelerometers placed in the pocket emphasized the need to measure activity for several days because of inter-day variability [66].

Many of the aforementioned studies, especially when looking at sedentary time, were based on actigraphy or activity counts, a technique that has been shown to correlate well with energy expenditure in specific conditions, but lacks information about the type of movement and its environment (indoor, outdoor), movement quantity such as speed or range of motion and the quality of the movement such as variability symmetry, or coordination. For example, estimating energy expenditure of walking on slopes using activity counts revealed large errors compared to reference measurement [67]. Therefore activity counts do not provide a complete characterization of the movement. Studies where sitting, standing, and walking were evaluated mainly used a single sensor placed either on the thigh or trunk, providing postural profiling, but again no other description such as the type of locomotion and gait parameters or quality and quantity of postural transitions. Therefore the number of applications remains rather low, especially with at-risk populations. Furthermore, there have been no studies reporting on the use of instrumented shoes in daily life monitoring.

In this thesis, one of the objectives is to characterize activities in daily life by performing gait and postural transition analysis for each walking bout or transition event, as well as a complexity metric (detailed in the following section). This has the potential of being much more informative than activity counts/METs or simple posture allocations, especially in rehabilitation studies (Chapters 6 and 7).

## 6 A note about physical behavior complexity

Research has shown that some physiological signals studied as time series exhibit non-linear and non-stationary dynamics: the organism does not always tend to go for an equilibrium state under healthy conditions [68]. Furthermore, two signals with similar overall mean and standard deviation do not necessarily reveal the same temporal patterns, therefore indicators of health and disease conditions could be missed by overlooking the signal patterns [69]. Further examination using fractal analysis, multi-scale entropy, approximate entropy, and Lyapunov exponents [70] show that the variations, over time, of heart rate and human locomotion have non-linear or “complex” behavior. The link between loss of complex behavior and aging/disease was made in the early 1990s. It was found that aging is accompanied by a deterioration in the human adaptation mechanisms and thus older adults are less capable of dealing with the same environmental stresses that younger persons are exposed to [71]. As a result, complexity decreases with aging and this implies that the organism adapts less to environmental inputs, thus paving the way to frailty [68] as depicted in Figure 1-5.

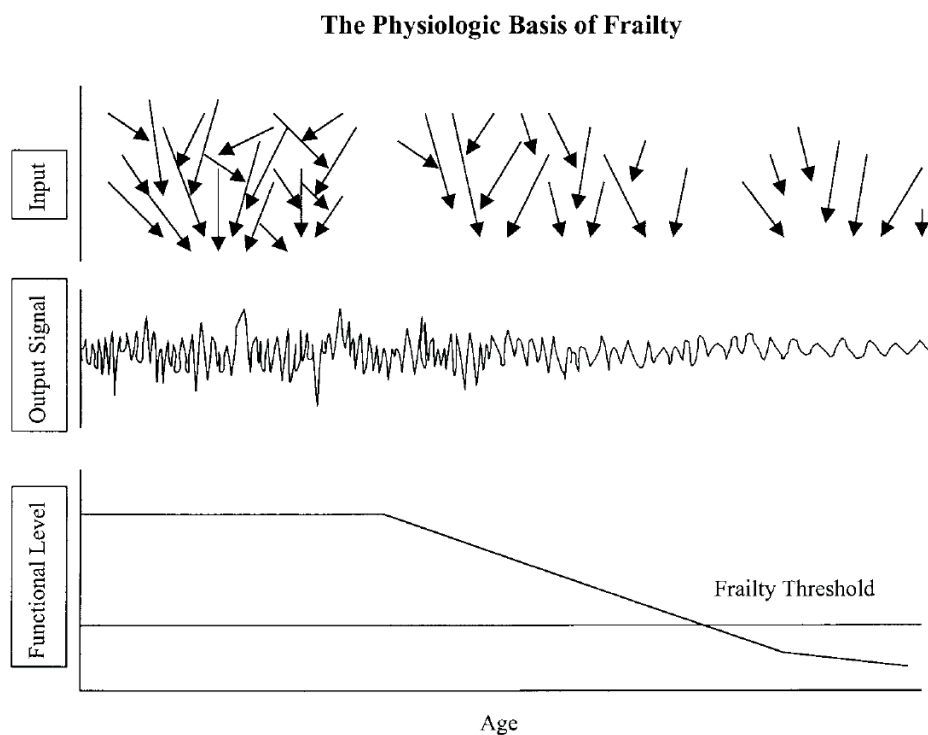


Figure 1-5 - Ageing and loss of complexity, (© Lipsitz [68])

The components of physical behavior are multidimensional and their interconnections are similarly complex [72]. In relation to this study, Paraschiv-Ionescu et al. [73] demonstrate that patterns of physical activity have inherent fractal properties and can be used to discern healthy subjects from subjects suffering chronic pain or disease. In a later study [74] they propose a physical activity barcoding scheme that can reliably provide a global picture of the activities (walking, sitting, lying), postural transitions, and most importantly activity patterns throughout the day using a complexity metric. Similar analyses are performed in Chapter 4 of this thesis, therefore a brief description of activity barcodes is relevant. Activity labels are obtained from a wearable sensor system [41] and separated into sedentary (sitting/lying), standing, and walking. For each activity, information about the movement intensity is obtained from the sensors. For sedentary and standing, thresholds are applied the trunk acceleration to obtain different barcode “states”, numerical identifiers that are represented in color codes with warmer colors indicating higher activity intensity (Figure 1-6). As for walking, both the duration and the cadence play a role in defining the barcode states. It can be directly inferred from Figure 1-6 that the top plot corresponding to a chronic pain patient is less rich in both state intensity and transitions between states, compared to a healthy person (bottom plot). Further analysis with the Lempel-Ziv complexity metric revealed that complexity is lower for patients compared to healthy persons, and could also be an indicator of the pain intensity [74].

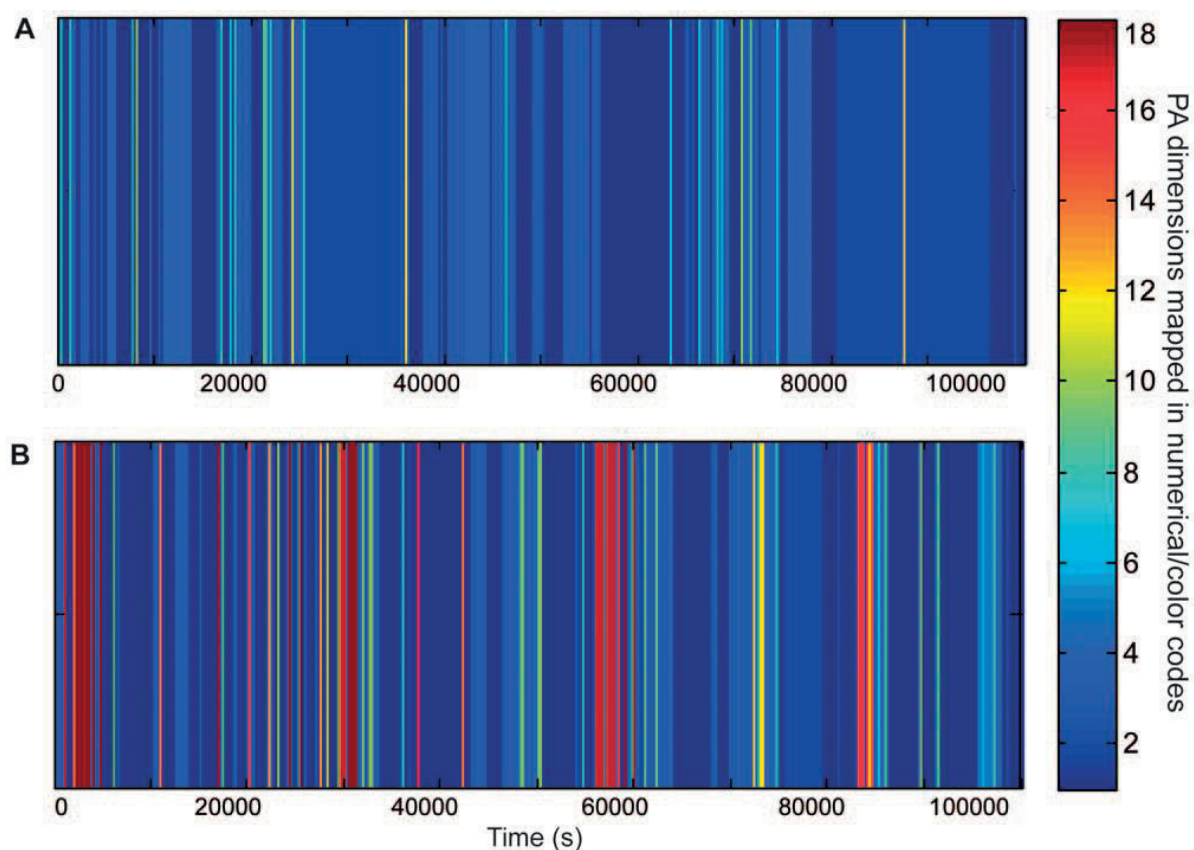


Figure 1-6 - Physical activity barcodes with color coding scale. Top: chronic pain patient, bottom: healthy person, © Paraschiv-Ionescu et al. [74]

Measuring physiological complexity has been accomplished using several methods, including: fractals, approximate entropy, multiscale entropy, Lyapunov exponents, and power law analysis [69], [75]–[78]. A comprehensive review of variability metrics that can be used to assess complexity can be found in [70].

One of the goals of this thesis is to show that the analysis of the complexity of physical behavior, through activity barcodes, is a metric that is highly sensitive to rehabilitation induced changes, and that it complements classical measures of posture, activity, and gait.

## **7 Concluding remarks and thesis objectives**

Based on the literature survey in daily activity monitoring, it is clear that there exists a tradeoff between number of sensors placed at different body locations and activity classification accuracy. On one hand, placing a large number of sensors is hindering and uncomfortable; on the other, a low number of sensors usually resulted in lower classification accuracy. Furthermore, whereas several applications of wearable sensors to activity monitoring in daily life of healthy older adults have been presented, such studies were less frequent with respect to patient rehabilitation monitoring.

Therefore, the objectives of the thesis are:

- Design an instrumented shoes system containing several sensors that are all placed in a single location, the foot/shoe, providing high accuracy as well as comfort and unobtrusiveness. The selection of this location was based on the assumptions that foot load, orientation and elevation could inform about different components of physical activity.
- Design of algorithms for activity classification capable of detecting the basic postures (sitting, standing, and walking) as well as locomotion types (level, stairs, and ramps) and activities with elevation change (e.g. elevator use). The algorithms should be robust and provide a high accuracy for the detection of each activity type.
- Technical validation of the activity classifier in controlled and free settings in terms of classifier performance, revealing a large number of parameters that could be obtained from the instrumented shoe system including activity, gait, postural transitions, and complexity.
- Design of a postural transition detection and characterization algorithm, which is capable of highly accurate recognition of transition type, as well as estimating its duration.
- Application of the instrumented shoes in rehabilitation monitoring, with an emphasis on the evolution of available metrics and their sensitivity to rehabilitation changes.

## **8 Thesis outline**

This thesis has two main scientific sections: system and algorithm design (Chapters 3, 4, and 5) and clinical application (Chapters 6 and 7) of the proposed instrumented shoes, Figure 1-7.



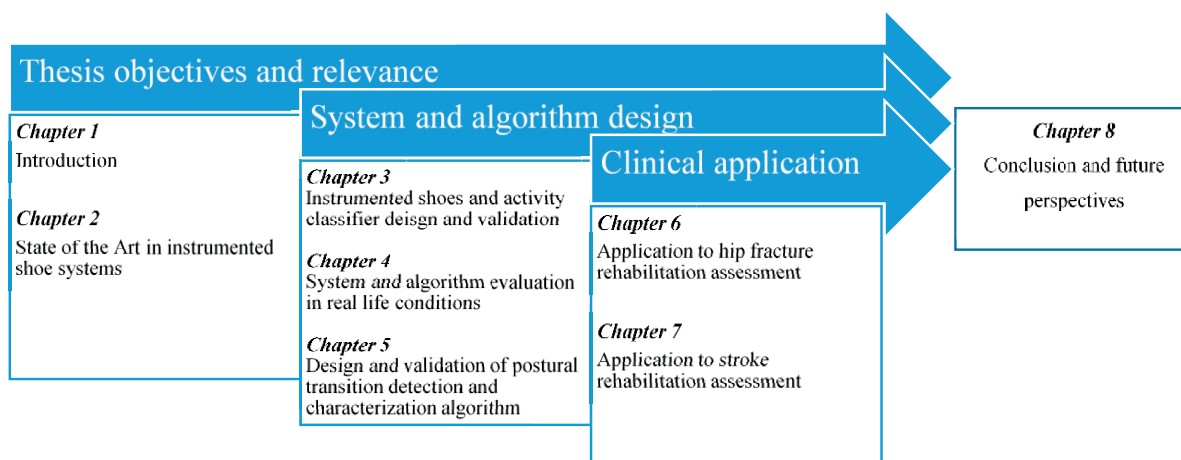


Figure 1-7 - Thesis outline

**Chapter 1** introduces physical behavior and the relevance of activity monitoring in real life conditions, with an emphasis on activity monitoring techniques using wearable sensors.

**Chapter 2** reviews the state of the art in shoe-based measurement systems, especially in terms of activity classification, gait analysis, and clinical/rehabilitation monitoring of diseased persons.

**Chapter 3** presents the design of instrumented shoes system and activity classification algorithm. The algorithm is validated in terms of classification accuracy and sensitivity to tuning parameters. This was done in quasi-real life conditions within a structured protocol with healthy older adult volunteers.

**Chapter 4** extends the use of instrumented shoes for activity classification in real life conditions, demonstrating the classification accuracy without the presence of an observer using a wearable reference system. Gait analysis results are reported and physical behavior complexity is introduced.

**Chapter 5** deals with the specific case of postural transitions, providing the design of an algorithm for transition detection and classification as well as the characterization of transition durations: a crucial parameter in daily life mobility. Total force measurement during transitions is also presented in this chapter.

*Chapter 6* draws upon algorithms of Chapters 3, 4, and 5 and reports the suitability of using instrumented shoes for rehabilitation monitoring of hip fracture inpatients. Activity profile, load, gait analysis, and complexity assessment constitute four analysis dimensions of rehabilitation that could be monitored with the proposed system. Sensitivity to change is performed to identify the most meaningful metrics.

*Chapter 7* describes rehabilitation outcomes of post stroke inpatients using the same parameters defined in Chapter 6, to identify which metrics are determinant of mobility improvement during rehabilitation at the clinic before discharge.

*Chapter 8* includes concluding remarks and future perspectives related to the use of instrumented shoes in movement analysis.

## Chapter 2

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### *A survey of shoe-based systems and applications for physical behavior and gait monitoring\**

#### **Abstract**

Physical behavior and locomotion play a crucial role in identifying mobility and functional levels in several at-risk populations including frail elderly, stroke patients, Parkinsonians, patients with orthopedic disease, and children with cerebral palsy. Wearable sensing is becoming a standard in today's health assessment because of its ability to objectively characterize behavior outside the lab environment. Both research-based systems and commercial trackers are witnessing a major expansion. Several algorithms have been validated for activity classification and gait analysis from systems with single or multiple sensors placed on different body locations. It appears that standalone shoe-based systems can perform coarse behavioral profiling in terms of activity classification, and a fine characterization of locomotion through gait analysis. Therefore, the aim of this review is to shed light on recent advances in foot-worn sensor systems for physical behavior and gait monitoring. The technical performances of foot-worn systems for behavior and gait analysis is presented, as well as clinical applications of these systems in at-risk populations. The literature reveals that there is major potential of including foot-worn sensors in routine clinical mobility assessment as well as monitoring behavior in daily life.

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\*Parts of this chapter were used for the following published article: Aminian K. and Moufawad el Achkar C., "La chaussure instrumentée pour l'analyse de la marche et de l'activité quotidienne", *Fachzeitschrift Rheuma Schweiz* Nr. 3 | 2016

## **1 Introduction**

Monitoring physical behavior and movement performance has become a standard in modern day healthcare. Evidence suggests that increased activity levels can lower mortality and morbidity rates and is generally linked with improved health [79]–[81]. Similarly, gait characteristics, especially gait speed, have been linked to health status and mortality [82], [83], or even fear of falling [84]. It is therefore crucial to reliably obtain quantitative information about activity and gait in patients as well as in healthy individuals. Laboratory-based techniques offer the possibility of characterizing human activity, e.g. recognizing movements from video recording [85], motion capture [86], or measuring ground reaction forces during different activities using force plates [87]. In particular, gait parameters have been obtained from instrumented floor mats, a well-known example being the GaitRite system [88]–[90]. Where these systems provide highly accurate representation of the studied movements, they lack in terms of usability outside of the laboratory environment. Therefore, their application is limited to the assessment of short activity durations in a confined space, usually within a structured protocol that does not reflect the real life behavior of the participants. In recent years, wearable systems and trackers have become the predominant choice in daily human movement monitoring. With the advent of microelectromechanical systems (MEMS) that are easily integrated in ergonomic designs, movement of different body segments can be determined. Accelerometers and gyroscopes, mostly combined as a single inertial measurement unit (6D IMU), have been chiefly used in human movement analysis [27], [91]–[93]. The location of these sensors on the body is crucial. In fact, the sensor location largely depends on the application. In terms of activity monitoring, the location can have an effect on activity classification accuracy [38]. Similarly, the estimation of gait parameter such as step or stride can vary based on the location of an IMU on the body [94]–[96].

Foot-worn sensors have gained increasing popularity in the last two decades for wearable movement monitoring. In fact, footwear is prevalent in most daily activities. From a biomechanical point of view, there are two main reasons that support using foot-worn sensors:

- The foot orientation and trajectory can be obtained using IMUs and can be used for gait analysis and locomotion mode recognition
- The interface between the foot/shoe and the ground is the best location to measure the plantar force distribution allowing force and center of pressure (CoP) estimation that could be used in disease assessment, rehabilitation or activity classification

Thin force sensing resistors (FSR) have been developed to measure plantar force. They can be integrated in shoe inserts because of their extremely low thickness ( $<0.5\text{mm}$ )<sup>1,2,3</sup> offering the possibility of concealing the sensors. This is advantageous for monitored patients or populations at risk because it eliminates potential stigmatization. This also protects the sensors and prevents them from falling or inadvertently getting detached by the wearer. These advantages of foot-worn sensor systems have encouraged researchers to build and validate prototypes to measure activity, gait, and plantar force as well as to use such systems in clinical assessment and rehabilitation.

This survey starts with an overview of foot-worn systems for physical behavior monitoring. Then it delves into the characterization of gait and load/CoP related measurements from foot sensors. Finally, applications of foot-worn systems in gait and activity monitoring, rehabilitation, and clinical studies are reviewed with a focus on elderly population. Most of the references were selected from the year 2000 onwards and based on their relevance in using footwear systems for the aforementioned applications.

## **2 Survey of foot-worn systems for physical behavior, gait and load/Center of pressure measurement**

### **2.1 Footwear and physical activity monitoring**

The use of foot-worn sensors for activity classification and monitoring has been mainly oriented towards the classification of different locomotion types. Plantar pressure during stairs locomotion has been characterized [97] but no effort to directly use events from pressure patterns for classification has been done. Alternatively, machine learning techniques have been employed to perform stairs classification using insole force data alone [98] or combined with 6D IMU [99]–[101]. Majumder et al. [102] used data from 4 FSR sensors under the foot to classify standing, level walking and stair locomotion using thresholding of total force values and reached accuracies of 76-88%. Similarly, Peng et al. [103] classified standing, walking and stair locomotion from pressure data of 7 FSR sensors using a support vector machine algorithm with accuracies ranging between 86-100%. They also showed that a reduction in the number of sensors led to a worse classification performance. Some work has also been conducted on the estimation of transportation modes (car, bus, bike, driving or by foot) using instrumented insoles. The classification was not very effective, but could be improved with the addition of GPS data [104].

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<sup>1</sup> <https://www.iee.lu/en/products/sports-healthcare/smart-foot-sensor> (accessed 26.05.2016)

<sup>2</sup> <http://www.interlinkelectronics.com/standard-products.php> (accessed 26.05.2016)

<sup>3</sup> <https://www.tekscan.com/fsr-standard-and-custom-force-sensitive-resistors> (accessed 26.05.2016)

Shoe mounted IMU was also used for locomotion classification. Santhiranayagam et al. [105] used features extracted from such a system to classify walking in three conditions: level, blindfolded, and while holding a glass. Accuracies of 83-84% were achieved using machine learning techniques. A particular angular velocity pattern is revealed during stair locomotion and has been used to differentiate stairs from level walking with high accuracies of 90-99% [106]–[108]. The classification of gait when carrying loads in different conditions such as front pack, backpack, carrying with the hands or on the sides was tested using an IMU and 8 FSR sensors in an insole, with accuracies varying between 43-100% based on a support vector machine algorithm [109].

In addition to locomotion type, sitting and standing can be recognized by footwear systems incorporating pressure sensors. Sazonov et al. [110] used a shoe-mounted accelerometer combined with 5 FSR sensors under the foot to classify sitting, standing, level walking/jogging, stairs locomotion and cycling. Their support vector machine algorithm achieved 98% overall global accuracy, with lower sensitivity for stair descent (80%) and precision for stair ascent (78%). Using the same system, Tang and Sazonov [33] increased the potential accuracy of all activity classed by performing support vector machine classification with rejection. However, this meant that more than 30% of the data had to be rejected to achieve an accuracy of 99.9%. Their instrumented shoe is shown in Figure 2-1. Adelsberger and Tröster [111] presented a wireless sensing insole based on FSRs and IMU and tested a support vector machine algorithm on data from their system. They achieved an accuracy exceeding 99% from measurements but in only one healthy subject performing sitting, standing and walking activities. Chen et al. [112] classified sitting, standing, level walking and stairs locomotion using insole pressure data only, and achieved accuracies exceeding 95% for all classes with 5 healthy volunteers and one below-knee amputee. They used linear discriminant analysis on features extracted from 4 FSR sensors under each foot to develop their algorithm. Lin et al. [113] performed a classification of sitting, standing and walking based on spatial warping of insole force patterns, reaching accuracies exceeding 90% for different activity conditions (e.g. carrying loads while walking). Kawsar et al. [114] reported promising classification accuracies for sitting, standing and walking using pressure sensors from an insole and a decision tree algorithm. An accuracy of 89% was achieved with data from one subject performing the different activities.

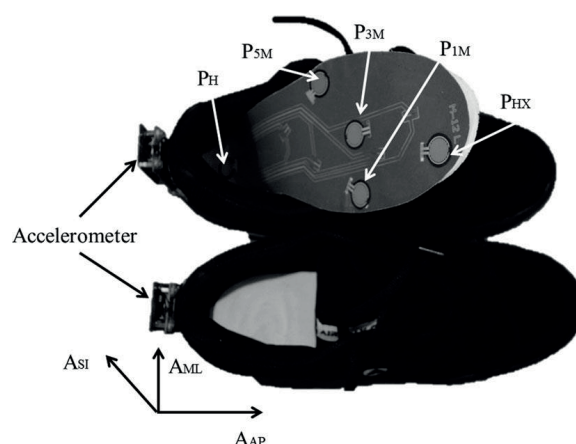


Figure 2-1 - Foot-worn system from Tang and Sazonov [33] used for activity classification, including 5 FSR sensors placed under the heel, first/third/fifth metatarsals, and the hallux, as well as a 3D accelerometer at the heel (© Tang and Sazonov [33])

Continuous monitoring of daily activity offers the possibility to detect rare but crucial events such as a fall. Fall detection using foot-worn sensors has been investigated by Tao et al. [115] where signals from 8 FSRs under the feet were used to classify falls based on artificial neural networks. Tests with one subject simulating falls yielded a classification accuracy of 75%. Acceleration thresholds on the foot were used to identify falls compared to activities of daily life in 3 subjects wearing accelerometers on the shoes, achieving a fall (simulated) detection sensitivity of 81.5% [116]. Several machine learning algorithms were evaluated for fall detection using a pressure sensing insole with decision trees reaching 87% sensitivity and 88% precision [117]. Lincoln and Bamberg [118] provided insights on the detection of slippage using pressure sensing insoles and foot-worn 3D accelerometers. The detection method was based on thresholding both sensors and revealed promising preliminary results. While there is evidence that simulated falls cannot be used for validation of real fall detection [119], these studies emphasize new possibilities offered by instrumented shoes.

To summarize, activity classification using instrumented shoes appears to be highly accurate especially for basic activity (sitting, standing, and walking) as well as locomotion types (level, stairs, ramps). Studies predominantly resorted to machine learning techniques to perform classification, which could be highly sensitive to training data and therefore only represent the activities of the specific monitored population. Furthermore, none of the previous studies performed activity monitoring in real life conditions; they did not assess the usability and validity of instrumented shoes in real daily life outside the lab. In this thesis, we propose two innovative aspects in shoe-based activity monitoring. Firstly, as an alternative to existing machine learning algorithms (that might not be generalizable due to specific training data), an

algorithm based on movement biomechanics using instrumented shoes is developed and validated for in-lab conditions using instrumented shoes in Chapter 4. Secondly, the algorithm is validated in daily life conditions in Chapter 5 to show the usability of this system outside the lab or clinical environment.

## **2.2 Footwear and gait analysis**

Gait analysis provides spatio-temporal parameters, kinematics and kinetics features as well as muscular activity during locomotion. Temporal parameters characterize the different phases of a gait cycle including gait cycle time (*GCT*), swing, stance, push, foot-flat, loading, and double support phases. The durations of these phases are usually calculated by identifying specific gait events such as initial contact (*IC*), toe off (*TO*), terminal contact (*TC*), foot strike (*FS*). Heel off and toe strike have also been defined as events in the gait cycle. For example, the gait cycle time is defined as the time between two consecutive gait events (mainly the *TO*), the stance phase occurs between *HS* and *TO* whereas the swing phase is from *TO* until the next *HS*. Spatial and kinematics information portray distance related parameters such as stride length and velocity, foot clearance, turning angle, and the foot segment angle during the different phases of a gait cycle. Walking is a periodic movement with period of *GCT* and in humans requires left and right lower limbs to alternate. Therefore two features can further characterize a normal walking and can be added to the aforementioned parameters for a more comprehensive analysis: first, the gait variability which expresses the inter-cycle variation of gait parameters and, second, gait symmetry that considers the difference in a gait cycle between left and right limb.

Foot-worn sensors have been extensively employed to estimate all the aforementioned parameters. Starting with temporal parameters, foot switches based on FSR technology have been the forerunners of gait event detection by thresholding their output to detect *TO* and *HS* events [120]. Srivises et al. [121] described a fuzzy logic algorithm using gyroscope and 4 FSR signals from an insole to detect gait events. Compared to video camera recording, 85% of the events were accurately detected. Kong et al. [122] also used fuzzy logic for continuous detection of gait phases based on 4 air pressure sensors placed in an insole and compared the results to discrete threshold-based detection. However, no error values were reported. Particle swarm optimization technique was used to classify gait phases using an IMU and 4 FSR sensors with an accuracy of 96% [123]. Gait event detection was also evaluated in participants with gait impairments. Lopez-Meyer et al. [124] performed thresholding on signals from 5 FSR sensors to identify temporal parameters in post-stroke patients. Temporal event estimation was performed in children with cerebral palsy using FSR sensors and errors ranged between 30-149ms [125].

The use of IMUs for gait event detection has been likewise investigated in foot-worn systems. Using acceleration and angular velocity of the foot and their respective derivatives Mariani et al. [126] evaluated



the different gait phases with errors between 1 and 5ms for gait events, and 1-30ms for gait phases compared to reference measurements in healthy participants and ankle arthrosis patients (Figure 2-2). Mannini and Sabatini [127] used Hidden Markov Models to identify strike and off events from pitch (medio-lateral) gyroscope signals owing to the cyclic nature of these gait events, and also obtained errors of about 3ms. Pappas et al. [128] used a combination of FSR sensors and a pitch gyroscope in a state machine to identify the four main gait events, achieving errors in the range of 35-70ms.

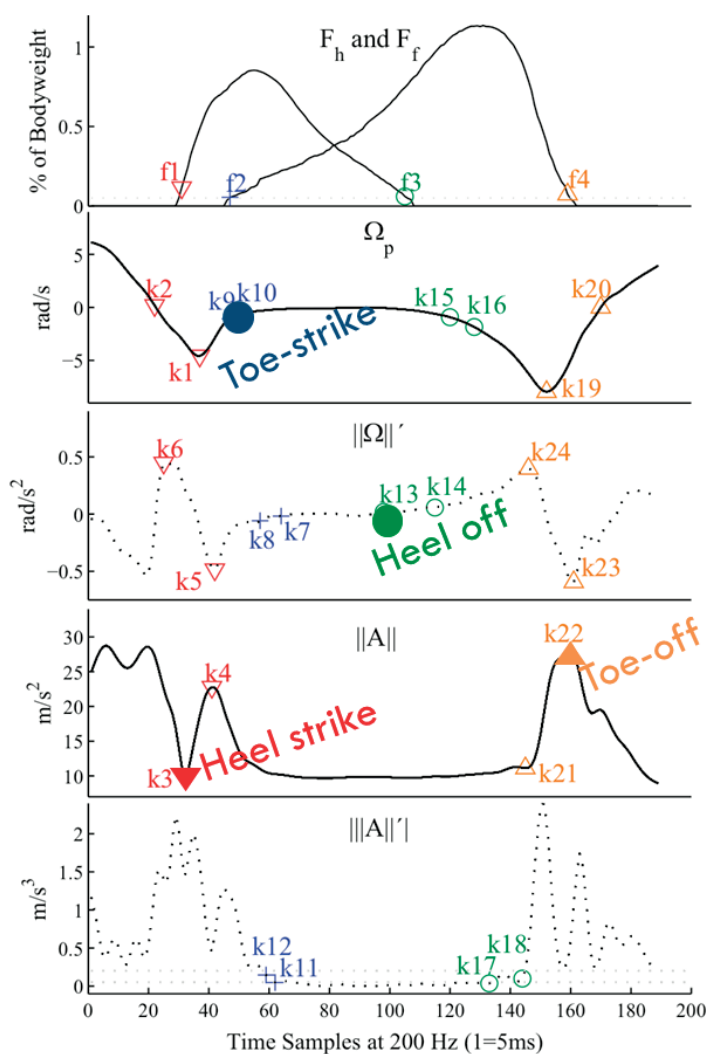


Figure 2-2 – IMU signals for gait events, adapted from Mariani et al. [126]. (a) Heel ( $F_h$ ) and forefoot force ( $F_f$ ) and (b) the corresponding pitch angular velocity ( $\Omega_p$ ) and (d) norm of foot acceleration  $\|A\|$  and (c) and (e) their derivatives. The actual value of heel strike ( $f_1$ ), heel-off ( $f_2$ ), Toe-strike ( $f_3$ ) and Toe-off ( $f_4$ ) obtained from force plate are compared to corresponding features detected by IMU signal ( $k_i$ ). The best features are highlighted in bold text (© Mariani et al. [126])

The detection of temporal events in activities other than level gait has also been studied. Examples include Runalyser, a pressure sensing insole, that demonstrated good agreement with an instrumented treadmill for temporal parameters during running [129], whereas gyroscopes have been used to identify temporal events during stair locomotion [130].

Besides the intrinsic importance of measuring temporal parameters, the accurate detection of heel strike and toe off events is crucial for calculating spatial parameters. The measurement of velocity and position through IMU requires integration and double integration, respectively, of acceleration signals. This integration is prone to drift, i.e. the integrated value can increase drastically due to sensor bias and noise levels [131]. This practically means that integration should only be performed in a short time window with known constraints, and an ideal window would be when the foot is moving between consecutive toe off and heel strike instants. The velocity and position can then be reset during stance [132].

In terms of spatial gait parameters, Sagawa et al. [133] used a uniaxial gyroscope, a 3D accelerometer and a barometric pressure sensor to estimate horizontal and vertical distance travelled during gait. The IMU was highly accurate in measuring horizontal distance whereas the barometer had larger errors in estimating vertical distance. Sabatini et al. [134] used the strap-down integration technique to estimate the foot orientation during the swing phase and subsequently calculated stride length and velocity, reporting an average error of 0.05m/s for stride velocity compared to the treadmill's reference speed. They additionally estimated the foot pitch angle with an average error of 1.52%. Bamberg et al. [135] developed an instrumented shoe with FSR sensors and IMU to measure stride length and velocity as well as foot pitch angle. They detected *TO* and *HS* events using FSR to set integration bounds for the gyroscope and removed the integration drift using iterative error correction. Both spatial and temporal events were estimated with low errors compared to motion capture reference. Mariani et al. [136] used drift correction methods and gravity cancellation to integrate (also using strap-down technique) acceleration and angular velocity signals from a foot-worn IMU for the calculation of stride velocity, stride length, foot clearance, and turning angle. The method proved to be reliable and repeatable in young and elderly subjects performing walking test, a timed up and go (TUG) test and a figure-of-eight walk. The efficacy of this method was also demonstrated in calculating spatial parameters of Parkinson's disease patients [137]. Drift correction was also applied in another study to measure the lateral foot displacement and the stride length from a 6D IMU on the foot, resulting in low estimation errors [138]. Hung and Suh [139] used a 3D accelerometer and a camera mounted on the front of one foot and an infrared marker on the back of the contralateral foot to estimate step length, with an error of 5.4cm.

Foot clearance is a valuable parameter for gait analysis since it plays a crucial role in stairs and obstacle negotiation. A quadratic regression model using vertical acceleration and pitch angular velocity

was built to estimate the minimum foot clearance with a mean error of  $17.34 \pm 48.50$ mm compared to a motion capture system [140]. The direct measurement of foot clearance using an IMU was achieved by modeling the shoe sensor location with respect to the heel and the toe and performing strap-down integration with drift removal to estimate the 3D position of the shoes in space [141]. A validation of this model in healthy elderly subjects yielded errors below 10% for maximum heel and toe clearance but up to 40% for minimum toe clearance. Benoussaad et al. [142] used a similar technique (strap-down and de-drifting) to obtain a global foot clearance measure with RMS errors below 15% in 10 healthy volunteers, compared to motion capture. Santhiranyagam et al. [143] used a generalized regression neural network machine learning technique to estimate the minimum toe clearance during a gait cycle, achieving root mean square errors around 7mm. The model required different features for young and elderly subjects. Besides inertial sensors, optical proximity sensors provided minimum foot clearance values that were highly comparable to motion capture [144]. One notable study investigated ultrasound sensors to measure the 3D foot displacement and clearance during gait, achieving low errors, but this method is only usable in a confined space because it requires stationary ultrasound anchors [145].

Infrared and ultrasound sensors were proposed to detect the distance between the foot and potential obstacles, reaching high accuracies exceeding 95% for detecting objects up to 1.5m [146]. Recently Weenk et al. [147] proposed an ultrasound sensor and actuator in combination with IMU fixed on an instrumented shoe to measure foot position and estimate the step width with an error of 12mm. The algorithm was based on an extended Kalman filter updated with the estimation distance between the feet obtained from the time of flight of ultrasound waves. While the system provided an accurate estimation of foot position, the proposed instrumented shoes are cumbersome for everyday life. Infrared range sensors placed medially on the shoes were alternatively used to measure the inter-foot distance during the swing phases of each gait cycle [148]. A combination of infrared and ultrasound sensors was also proposed to measure this distance [149].

In conclusion, instrumented shoes have been extensively used in spatio-temporal gait analysis to provide accurate measurement of gait parameters. The main drawback of the aforementioned studies was the lack of daily life gait assessment. In fact, tests were conducted either on a treadmill or during a short gait test, limiting the analysis to only a few gait cycles. None of the systems were used for physical activity monitoring and gait analysis simultaneously. This is critical for daily life gait assessment, since it would require the correct identification of locomotion periods and their type to perform gait analysis on only those periods that are correctly classified. In Chapter 4, we report gait analysis in daily life for level locomotion periods classified by the instrumented shoes. Gait analysis is also used as an outcome measure for

rehabilitation in Chapters 6 and 7. Both these aspects are novel with respect to the use of instrumented shoes in daily life.

### **2.3 Footwear and load/Center of Pressure measurements**

Plantar pressure or force sensors located in shoe inserts or in the shoes themselves provide an ideal framework for total or partial load estimation and reconstruction of the CoP during different activities. The direct measurement of the 3D ground reaction force (GRF) in footwear has been studied using miniature triaxial force transducers. Liedtke et al. [150] described an instrumented shoe consisting of two such force transducers placed under the shoes, one under the heel and the other under the forefoot, to measure the 3D GRF and CoP during gait, Figure 2-3. The system demonstrated high accuracy with low root mean square (RMS) errors except for the antero-posterior (sagittal plane) force with 37.2% mean error. The system was also able to measure loads accurately in several lifting tasks and locomotion modes [151]. Tao et al. [152] obtained similar errors using two force transducers placed in an insole inside the shoes. A system using 5 triaxial force transducers placed under the heel, lateral arch and forefoot was validated for 3D GRF measurement with RMS errors below 10% and CoP calculation with  $1.4 \pm 0.2\%$  RMS error [153]. The main drawback of such GRF calculation systems is the sensor thickness (~2cm) and weight (~15g per sensor) [154]. This could possibly alter gait performance especially in diseased persons and would be uncomfortable for long-term GRF and CoP monitoring.



*Figure 2-3 – Force sensing shoes from Schepers et al. [138] , same system used by Liedtke et al. [150] (©Schepers et al. [138])*

The vertical load and CoP measurement accuracy of commercial systems with high density sensor meshes has been demonstrated, well known examples being the Pedar system (Novel, DE) [155], [156], the F-scan system (Tekscan Inc., U.S.A) [157], [158], and the Parotec system (Paromed GmbH & Co., DE) [159]. Figure 2-4 shows the Pedar and F-scan systems.

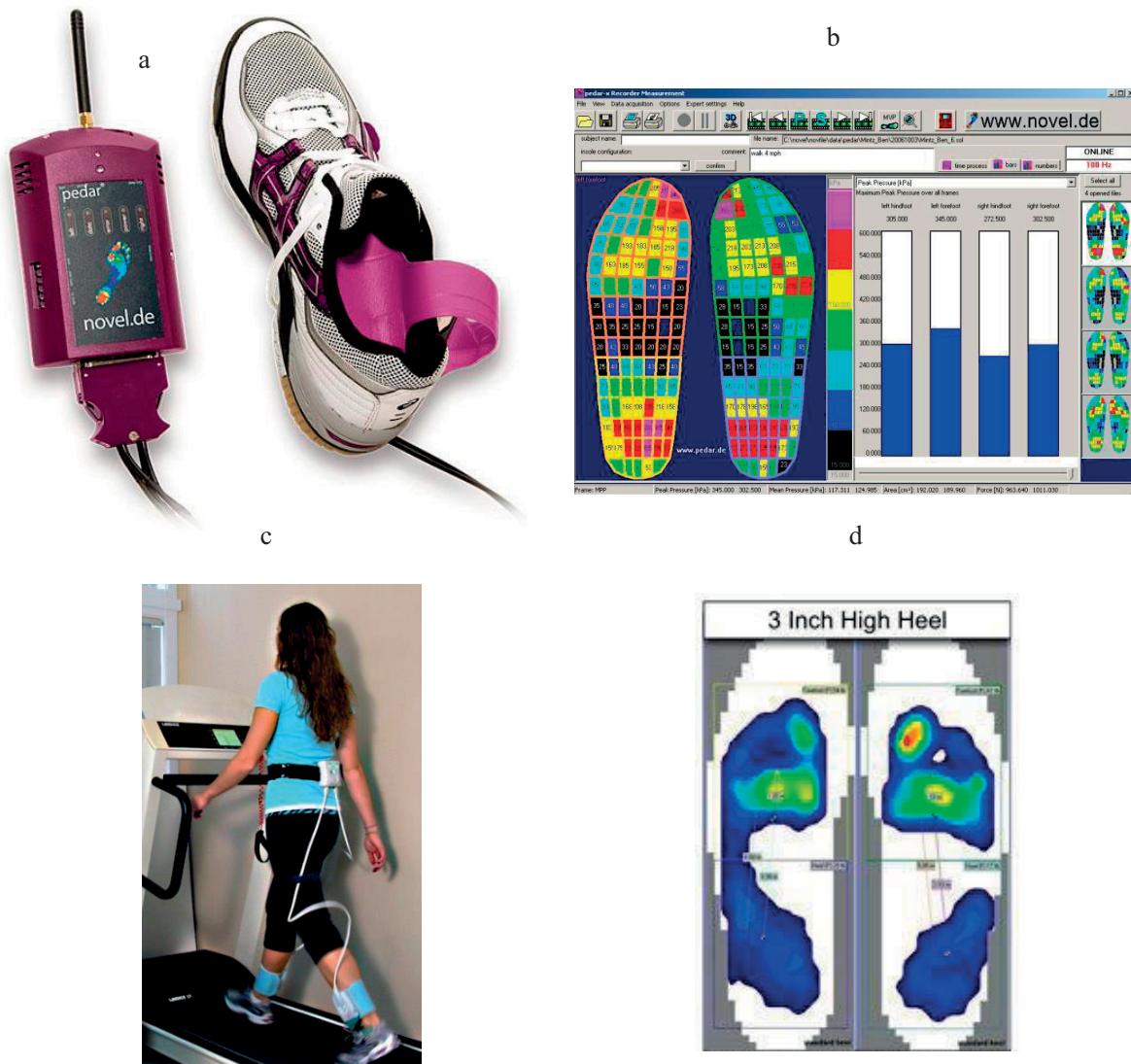


Figure 2-4 – Commercial insole systems for load measurement: a) Pedar system with insole and data acquisition system (usually worn in a belt), b) snapshot of Pedar data acquisition from 99 sensor cells<sup>4</sup>, c) F-scan system used worn by a user on a treadmill with insoles in the shoes and the data logger in a belt, d) snapshot of F-scan data acquisition<sup>5</sup> (© Pedar, Novel, DE and F-scan, Tekscan Inc., U.S.A)

These systems are unable to directly measure the 3D GRF, although some studies have targeted the estimation of the 3D GRF from insole vertical force data using machine learning or inverse dynamics. Savelberg and de Lange [160] estimated the antero-posterior shear force by using neural networks and 8 subdivisions of the Micro-Emed® insole (predecessor of Pedar) and found that the method was

<sup>4</sup> <http://novelusa.com/index.php?fuseaction=systems.pedar> (accessed 26.05.2016)

<sup>5</sup> <https://www.tekscan.com/applications/footwear-research-and-development-f-scan> (accessed 26.05.2016)

generalizable over different gait speeds in healthy subjects. Forner Cordero et al. [161] used the CoP and force measurement from Pedar insoles to estimate the 3D GRF obtaining relatively low estimation errors. The method required a motion capture system to compute inverse dynamics and to align the insole with the force plate reference. Based on the hypothesis that shear force changes the distribution of the pressure in the vicinity of the CoP along the stance phase, Rouhani et al. [162] proposed a neural network and locally linear neuro-fuzzy mapping to estimate 3D GRF from Pedar insoles, Figure 2-5. Principal component analysis led to a minimum of 10 features for the estimation of 3D GRF during walking with errors ranging between 4% (vertical force) and 11.3% (medio-lateral force) of maximum force. The system was further developed to estimate ankle force and moment using inverse dynamics with an IMU placed at the foot [163]. Similarly, Fong et al. [164] used linear regression from individual Pedar load cells to estimate the 3D GRF, with root mean square errors (RMSE) compared to force plate reference of 5, 12 and 28% for peak vertical, antero-posterior and medio-lateral force, respectively. Besides the aforementioned commercial systems, Jacobs and Ferris [165] designed an insole with 8 gauge pressure sensors located under the heel and forefoot. They estimated the 3D GRF and CoP during gait and calf raises using neural networks with peak RMSE below 10%. A foot-worn system with load cells was evaluated to measure vertical force and CoP during standing and walking, with RMSE below 10% for peak vertical force calculation but up to 19.2% for CoP during walking [166].



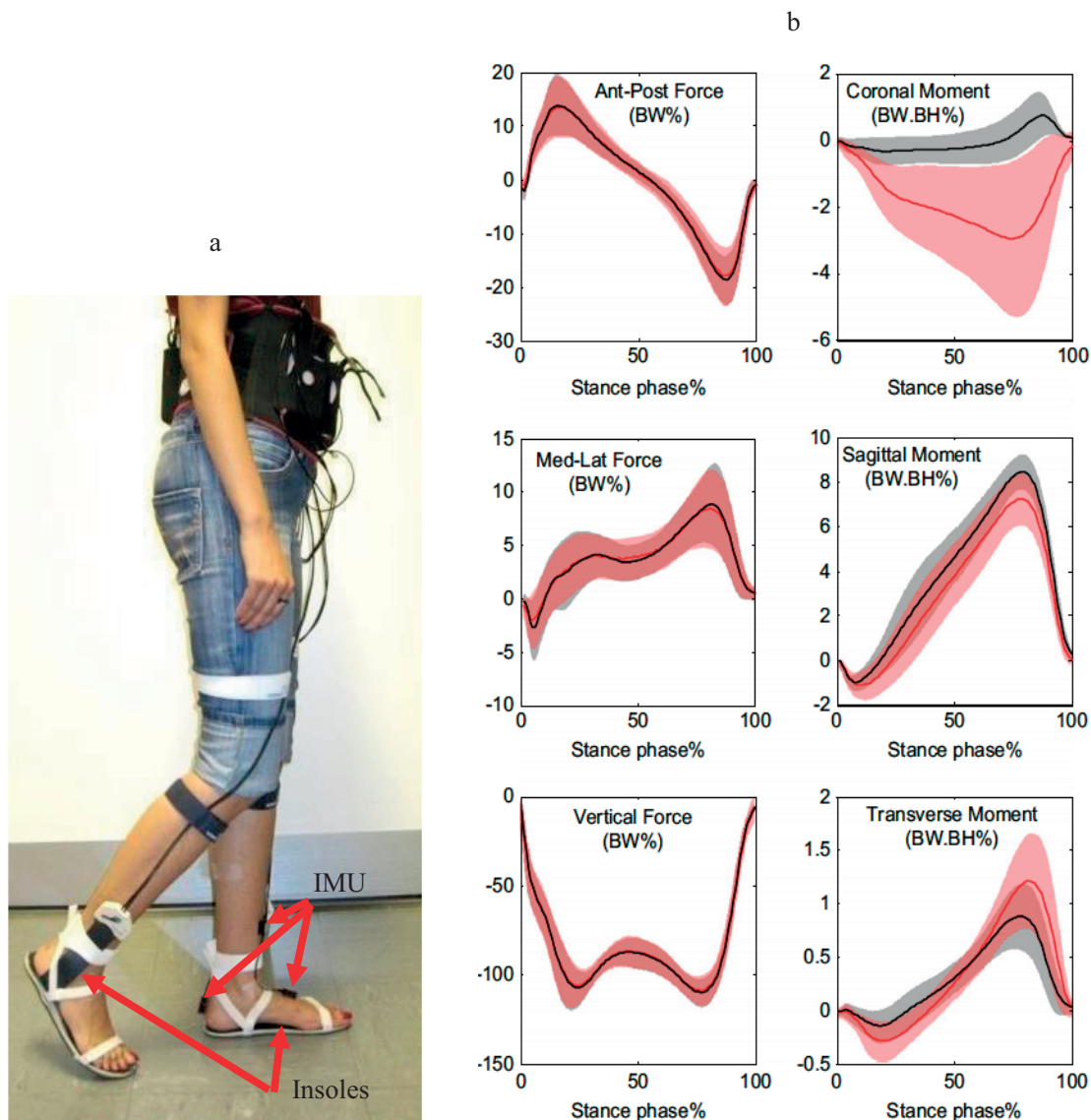


Figure 2-5 (a) Foot pressure insole (Pedar, Novel, DE) and IMU placed on the foot were used to measure GRF and ankle forces and moment using pressure insole and inertial sensors (red) compared to stationary system (black). Mean (solid curve) and mean $\pm$ SD (shaded area) are presented for the healthy group. Adapted from [163], [167]

Despite the high accuracy of these systems, their use is limited to short periods of measurement because of high power consumption and the need for a computing unit usually worn by the subject in a belt to acquire data from a large number of sensors (Pedar encapsulates 99 capacitive sensors, the F-scan has a sensor density of  $\sim 4$  resistive sensor cells per  $\text{cm}^2$ ; the total number varies depending on shoe size). Researchers have therefore devised prototypes with less sensors while attempting to maintain similar accuracy in load and CoP measurements. FSR sensors have been most common in the design of

pressure-sensing insoles, where arrays with a selected number of sensors were used to evaluate the vertical load. Hellstrom et al. [168] showed that weight is overestimated by 3 FSR sensors when a person carries different loads. Sazonova et al. [169] obtained varying results for weight estimation with 5 FSR sensors with an average RMS error of 10kg. Chen et al. [170] estimated plantar pressure using support vector regression from 8 FSR sensors with mean square errors of less than 1kPa compared to force plate reference. Howell et al. [171] observed similar shapes in vertical plantar force obtained from 32 FSR sensors compared to force plate measurements but did not report estimation errors. The vitaliSHOE [172], consisting of 4 FSR sensors, 3D accelerometer, and 3D gyroscope, proved to correlate well with pressure and foot angle measured by instrumented treadmill and motion capture, as shown in Figure 2-6.

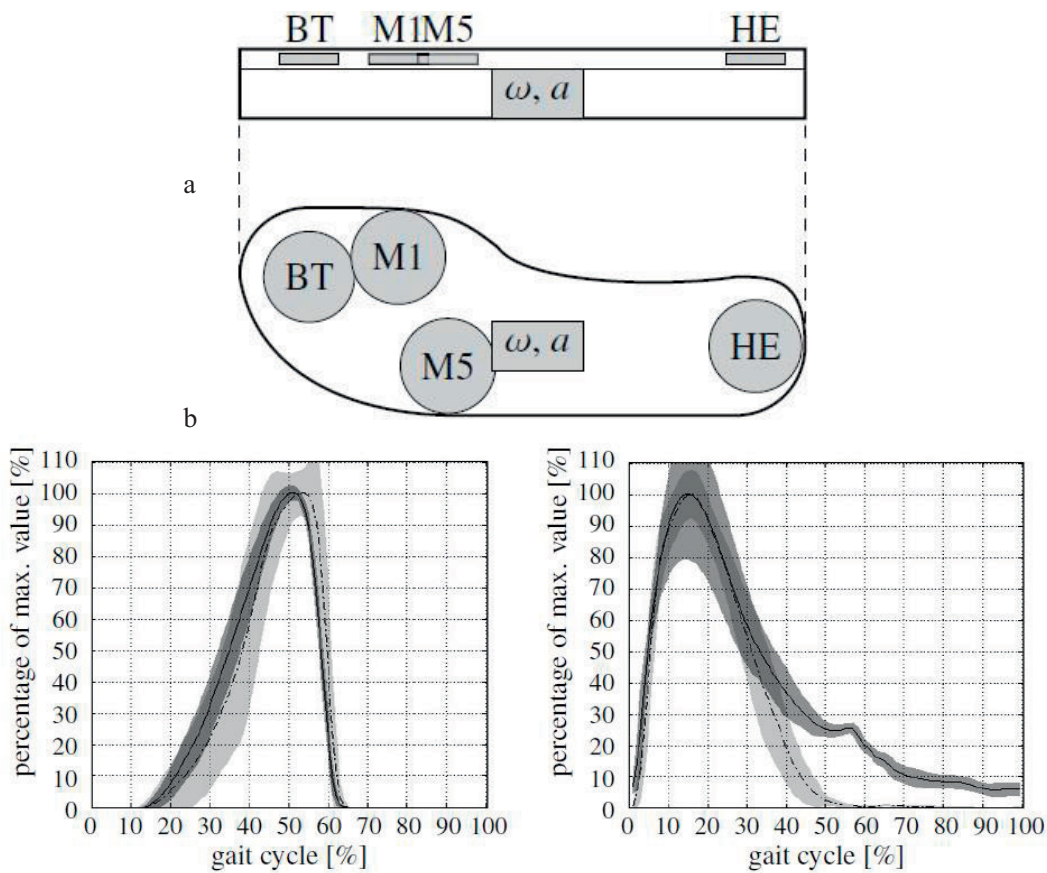


Figure 2-6 - Instrumented insole proposed by Jagos et al. [173] showing a) the different FSR sensor locations ( $\omega$  and  $a$  represent gyroscope and accelerometer, respectively) and b) percentage of total force measured by the heel (left) and the big toe (right) sensors during gait. Solid lines represent mean force plate reference, dashed lines mean insole measurements, with the standard deviation represented in the shading (dark for force plate, light for insole)



Other technologies used to build insoles for load and/or CoP measurement include pressure sensing resistive fabric [174], piezoresistors [175], piezoelectric transducers [176] or films [177], capacitive sensors [178]–[180], air pressure sensors [181], and electro mechanical films (EMFI) [182]. Abdul Razak et al. [183] reviewed systems to measure foot plantar pressure with publications until 2012. Several notable new systems have since been proposed in the literature [184]–[193]. In these new systems there is a shift towards providing real time force data with wireless insoles for different clinical applications, as well as miniaturization in terms of the number of sensors used while providing utmost comfort to the user. These systems have not yet been tested in clinical application but show promise in monitoring plantar force during daily life.

Summing up, force and pressure measurement under the foot was shown to be feasible for load monitoring under the feet compared to stationary force plates. Measuring 3D forces requires thick plates and such systems are thus unsuitable for applications in daily life. Systems with dense sensor meshes are also unusable for long term force monitoring because of power and comfort constraints. Therefore, instrumented insoles with a lower number of sensors appear to be the best choice for daily life applications. In the framework of this thesis, an insole with 8 resistive force sensors dedicated for highly dynamic measurements is incorporated into the instrumented shoes system. Even though an accurate 3D force measurement was not required, the vertical force estimation related to weight was achieved and its accuracy is demonstrated in Chapter 5. Furthermore, an innovative use of force measuring insoles is presented in Chapter 5: the detection and characterization of postural transitions.

### **3 Applications of foot-worn sensor systems in clinical assessment and rehabilitation**

Foot-worn systems have been extensively used in the assessment of persons with mobility disorders such as amputees, post-stroke patients, Parkinsonian patients, children with cerebral palsy, frail older adults, arthritis patients and other at-risk populations. Additionally, several systems were proposed for rehabilitation and feedback purposes, mainly providing external stimuli to correct impaired gait.

#### **3.1 Older adults**

Normative spatio-temporal gait parameters have been established in a cohort of older adults (aged 65 or older) of more than 1400 subjects using foot-worn IMUs [194]. While many spatio-temporal gait

parameters are correlated with gait speed, it was shown that foot clearance parameters have no significant correlation with gait speed, and that foot clearance parameters account for more than 68% of variability in gait data [195]. More recently foot clearance parameters obtained with foot-worn IMU were shown to be an indicator of fall risk in elderly subjects [196]. These results underlined the importance of foot clearance, which is rarely studied in real-life condition. We estimated foot clearance in daily life in healthy older adults in Chapter 4 as well as in at-risk populations in Chapters 6 and 7. Dual task paradigm, e.g. walking while counting backwards was successfully tested on elderly subjects using foot-worn inertial sensors [197]. Gait under dual-task condition was evaluated with the F-scan system revealing significant differences compared to normal walking in terms of temporal gait parameters such as stride, stance and swing time [198]. The study was extended to identify gait differences between fallers and non-fallers under dual tasking conditions, but concluded that these parameters were insufficient to dissociate the two groups under the testing condition, i.e. walking for only 7.5m [199].

Using foot pressure switches and de-trended fluctuation analysis, Hausdorff et al. [200] computed a fractal scaling exponent for the gait cycle time. Interestingly this fractal scaling was lower in older adults than in young subjects, suggesting that neural control of gait changes with ageing as shown in Figure 2-7. In another study by Paterson et al. [201], a foot-mounted accelerometer was used to compute the fractal scaling exponent for the stride time in older women performing 7 minute over-ground walking in a gait lab. The fractal scaling exponent of stride time revealed significant differences between limbs in multiple fallers that were not observed in non-fallers.

Foot load differences during gait were compared between healthy older adult and young participants using the Pedar system showing that older adults have less relative pressure under the medial side of the foot [202]. Load symmetry indices were analyzed for elderly hip osteoarthritis patients with an instrumented force shoe, with results indicating that symmetry is complementary to gait speed in the assessment of populations with unilateral lower limb problems [203]. Instrumented insoles were also employed to evaluate the effectiveness of a post-hip fracture intervention, showing that improvements can be perceived with CoP and load measurements [204].

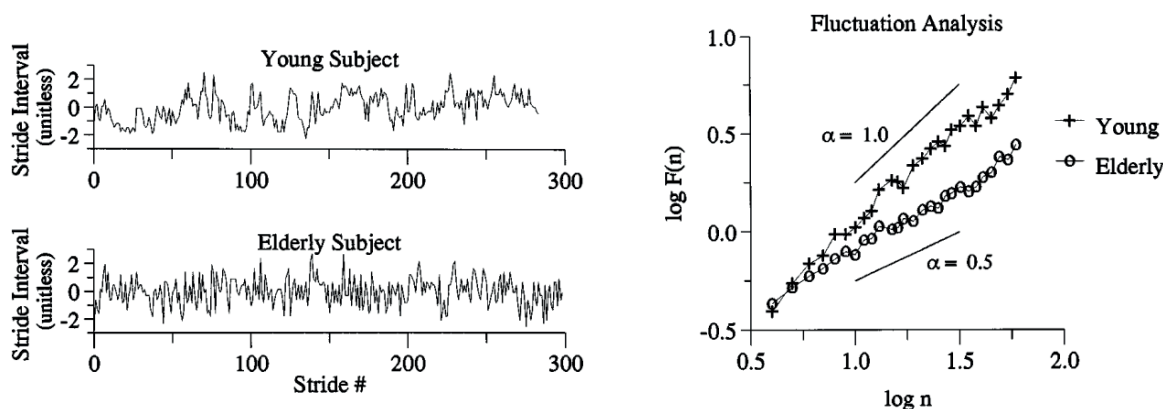


Figure 2-7 – Left: Stride interval (gait cycle time) observed for young and elderly subjects. Right: power law fluctuation analysis of the stride interval time series, showing a lower fractal coefficient ( $\alpha$ ) for elderly subjects (© Hausdorff et al. [200])

### 3.2 Stroke

Gait parameters obtained from the F-Scan system showed that load and temporal parameters as well as the variability of the CoP trajectory improved during robotic-assisted walking in post-stroke patients [205]. Other studies used the Pedar system to obtain load and temporal parameters from stroke patients [206], [207]. A comparison to healthy controls revealed significant differences in gait parameters.

Hegde et al. [208] designed a real-time feedback on stance percent duration of the affected limb in post-stroke patients. The feedback could be delivered via auditory cues or vibrations of a motor inside an insole that also contains two FSR sensors to detect gait phases, Figure 2-8. They noticed improvement in stance percent duration in one participant over 3 sessions of feedback during level gait (trial lengths of ~200 steps).

However, the main application of foot-worn sensors has been related to functional electrical stimulation (FES) to activate nerves during gait swing and correct problems such as foot drop. Ring et al. [209] used footswitches to control the movement a neuroprosthesis at different parts of the gait cycle through temporal gait event detection. Compared to classical ankle-foot orthoses, the system showed a decrease in average stride time and in swing time variability, revealing rehabilitation potential in post-stroke or traumatic brain injury patients. Footswitches were further used to detect stance and swing times to perform FES in stroke patients and measure the tibialis anterior muscle activity during swing, demonstrating improved activity of this muscle after FES [210]. Other foot-worn systems have been designed with FES

application as a target, even though no direct validation studies with stroke patients were reported, using FSR [211] or IMU [212].

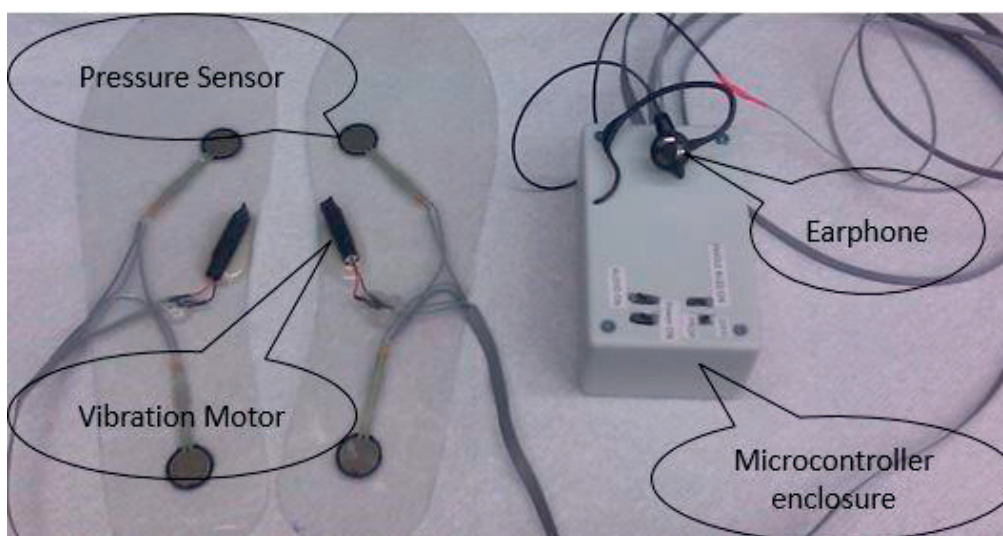


Figure 2-8 - Feedback system for stroke patients showing FSR sensors, vibration motor and earphone (© Hegde et al. [208])

### 3.3 Other populations

#### 3.3.1 Children with cerebral palsy

Foot-worn systems have shown great potential in the assessment of cerebral palsy in children. Femery et al. [213] concluded that plantar pressure data collected during gait from the Parotec system revealed significant differences between children with mild spasticity, severe spasticity, and healthy controls. The CoP trajectories measured from pressure sensing insoles were used to accurately classify gait disorder severity based on the Edinburgh Visual Scale, Figure 2-9 [214]–[216]. Several spatio-temporal gait parameters evaluated in children with cerebral palsy using foot-worn Physilog® IMUs (Gait Up, CH) proved to be significantly different compared to age-matched controls, especially stride length and velocity, gait phases, and foot angle during strike and lift-off [217]. In children with idiopathic toe-walking, a similar gait pattern to that of cerebral palsy patients can be observed where the toe hits the floor before the heel. A method was proposed to detect such gait patterns by using accelerometers mounted on a shoe, reaching a detection accuracy of 98.5% [218].

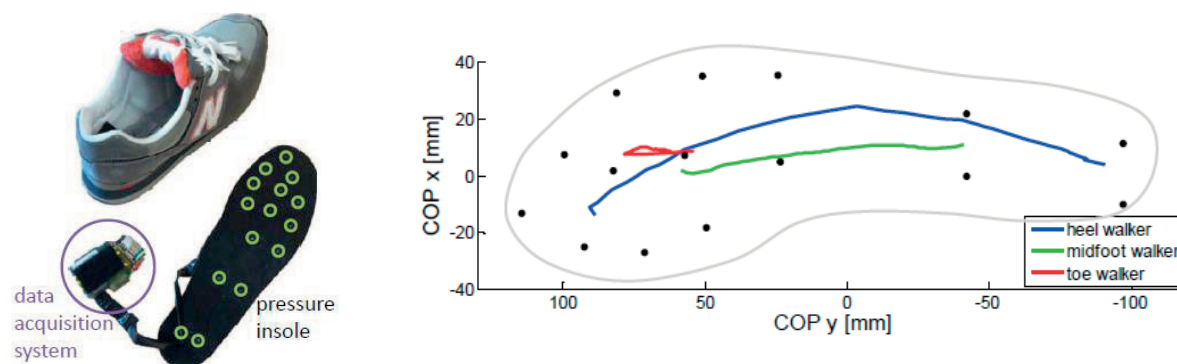


Figure 2-9 - Instrumented insole system for gait analysis in children with cerebral palsy, a) ActiveGait (Simbex LLC, Lebanon, NH) insole with 15 sensors, b) typical CoP for healthy, midfoot and toe walker (© Strohrmann et al. [214])

### 3.3.2 Amputees

Yang et al. [219] defined a stance symmetry ratio computed from a pressure sensing insole to provide auditory feedback to transtibial amputees when the symmetry ratio is lower than a predefined threshold. The method's potential was revealed in tests with three amputees, two of which improved after 6 sessions of training with this feedback system. Crea et al. [220] tested a vibrotactile feedback system that collects load, CoP, and gait phase data from a pressure sensing insole and sends vibrational feedback at the thigh level, Figure 2-10. The system is intended for lower limb amputees and its feasibility was positively evaluated with 10 young, healthy subjects. Gait tests with trans-femoral and trans-tibial amputees revealed that CoP path and variability can distinguish between hard and soft ground walking and also correlate well with clinical mobility test results [221]. Instability of over-ground walking due to change in surface type was shown to be identifiable by CoP measures from the F-scan system in unilateral amputees, showing that more than 80% of variability in clinical balance tests could be explained by parameters extracted from the CoP measurement [221].



Figure 2-10 - Feedback system for amputees, a) system components at the thigh, prosthesis and shoe level, b) instrumented insole, c) insole cover placed laterally on the shoe (adapted from [220], [222])

### 3.3.3 Parkinson's disease

Foot loading during gait of Parkinsonian patients, evaluated with the Pedar® system, revealed significant differences compared to healthy gait [223]. The classification of Parkinsonian gait versus healthy controls was achieved with high accuracy using an IMU on the foot during laboratory gait tasks, with additional classification of different phases of the disease [224]. Substantial work has been conducted on analyzing the structure of temporal gait events in Parkinson's disease patients using footswitches [225]–[227].

Feedback to Parkinson's disease patients through visual, auditory and vibrational cues has been extensively tested. At the shoe level, several systems have been proposed, mainly based on vibrating motors or actuators that use inertial and force sensing data from the shoes to deliver vibrational cues at strategic



instants during gait cycles [228], [229]. The reader is also referred to a recent review on the applications of foot-worn systems in Parkinson's disease rehabilitation by Maculewicz et al. [230]. This review highlighted the capabilities of instrumented shoes in providing sensory feedback to Parkinson's disease patients and emphasized the need for sensor miniaturization and tailoring to the individual, as well as potential outdoor testing of feedback systems, outside the lab or clinic.

### **3.3.4 Orthopedics**

Shoe-based sensors have been applied to the analysis of orthopedic conditions. Load measurement in persons with knee osteoarthritis using the force shoes previously described in [138] was used to measure the knee adduction moment, achieving errors of 5-22% [231]. The suitability of using these shoes was previously studied and showed that the system had negligible difference with a control shoe (i.e. without the sensors) [232]. The Pedar® system was employed in gait analysis of post ankle arthrodesis or total ankle replacement patients, revealing that pressure parameters for the latter are closer to controls than the former [233]. After further symmetry analysis, Chopra et al. concluded that total ankle replacement resulted in better improvements than ankle arthrodesis as a treatment of ankle osteoarthritis [234].

Finally, some other notable examples not pertaining to any of the aforementioned categories are described. The assessment of static balance using foot-worn sensors was proposed by Bamberg et al. [235] from an insole with 16 FSR sensors under each foot. The standard deviation of the load during standing and postural transitions led to observing preliminary differences between healthy participants and subjects with balance problems. Systems for gait and balance rehabilitation using motors or actuators in insoles or shoes have also been proposed in recent years [236], [237].

Several works based on the ACHILE instrumented shoe consisting of 3D accelerometer, 3D gyroscope, 5 FSRs, bending resistor, temperature and humidity sensor, as well as a vibrating motor [238] have been conducted to design an exergame for quantitative balance measurement [239]–[243].

## **4 Discussion**

This review aimed at shedding light on foot-worn sensor systems for activity classification, gait analysis and load measurement. The high number of validation studies, proposed systems, and versatile applications asserts the increasing interest in this sub-family of wearable sensors.

The time spent in different postures can be an important indicator of mobility status. Activity types were classified with accuracies exceeding 90% by using inertial, force and barometric pressure sensors integrated in foot-worn systems. Several techniques were employed to create the classification algorithms such as event detection, machine learning, and pattern matching. The basic activities of daily life i.e. sitting, standing, and walking were classified with high accuracies, again exceeding 90%. From a metabolic perspective, locomotion modes have different energy expenditure requirements and therefore can also inform about a subject's capacities. Different locomotion modes such as level, stair and ramp ambulation were recognized with equally high accuracies to provide a better activity profiling. Accuracies exceeding 90% were reported from most studies on foot-worn activity classification. These values are at least similar to or higher than what can be achieved with single sensor systems placed on other body locations, e.g. trunk [48], [244] and particularly in the detection of sitting or standing postures. These accuracies are quite similar to what is reported by multi-sensor systems placed on more than one body location as well [40], [41]. However, validation protocols were mainly structured and conducted in confined environments, not reflecting real-life activity and behavior. Nevertheless, the potential in quantifying physical activity in healthy and diseased populations is evident, and future studies could reveal the clinical benefits of using foot-worn systems in long-term activity monitoring. Furthermore, the possibility of real-time activity monitoring and data transmission to smartphones can enhance tailored interventions through feedback on activity levels.

In terms of gait analysis, foot-worn sensors have revealed the possibility of accurately and reliably estimating spatio-temporal gait parameters mainly using IMUs. The main advantage of foot-worn systems over other sensor locations is the direct measurement of foot orientation, allowing stride by stride estimation of velocity, stride length, and foot clearance for each foot. The clinical relevance of these parameters has already been established using other stationary or wearable systems, but their measurement in routine clinical analysis or in daily life was shown to be simpler using foot-worn systems. Gait assessment of at-risk populations highlighted several differences between normal and pathological gait. These differences can be used by clinicians to improve interventions and rehabilitation. As was the case with activity monitoring, gait measured with foot-worn sensors was mainly performed in laboratory conditions. Again, the potential of foot-worn systems can be translated to the home environment for gait analysis in daily life, especially since performances during in-lab tests do not necessarily reflect daily life gait profile.

Load and CoP measurement with foot-worn systems was shown to be accurate with several types of force measuring sensors. Some of the most accurate systems incorporate relatively thick sensors (e.g. load cells) or a highly dense sensor mesh (e.g. Pedar or F-Scan). These systems are more suitable for in-lab assessment of load bearing activities. The predominant sensor used in thin insole inserts has been the force



sensing resistor. Other types of force sensors have been proposed, and research is ongoing to improve the integration of newly designed thin force sensors in foot-worn systems. Today, several foot-worn sensor systems intended for general public are commercially available. The Mettis Trainer®<sup>6</sup> incorporates 3 bending sensors in each insole to measure the performance of golfers. SmartBalance® (Smart2Move, CH)<sup>7</sup> is a wireless insole that also mainly targets golfers. Runscribe<sup>8</sup> [245] consists of a foot-worn IMU designated for runners, evaluating several parameters including step counts, impact load, pronation and foot strike type. Digitsole<sup>9</sup> [246] proposes a smart shoe to track daily activity and calories as well as in-shoe heating, and a separate smart insole that tracks movement and posture. All the aforementioned commercial systems send insole or IMU data wirelessly to a smartphone to give feedback to the user.

Finally, to exemplify the impact of foot-worn system development, a recent European project, WIISEL<sup>10</sup>, was dedicated to the design of an insole with multiple sensors to monitor gait and activity for the purpose of fall risk prediction [190], [247], [248]. The instrumented shoes developed in this thesis were also part of a European project, FARSEEING<sup>11</sup>, aimed at reducing falls in older adults.

## **5 Conclusion**

Foot-worn sensors are suitable for a detailed profiling of human movement. It was evident from this review that pressure sensing insoles were highly effective in activity classification and load/CoP measurement, whereas IMUs performed exceptionally well in gait analysis. The conclusion is that a system combining both pressure and inertial sensing can provide extremely rich information about foot movement and therefore foot-worn sensors are likely to play an important role in human movement analysis in the coming years. Furthermore, the translational aspect of most systems described in this review has not yet reached its full development, aside from the well-known commercially available systems such as the Pedar® and F-Scan®. Relatively few systems were extended for clinical applications, especially in terms of daily-life physical activity monitoring. However, technical validation results were overall satisfactory and pave the way for broader applications in clinical analysis and rehabilitation. In this thesis, we aim to address both a technical validation of the proposed instrumented shoes system as well as clinical application with at-risk populations: post-hip fracture in older adults and stroke patients, as specified in Chapter 1.

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<sup>6</sup> <http://www.mettistrainer.com/> (accessed 26.05.2016)

<sup>7</sup> <https://smart2move.com/> (accessed 26.05.2016)

<sup>8</sup> <http://www.runscribe.com/> (accessed 26.05.2016)

<sup>9</sup> <http://www.digitsole.com/index.php> (accessed 26.05.2016)

<sup>10</sup> <http://www.wiisel.eu/> (accessed 26.05.2016)

<sup>11</sup> <http://farseeingresearch.eu/> (accessed 26.05.2016)

# Chapter 3

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## *Instrumented shoes for activity classification in the elderly\**

### **Abstract**

Quantifying daily physical activity in older adults can provide relevant monitoring and diagnostic information about risk of fall and frailty. In this study, we introduce instrumented shoes capable of recording movement and foot loading data unobtrusively throughout the day. Recorded data were used to devise an activity classification algorithm. Ten elderly persons wore the instrumented shoe system consisting of insoles inside the shoes and inertial measurement units on the shoes, and performed a series of activities of daily life as part of a semi-structured protocol. We hypothesized that foot loading, orientation, and elevation can be used to classify postural transitions, locomotion, and walking type. Additional sensors worn at the right thigh and the trunk were used as reference, along with an event marker. An activity classification algorithm was built based on a decision tree that incorporates rules inspired from movement biomechanics. The algorithm revealed excellent performance with respect to the reference system with an overall accuracy of 97% across all activities. The algorithm was also capable of recognizing all postural transitions and locomotion periods with elevation changes. Furthermore, the algorithm proved to be robust against small changes of tuning parameters. This instrumented shoe system is suitable for daily activity monitoring in elderly persons and can additionally provide gait parameters, which, combined with activity parameters, can supply useful clinical information regarding the mobility of elderly persons.

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## 1 **Introduction**

Ageing is frequently accompanied by loss of mobility, frailty, fear of falling and a greater risk of injury or disease caused by declining physiologic system dynamics [68]. It is crucial to remain active or become active again while aging, since suitable levels of physical activity (PA) can improve one's health and quality of life [13]. An increase in PA is linked to lower morbidity and mortality [79] by reducing the risk of cardiovascular diseases, stroke, dementia, diabetes and osteoporosis [249]–[251]. Consequently, a major focus in current geriatrics research is PA quantification in older adults and timely intervention delivery to preserve or improve mobility.

PA monitoring in older adults should provide information on activity behavior to be clinically useful. Therefore, the separation of sedentary periods, such as sitting or lying, from activity periods (standing and walking) is important. The evaluation can be improved if one can assess avoidance behavior e.g. using the elevator instead of climbing stairs. Finally, a detailed analysis of walking in terms of number of steps and gait velocity is essential in providing unique diagnostic and prognostic information [83].

Monitoring PA in daily life has seen major advances in recent years due to progresses in wearable technology, sensors miniaturization, and a boom of motion tracker devices and smartphone applications available on the market [28]. The focus of commercial devices is mainly on step counting or energy expenditure overview, rather than specific classification and quantification of activity type [252]. However, research studies have increasingly reported activity classification results and their importance in elderly participants [47], [48], [253], [254].

Multi-sensor configurations appear to provide better results for activity classification but are more hindering during long term monitoring. This raises an important issue regarding sensor location: inertial sensors at the foot or tibia level could miss detecting sit-to-stand transitions, whereas sensors at the trunk level could misclassify stair locomotion [38]. Low accuracies were consistently reported for postural transition classification using single sensor locations in the aforementioned studies. While upper limbs provide useful information about body posture, a more accurate estimation of gait parameters can be obtained with lower limb sensors. The shank and the foot were shown to be excellent sensor positions for gait analysis in elderly subjects [95], [136], [255]. Considering this advantage, shoe-based sensors have been previously used to classify PA [33], [256]–[258]. Several shoe-based systems for gait analysis and rehabilitation have been proposed in the literature [135], [259], [260], revealing major interest in this sub family of wearable sensors. This evidence strongly suggests employing shoe-based sensors to classify activities and simultaneously provide specific gait analysis from a single body sensor location. However,

none of the aforementioned concepts is currently outperforming the others in activity classification and daily life monitoring.

The present study aims to reduce the number of sensor locations while accurately recognizing activities in elderly users. Although several sensors were used, all were located only at the shoes. The system includes inertial and barometric pressure sensors, and an insole for foot pressure measurement. It was hypothesized that barometric pressure could inform about body elevation variations during locomotion and rest (e.g. level/incline, stairs locomotion or elevators). Moreover we assumed that foot loading is related to posture (e.g. sitting, standing), and foot orientation may indicate the type of walking (e.g. level, ramp or stairs).

## **2 Methods**

### **2.1 Instrumented shoe system and reference system**

The instrumented shoe system comprises the Physilog® (GaitUp, CH) including an inertial sensor (3 D accelerometer, 3 D gyroscope, 3 D magnetometer), barometric sensor and the force sensing insole (IEE, LU), Figure 3-1 (a). Physilog® is thin (9.2mm thickness) and light (<20grams) and includes a data logger. The insole has 8 sensors under the heel, arch, metatarsals, hallux and toes, sandwiched between two layers of neoprene, Figure 3-1 (b). The insole is powered by the Physilog® battery. The force data is amplified and digitized by custom-made converting electronics placed in a separate box, Figure 3-1 (a). An insole was placed inside each shoe, and a Physilog® module was strapped to the upper part of the shoe. The electronics box was strapped to the ankle.

For validation purposes, two additional Physilog modules were fixed to the right thigh and the trunk [41]. The reference classification algorithm proved concurrent validity with observation with both sensitivity and specificity for detection and classification of transitions and basic activity (siting, standing, walking) greater than 98%.



Figure 3-1 - (a) Instrumented shoes system. The Inertial Measurement Unit (IMU), force sensing insole and converting electronics (Gray box with blue handles). (b) Force sensing insole with 8 sensors.

## 2.2 Data collection protocol

Ten elderly subjects (8 men, 2 women, age 65-75 years, weight 62-114 Kg, height 162-184 cm) were recruited (convenient sample of community-dwelling older persons). Participants gave written consent to participate. The study was approved by the university's ethical committee: "Quantification of postural transitions using multimodal sensory input" under reference "EK 2012-N-32".

Each participant wore the instrumented shoes and the reference system. Data collection was carried out on campus at the university. A predefined track was followed by each participant, to mimic physical activities of daily life (~1 hour of measurement per participant) and included level walking, sit-to-stand and stand-to-sit transfers, sitting and standing bouts, uphill/downhill and upstairs/downstairs walking, and elevator use.

Activities were carried out in a semi-structured protocol. Participants were free to perform all movements at their comfortable speed. An observer followed the participants and marked each period of stair climbing, elevator use, and uphill/downhill walking since these are not extracted from the reference algorithm, unlike sitting, standing, and level walking.

### 2.3 Activity classifier

*Calibration:* Data from all sensors were sampled at 200 Hz. Inertial sensors were calibrated in static position to remove offset and adjust gain [261], and to the foot-frame during a walking period of 10 steps by finding the gravitational axis when the foot was static and the medio-lateral axis during swing events (by assuming that the movement is mainly in the sagittal plane) [136].

The insole was calibrated to each participant's body weight (BW) during a 5 second period of static standing, by summing all sensors from both insoles and scaling the sum to the participant's weight. This is referred to as the total force (*TF*).

Pressure was converted to elevation by the barometric formula:

$$elevation = 44330 \times \left( 1 - \left( \frac{P}{P_0} \right)^{1/5.255} \right) \quad (1)$$

Where *P* is the pressure measured by the barometer and *P*<sub>0</sub> is the static pressure at sea level. The elevation was low-pass filtered (Butterworth order 10 filter, 0.1 Hz cutoff) to remove high-frequency noise caused by gait and weather fluctuations that could mask an elevation change.

*Biomechanics-inspired expert-based decision tree:* The activity classification algorithm relies on expert-based rules inspired from movement biomechanics, Figure 3-2. At each node, the data from one sensor are used to detect the activity at the node's output. First, the pitch angular velocity is used to distinguish locomotion from non-locomotion by performing step detection. Second, the estimated *TF* from the insoles is subjected to a threshold that separates sitting from standing. Third, the elevation obtained from the barometric pressure sensor allows the identification of activities with elevation change. Finally, the accelerometers are used to calculate the foot angle and distinguish between stairs and ramps climbing.

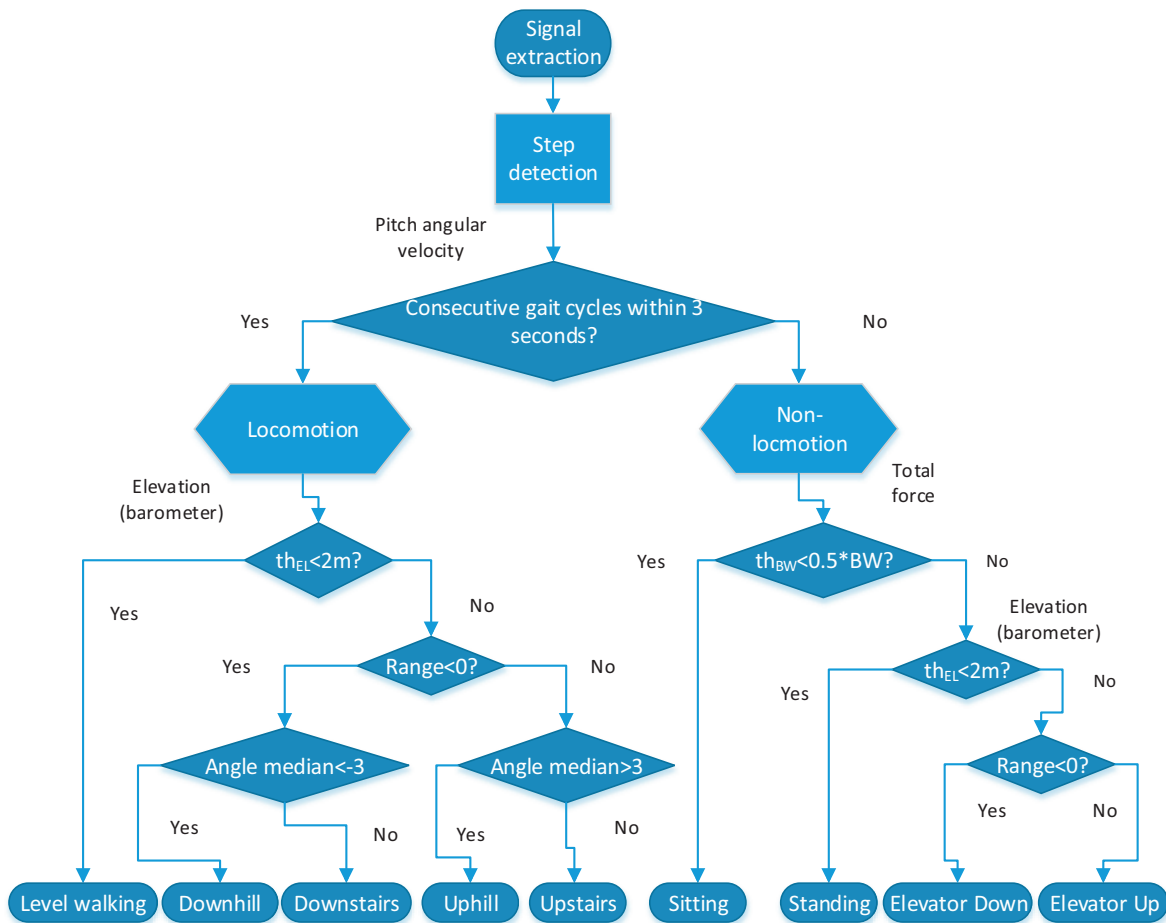


Figure 3-2 - Algorithm flowchart for activity classification using instrumented shoe signals

*Locomotion/non-locomotion:* The detection of locomotion relied on step detection based on toe off ( $TO$ ) instant, the common event to all locomotion types. The  $TO$  was detected as a negative peak in the clockwise pitch angular velocity obtained from the gyroscope signal using wavelet approximation [95]. A gait cycle was defined as the time between two consecutive  $TO$  instants of the same foot. Gait cycles shorter than 0.75 seconds were removed and consecutive gait cycles less than 3 seconds apart were aggregated to form locomotion periods. Hence, the detected cadence was 40-160 steps/min which sufficiently covers the cadence range observed in elderly subjects [255]. The remaining data were labeled as non-locomotion.

*Sitting/standing:* Since the sit-to-stand corresponds to a transfer of  $BW$  to the legs until reaching an upright position, a threshold ( $th_{BW}$ ) corresponding to 50%  $BW$  was set on  $TF$  to distinguish between sitting and standing. The activity was classified as sitting when  $TF$  was lower than  $th_{BW}$ , otherwise as standing.

This threshold was inspired from a transition model where the 50% BW shift occurs around the middle of the initial incline phase before being fully upright [262]. To confirm the suitability of this threshold, a sensitivity analysis was performed by varying  $th_{BW}$  between 10-90% BW. Transitions occurred when the activity changed from sitting to standing (Sit-to-Stand) and standing to sitting (Stand-to-Sit).

*Elevator up/down:* When the *elevation* range during a standing period exceeded a threshold ( $th_{EL}$ ) of 2m, an elevator up (>2m) or down (<-2m) period was identified.

*Non-level locomotion:* During locomotion periods, the *elevation* signal was used to separate stairs and incline walking from level walking. Up/down periods were detected when the positive/negative elevation range exceeded  $th_{FL}$ . Steps during up/down periods were segmented and the ground slope  $\alpha$  was calculated from the frontal and vertical accelerations  $a_{f,foot}$  and  $a_{v,foot}$  during foot-flat, by assuming that the foot inclination during foot-flat corresponds to the ground slope and that the accelerometer measures gravitational acceleration only in this condition:

$$\alpha = \arctan\left(\text{mean}\left(\frac{a_{f,foot}}{a_{v,foot}}\right)\right) \quad (2)$$

If the absolute median value of  $\alpha$  for all steps during an up/down period was higher than 2.9 degrees (5%), an uphill/downhill walking period was identified respectively. Otherwise, up/down periods were labeled upstairs/downstairs, respectively. The 5% slope was selected because accelerometer noise is a limiting factor in accurately calculating lower angles. From an energy expenditure point of view, walking at lower slopes has similar costs compared to level walking [263]. The selection of  $th_{EL}$  was assessed by varying this threshold between 1-3m and evaluating classifier performance.

A sigmoidal nonlinear fitting was applied to the elevation data of each up/down period to detect its beginning/ending:

$$\text{sigmoid} = \text{level}_{min} + \left(\frac{\text{level}_{max} - \text{level}_{min}}{1 + 10^{(\text{midcross} - \text{elevation}) \times \text{slewrates}}}\right) \quad (3)$$

The minimum ( $\text{level}_{min}$ ) and maximum levels ( $\text{level}_{max}$ ) were obtained by computing a histogram with 100 equal-sized bins applied to the elevation data and finding the two bins with the most data points. The point where the height reaches 50% of the levels difference (*midcross*), and the rising/falling slope between the two levels (*slewrates*) were obtained using [264]. The beginning/ending of the up/down periods were calculated as the 5% and 95% lower and upper level crossings of the total *sigmoid*



range. These percentages were selected for a consistent detection of the beginning/ending across all up/down periods.

Figure 3-3 shows typical signals summarizing the decision tree classifier: 1) step detection based on  $TO$  from the pitch gyroscope signal; 2) thresholding on  $TF$  as a percentage of  $BW$  to distinguish sitting from standing; 3) sigmoid approximation of elevation to identify the initiation and end of up/down periods; 4) foot angle calculation from accelerometers to recognize stairs from inclines climbing.

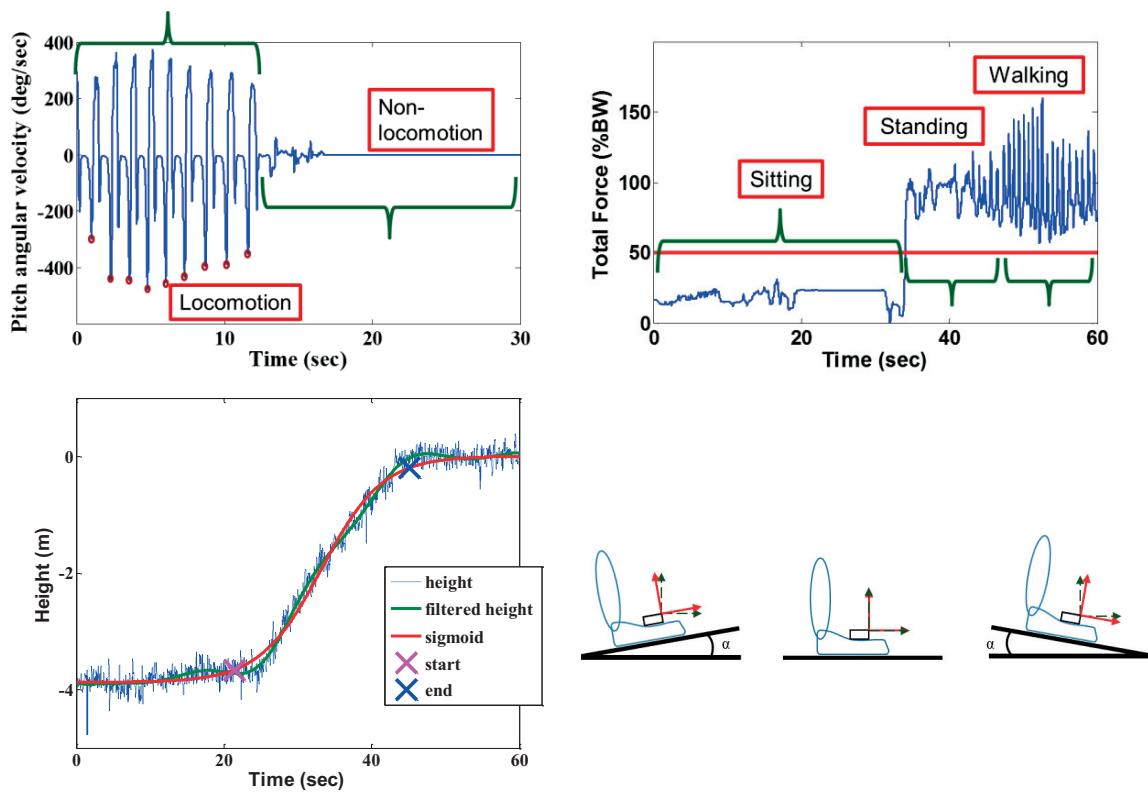


Figure 3-3 - Top left: detection of locomotion using the pitch angular velocity. The circles represent the detected  $TO$  instants. Top right: distinction between sitting and standing using the total force signal. The horizontal line represents the 50% body weight ( $BW$ ) threshold. Bottom left: the sigmoid used to estimate the start and end of an up/down period after filtering the barometer signal. The start and end points correspond to the 5% and 95% levels of the sigmoid, respectively. Bottom right: the foot angle corresponding to the ground slope calculated by the accelerometers. The dashed arrows represent the global frame and the straight arrows the foot frame, both in the sagittal plane.

## 2.4 Validation

The classification algorithm was applied and tested on the entire dataset for the initial rules and for the sensitivity analysis, i.e. when the initial threshold values were varied to identify their effect on the classification performance. Therefore, the entire dataset was considered for testing and no training was applied since the classification rules were predefined. The activity output from the algorithm and from the reference were segmented into 5 second windows with 2.5 second overlaps. Each activity type was assigned a numerical value. For both outputs, the median value was calculated and used for validation. The performance of the classifier was evaluated against the reference by calculating sensitivity, specificity, precision and accuracy. For postural transitions, the reference algorithms outputs the occurrence time of each transition; this was used separately to validate transitions obtained from the instrumented shoes. The performance measures are computed by calculating the four main components, the True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN); by counting the events from the confusion matrix (Table 3-1).

$$Sensitivity = \frac{\#TP}{\#TP + \#FN}$$

$$Specificity = \frac{\#TN}{\#TN + \#FP}$$

$$Precision = \frac{\#TP}{\#TP + \#FP}$$

$$Accuracy = \frac{\#TP + \#TN}{\#positives + \#negatives} \text{ (single activity)}$$

$$Global Accuracy = \frac{\#TP + \#TN}{total\ sample\ number} \text{ (all activities)}$$

## 3 Results

For each 5 second epoch, the classifier output was compared to the reference labels in a confusion matrix, Table 3-1. Table 3-2 summarizes the performance of the classifier. Sensitivities and precisions for sitting, standing and walking exceeded 95%. The lowest precision was 89% for stair climbing and the lowest sensitivity for elevator up (79%) and down (78%). However, misclassifications of these activities occurred in the parent class, i.e. stair and ramp were misclassified as walking, and elevator as standing. Furthermore, a total of N=20 stair and N=20 ramp periods were correctly classified, and only one out of 22 elevator up/down periods was misclassified into standing. The overall accuracy of the algorithm was 97.41%.

Table 3-1-Confusion matrix of activities. Each unit in this table corresponds to a 5-second activity window. Sit: sitting; Stand: standing; LW: level walking; USt: upstairs; DSt: downstairs; UH: uphill; DH: downhill; EIU: elevator up; EID: elevator down

<b>Reference →</b>	<b>Sit</b>	<b>Stand</b>	<b>LW</b>	<b>USt</b>	<b>DSt</b>	<b>UH</b>	<b>DH</b>	<b>EIU</b>	<b>EID</b>
<b>Predicted ↓</b>									
<b>Sit</b>	6452	53	1	0	0	0	0	0	0
<b>Stand</b>	0	2999	123	0	0	1	0	8	7
<b>LW</b>	23	81	2586	1	2	5	2	0	1
<b>USt</b>	0	1	7	67	0	0	0	0	0
<b>DSt</b>	0	1	3	0	78	0	1	0	0
<b>UH</b>	0	0	9	0	0	152	0	0	0
<b>DH</b>	0	0	0	0	0	0	159	0	0
<b>EIU</b>	0	1	0	0	0	0	0	30	0
<b>EID</b>	0	3	0	0	0	0	0	0	28

A total of 67 Sit-to-Stand and 69 Stand-to-Sit transitions were detected by both the reference system and the classifier. No false positives occurred in classification of postural transitions, hence sensitivity and precision of classifying postural transitions were both 1.

Table 3-2-Sensitivity, specificity, precision and accuracy of the classifier

<b>Activity</b>	<b>Sensitivity</b>	<b>Specificity</b>	<b>Accuracy</b>	<b>Precision</b>
<b>Sitting</b>	0.9964	0.9916	0.9940	0.9917
<b>Standing</b>	0.9554	0.9857	0.9783	0.9558
<b>Level Walking</b>	0.9476	0.9887	0.9800	0.9575
<b>Upstairs</b>	0.9853	0.9994	0.9993	0.8934
<b>Downstairs</b>	0.9750	0.9996	0.9995	0.9398
<b>Uphill</b>	0.9620	0.9993	0.9988	0.9441
<b>Downhill</b>	0.9814	1	0.9998	1
<b>Elevator Up</b>	0.7895	0.9999	0.9993	0.9677
<b>Elevator Down</b>	0.7778	0.9998	0.9991	0.9032

### 3.1 **Sensitivity to threshold analysis**

The best sensitivity and specificity for sitting and standing after varying  $th_{BW}$  were obtained for 50%BW. The performance of the classifier changed by less than 2% for these activities when  $th_{BW}$  40-70%BW. The best performances in terms of activities with elevation change were obtained for  $th_{EL}$  of 2 or 2.5m, with the exception of the elevator down sensitivity (16% improvement at 2.5m). The performance change was negligible for  $th_{EL}$  1.5m except for the sensitivity of upstairs (25% reduction) and elevator down (29% reduction) activities.

## 4 **Discussion**

### 4.1 **Classifier performance**

In this study, we confirmed our hypotheses regarding PA classification, i.e. possibility to recognize: body elevation, postural transitions, and locomotion type, respectively from barometric pressure, foot pressure and inertial sensors embedded in the shoe-based system. Results show an outstanding level of accuracy, 97% overall, and are extremely convincing from several perspectives.

Firstly, the detection of locomotion was achieved with a high sensitivity (>94%). The detection of *TO* events in a cadence range of 40-160 steps/min proved adequate for walking classification. Notably, very few ( $23/6452=0.4\%$ ) misclassifications between sitting and walking were observed.

Secondly, the distinction of sitting and standing postures using estimated *TF* was highly accurate (sensitivities of 99% for sitting and 96% for standing). All postural transitions were correctly classified without false positives. However, it should be noted that no confounding activities were performed; this could have boosted the postural transition classification performances.

Thirdly, activities with elevation changes were classified with high sensitivities (>96%) except for elevator use. However, incorrectly classified periods of elevator use were classified into the parent class, standing. Moreover, results showed a perfect identification of stairs and incline walking periods. The low pass filtering of elevation data eliminated several potential false positives that could have been caused by high frequency noise and drift.

Finally, results were extremely impressive in terms of precision. Specificities and accuracies for all activities exceeded 97%, reflecting the excellent classification performance. Nevertheless, care must be taken in interpreting these results for up/down periods due to class imbalance.

The sensitivity analysis varying  $th_{BW}$  between 10%-90% BW to distinguish sitting from standing confirmed the pertinence of this threshold. By changing  $th_{BW}$  between 40-70%, the performance changed by less than 2%, meaning the threshold is robust to changes up to 20% of its value. A similar analysis for the  $th_{EL}$  revealed best performances at 2-2.5m, with only two activities having lower sensitivities at 1.5m. This confirmed the selection of  $th_{EL}$  and its robustness to changes up to 25%.

This study is among the first to achieve such performance levels in classification. The algorithm outperformed other classifiers based on a single body location in terms of activity type [47], transitions [48] and overall accuracy [253]. An overall accuracy of 99% was reported in [33] using instrumented shoes after rejecting more than 30% of the available data. However, the performance before rejection is comparable to the results of this study, with better sensitivity and precision on stair classification of our current algorithm.

As for systems with several body locations, the performances reported in [40] revealed an overall accuracy of 99% using 5 sensors. However, this system has been mainly used for activity reference because of its setup complexity. The four-sensor system presented in [254] reported an overall accuracy of 96.4% comparable to our results. This asserts the validity of using a single sensor location for accurate activity classification

## 4.2 System advantages

There are several novelties in the proposed algorithm. The use of an adequate sensor at each node of the activity classifier shows the direct relationship between the nature of data (pressure, angular velocity, inclination, elevation) and the activity output (load change during stand/sit, leg swing during locomotion, incline walking, stairs climbing).

The algorithm rules are inspired from movement biomechanics and not resulting from a training/testing procedure. This could be advantageous when applying the algorithm to other populations since retraining would not be an issue. The classification rules were inspired from the literature, but these rules were not applied for classification beforehand. For example, the sit-to-stand model in [262] was used to characterize transitions in lab conditions and not to classify transitions with respect to other activities. Similarly, the *TO* detection from [17] was used to identify events for gait analysis during walking only rather than classifying gait in daily life.

### **4.3 Clinical perspectives**

Combining activity monitoring and gait analysis appears very attractive for future clinical applications. Gait analysis of walking periods can be performed with the instrumented shoes to obtain spatio-temporal gait parameters such as gait speed, cadence, foot clearance, stride length and variability [136]. These parameters provide important diagnostic and prognostic information related to fall risk and frailty in elderly persons. An additional original contribution of the current study is the possibility to investigate avoidance behavior. For instance, taking elevators instead of stairs could reflect different processes, ranging from avoidance due to fear of falling (e.g. descending stairs), to the high energetic cost of stair climbing, or loss of strength. Thus, the number of stairs taken during a day can be a valuable mobility indicator for a clinician, potentially signaling early modifications in endurance and health status. This represents a major advantage compared to other systems that can only characterize stair climbing in terms of number of floors. Furthermore, postural transitions could be characterized in daily life with this system using the foot loading data from the insole. Similarly, monitoring changes in transitions performance could enhance early detection of significant health changes.

## Chapter 4

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### *Physical behavior in older persons during daily life: Insights from instrumented shoes\**

#### **Abstract**

Activity level and gait parameters during daily life are important indicators for clinicians because they could provide critical insights into modifications of mobility and function over time. Wearable activity monitoring has been gaining momentum in daily life health assessment. Consequently, this study seeks to validate an algorithm for the classification of daily life activities and to provide a detailed gait analysis in older adults. A system consisting of an inertial sensor combined with a pressure sensing insole has been developed. Using an algorithm that we previously validated during a semi structured protocol, activities in 10 healthy elderly participants were recorded and compared to a wearable reference system over a 4-hour recording period at home. Detailed gait parameters were calculated from inertial sensors. Dynamics of physical behavior were characterized using barcodes that express the measure of behavioral complexity. Activity classification based on the algorithm led to a 93% accuracy in classifying basic activities of daily life. Gait analysis emphasized the importance of metrics such as foot clearance in daily life assessment. Results also underlined that measures of physical behavior and gait performance are complementary. Participants gave positive feedback regarding the use of the instrumented shoes. The results confirm the validity of the instrumented shoes for physical behavior monitoring in older adults.

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## 1 Introduction

Physical activity and behavior are critical to maintain a healthy long-term lifestyle. Several chronic health conditions and diseases are caused or aggravated by physical inactivity [265], and sedentary behavior (time spent in sitting or lying posture) is linked to higher mortality rates even in relatively active persons [266]. In older adults increased activity levels can sustain independence and delay the onset of decline [252], and lower fall risk [267].

Today's standard in activity assessment is shifting from questionnaires to sensor-based technologies, triggered by the poor recall and subjectivity of the former compared to objective measures obtained from the latter [17]. Body worn motion sensors, mainly based on inertial measurement units (IMU) [27], [91] offer a pervasive (indoor/outdoor) monitoring. The main challenge remains in the validation of activity classification algorithms relying on wearable sensor data, which are mostly based on machine learning rules, i.e. learning from a training set and extending classification to a testing dataset. Validation procedure is generally performed in laboratory conditions, where performed activities are scripted and annotated by an observer following the participant. Alternatively, validation can be performed freely in daily life without restrictions (other than those pertaining to wearing the sensor systems e.g. showering during monitoring) and without the presence of an observer [268]. Semi-structured data collection protocols were recently recommended whereby the participant performs a series of activities in a lifelike scenario (e.g. walking along a track with stop points for sitting) for at least 30 min at their comfortable speed and in the manner they prefer [52]. This latter type of data collection could be extremely useful for algorithm development before validation in real-life conditions.

The difficulty in validating algorithms to classify activity when using wearable sensors lies in acquiring the ground-truth, i.e., the real activity used as reference. To date, three main ground-truth reference systems have been used: video observation [42], [43], [47], [269], direct observation with annotation [44], [48], and self-annotation by the participant [45], [46], [49]. Video and direct observations both enable accurate reporting of activity reference but have several drawbacks. In direct observation, the study investigator has to write down the activities in real time as they occur, and subsequently add a manual labeling step by evaluating the sensor signals. This task is highly time-, effort-, and resource-consuming [35]. Moreover, it interferes obtrusively with the regular activities of monitored subjects in their home environment. Video observation also requires tedious post-analysis to label the activities from the recordings and poses inevitable privacy concerns [92]. Additionally, it is recommended that at least two investigators label activity reference from video or direct observation to minimize observer errors [52]. Self-reporting is certainly less intrusive than the two other approaches. However, it can lack accurate activity labeling due to



subject forgetfulness and has been shown to misestimate activities as well as, in some cases, to result in over-reporting higher intensity instances [270]. Since most activity monitoring targets populations that are somewhat diseased or at-risk, self-reporting can be unreliable, especially when considering cognitively impaired older persons.

The use of an already validated wearable monitoring system is an alternative to the aforementioned validation techniques that has been applied in other works [50], [271]. Validations relying on such systems eliminate the need for an external observer or intrusive video recording, and profoundly reduce post-processing complexity. The ground-truth activity labels can be simply obtained by applying the validated algorithms on collected data. However, participants might be required to wear or carry additional sensors during the validation phase. It is recommended that a wearable reference system has at least 90% sensitivity and specificity for activity classification [52], which has already been demonstrated by some multi-sensor systems [40], [41].

Walking is an important activity in daily life. Nevertheless, its assessment is usually performed in the laboratory, using stationary gait analysis systems. Lab-based gait analysis has shown efficacy in fall risk evaluation [272], and fear-of-falling related gait modifications [84]. Gait parameters such as stride velocity and cadence have been associated with mortality [83], [273], whereas foot clearance might reveal different obstacle avoidance strategies in young and elderly subjects [274]. Building on lab-based assessment, gait monitoring during daily life has provided promising preliminary results in recent years, including fall prediction and risk estimation [267] as well as insights on the association between fall incidence and gait performance [275]. Nevertheless, due to the predominant sensor configuration (i.e., trunk attached sensor) in studies of gait under real-life conditions, only a limited number of gait parameters have been studied so far.

The complexity of physical behavior in daily life has been recently revealed by multi-sensor systems combining the different activity determinants, (i.e., FITT principle for frequency, intensity, time, and type), in a barcode and calculating the entropy of the activity barcode [74]. This combination provides a global index of physical behavior and its dynamics. Applying complexity measures in physical behavior analyses has proved very useful in providing improved assessment in patients suffering from chronic pain. The information from activity barcodes is extremely rich and its application to other population, such as elderly persons, could provide complementary information beyond those obtained from classical analyses of physical behavior and gait performance.

Consequently, there is an evident need for an instrument that can combine capturing reliably, easily, and for a long period both the coarse-grained daily activity of older adults in terms of activity type, and the

fine-grained gait analysis of locomotion periods. We previously developed instrumented shoes and validated an activity classification algorithm using a wearable reference system and applying a semi-structured activity protocol in healthy elderly subjects [276]. The instrumented shoes system has multiple sensor modalities capable of measuring the load under each foot and its movement, all contained in a single location. A global accuracy of 97% was achieved by using an event-driven algorithm inspired from movement biomechanics, revealing the advantage of using the foot (or shoe) as a single sensor location. In fact, compared to systems with sensors placed on multiple body locations, the algorithm revealed similar activity classification performances. However, the system has so far not been validated in real-life conditions. Furthermore, by recognizing daily walking activity, gait parameters could be estimated using an IMU-based algorithm [136]. Activity barcodes could be built using the activity output of the classification algorithm combined with pertinent gait parameters. Therefore the objectives of this study were, first, to demonstrate the concurrent validity of the instrumented shoes system in classifying basic activity types in real-life conditions. Secondly, we aimed to provide a refined analysis of locomotion periods by presenting clinically relevant gait parameters that until now cannot be obtained routinely outside of a laboratory setting. Finally, the potential of calculating a physical behavior complexity metric using the instrumented shoes was evaluated.

## **2 Materials and Methods**

### **2.1 Instrumented shoe and reference systems**

The instrumented shoe system consists of two main components: an inertial measurement unit (IMU) Physilog® (GaitUp, CH) with 3D accelerometer, 3D gyroscope, 3D magnetometer, temperature and barometric sensor and a force sensing insole (IEE, LU) that measures the pressure under 8 regions of the foot: hallux, the remaining toes, the first, third and fifth metatarsals' heads, the lateral longitudinal arch, the lateral and medial heel. The pressure sensing insole is sandwiched between two layers of neoprene for protection, humidity resistance and increased comfort. The complete insole has a thickness of 3 mm. The Physilog® has a thickness inferior to 1 cm and weighs less than 20 g. The system components are shown in Figure 4-1. All sensors are powered by a battery and data are acquired on a memory card, both integrated in the Physilog® module. The insole data is digitized and amplified by custom-made electronics placed in a separate box. One Physilog® was placed on the dorsal aspect of each shoe and one insole was inserted into each shoe. The box containing the electronics was strapped to the ankle.

Participants were additionally equipped with a reference system consisting of one Physilog® sensor on the right thigh and another on the trunk, both fixed with hypoallergenic tape to minimize discomfort and

protect the sensors from humidity. These two sensors were used to provide the reference activity for validation purposes [41]. This reference system has proven high sensitivity and specificity (>90%) in classifying *sitting*, *standing* and *walking*, and has already been used for similar validation purposes in other studies [271], [277].

Instrumented shoes and reference systems were synchronized electronically by radio frequency and all data were sampled at 200 Hz, offering an autonomy of more than 16 hours.



*Figure 4-1 - Instrumented shoe system (right shoe). The Physilog® (GaitUp, CH) is placed on a strap looping around the shoe with Velcro® tape. The insole (in blue) is placed inside the shoe and linked to the Physilog® by a cable. Converting electronics are in the box with handles (lateral side of the shoe), connected to the strip stemming from the insole.*

## **2.2 Participants and data collection**

Ten healthy community-dwelling elderly participants were recruited for this study, 8 men and 2 women. Overall physical characteristics of this convenience sample were (mean  $\pm$  standard deviation): age  $69.9 \pm 3.1$  years old, weight  $80.1 \pm 14.7$  Kg, height  $171.7 \pm 8.9$  cm, shoe size range 39-45 EU.

Participants came to the laboratory and were equipped with the instrumented shoes and reference system. Two tests were performed for the purpose of calibration: a) standing still for 5 seconds; b) level walking for 10 straight steps. A semi-structured activity protocol was then followed by each participant, the results of which have already been reported [276]. Participants then returned to their daily activities outside the laboratory after the sensor setup. They were simply requested to keep their shoes on over a 4-hour monitoring period, used for the analyses in this study. Once the measurement time had elapsed, a study

investigator retrieved the sensors from the participant. No observer followed the participants around, so they were free to perform their activities independently. All data were stored anonymously on a PC for post-processing and analysis. All participants gave written consent to participate and the study was approved by the university's ethical committee: "Quantification of postural transitions using multimodal sensory input" under reference "EK 2012-N-32".

### 2.3 Sensors calibration

Inertial sensors were calibrated in static position to correct for any gain and offset errors by using Ferraris' method [261]. The sensors were then aligned to the foot frame during a level walking period of 10 steps at the laboratory. The gravity alignment was done during foot static periods (stance phase) and the medio-lateral axis was found as the principal component during swing phase of the foot by assuming that the movement was mainly in the sagittal plane.

Raw pressure data from the insole were calibrated to the body weight (BW). The sum of all 16 sensors from both feet was divided by BW which was obtained during 5 seconds of static standing initially performed in the laboratory. This provided an estimation of the total force ( $TF$ ) under the feet, eq.1.

$$TF = \frac{\sum right_{insole(i)} + \sum left_{insole(i)}}{BW} \quad (\text{eq.1})$$

where  $i$  ranges from 1-8.

### 2.4 Event-driven activity classification algorithm

The algorithm is based on a previous study that evaluated the activity classification in a semi-structured protocol [276]. The algorithm is capable of classifying the basic activities such as *sitting*, *standing*, *walking*; and activity subclasses including *stair climbing*, *incline walking*, and *elevator use*. An event-driven classification tree was applied to classify the activities at each node by using data input from the different sensors in the instrumented shoes. *Locomotion periods* were identified by step detection using Toe Off ( $TO$ ) instants. The pitch angular velocity (foot rotation around the medio-lateral axis) was subjected to a wavelet transform enhancing the  $TO$ , as well as other gait events, i.e. mid swing and Heel Strike ( $HS$ ) instants. A Coiflet order 5 wavelet was used to decompose the signal into 10 scales, and two combinations were used. Subtracting the 9<sup>th</sup> approximation from the first emphasized  $HS$ , while subtracting it from the third emphasized  $TO$  [95]. *Stair climbing* and *elevator use* were detected by using barometric pressure, whereas foot inclination from IMU during stance was used for *incline* and *level walking* identification. A

threshold on the  $TF$  estimate is applied on the non-locomotion data to classify *sitting* and *standing*. *Lying* and *sitting* were considered as a single activity type in this study.

## 2.5 Evaluation of the activity classification algorithm

The reference activity classification algorithm combines information from trunk and thigh IMU in order to classify basic activity [23]. In the current study, the validation is mainly intended for these basic activities (*walking*, *sitting/lying*, and *standing*) since there was no reference data for the remaining subclasses. The activity outputs from the instrumented shoes classifier and reference algorithm were segmented into 6s windows to remove spurious activities. The median activity from the instrumented shoes' and the reference system's classification algorithms were compared for each 6s window and the true positives (TP), true negatives (TN), false positives (FP), false negatives (FN) are obtained. Sensitivity, specificity, precision, F1-score (F-measure) and global accuracy were calculated for each activity class according to the following equations:

$$Sensitivity = \frac{\#TP}{\#TP + \#FN}$$

$$Specificity = \frac{\#TN}{\#TN + \#FP}$$

$$Precision = \frac{\#TP}{\#TP + \#FP}$$

$$F1 - score = \frac{2 \times precision \times sensitivity}{precision + sensitivity}$$

$$Global Accuracy = \frac{\#TP + \#TN}{total\ sample\ number}$$

## 2.6 Gait analysis

Locomotion periods obtained through the activity classifier were retained for this specific analysis. The cumulative distribution of locomotion bouts was extracted by taking into consideration any period with 3 or more detected steps, corresponding to a minimum of 1 gait cycle (e.g. left-right-left or right-left-right step sequences). The minimum of 3 steps has been applied for gait detection in several other studies [54], [275] since this ultimately prevents the algorithm from classifying spurious foot movement. A gait cycle based on the locomotion detection algorithm is defined between two successive  $TO$  instants of each foot

(Figure 4-2). Cadence distribution is estimated with a histogram of 1 step/min bins. The number of bouts, total duration and total number of steps are tabulated for upstairs, downstairs, uphill and downhill periods, respectively.

Gait analysis was performed in terms of spatio-temporal parameters i.e. stride velocity, stride length, cadence, inter-stride gait cycle time variability, and foot clearance parameters, i.e. maximal heel clearance ( $HC$ ), and minimum toe clearance ( $TC$ ) [141].  $HC$  corresponds to the maximum heel height above the ground at the beginning of the swing phase whereas  $TC$  corresponds to the minimum toe height above the ground in the middle of the swing phase [141]. These gait parameters were extracted from locomotion periods with at least 20 steps (combined right and left feet) to achieve steady-state gait [278]. Initiation and turning steps, i.e. steps with a turning angle higher than 20 degrees, were detected [136] but omitted for the parameter extraction since they do not pertain to steady-state gait analysis. Stair and slope locomotion (ground inclination of more than 5% or 3 degrees) was also excluded from the analysis.

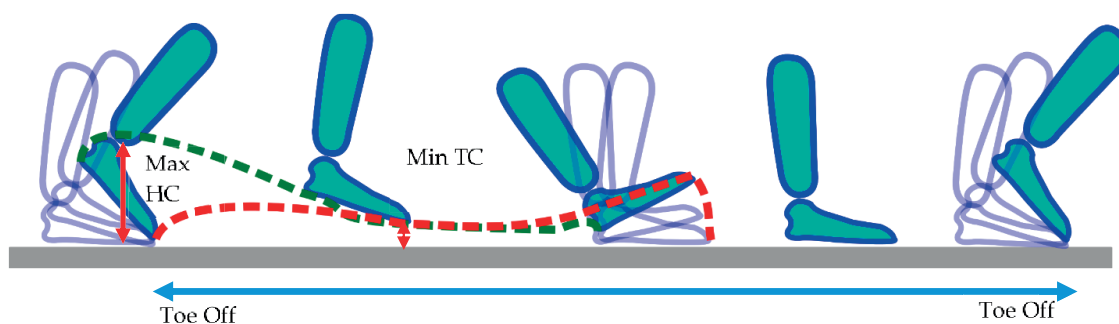


Figure 4-2 - Foot clearance during a step from a single foot. The maximum heel ( $HC$ ) and minimum toe ( $TC$ ) clearance are shown with arrows. Two consecutive toe off instants are shown, forming a complete gait cycle

## 2.7 Complexity and activity barcodes

Activity levels were obtained from the states defined by Paraschiv-Ionescu et al. [74]. In summary, these states start by low levels pertaining to low intensity during *sitting* and *standing*, going to higher levels of activity obtained by combining gait cadence and duration of locomotion periods. Overall, this classification yields 18 ranked states, where each state is represented by a color code, with warmer colors indicating higher activity intensity. The barcodes are based on 1s-windows represented by a color corresponding to the median of the activity state over the samples forming the window. Previous work has

shown that such a barcode has higher color (state) entropy in healthy subjects compared to subjects with pain or disease [74]. Using the outcome of instrumented shoes, activity barcodes were similarly evaluated by using 14 states (represented by numeric codes) instead of 18 (Table 4-1). This reduction resulted from assigning only a single numeric code to both *sitting* (1) and *standing* (2) whereas, in the original activity barcode, *sitting* and *standing* were assigned 2 and 4 numeric codes respectively, based on trunk movement intensity. These states were reduced to 2 in the present study to avoid using trunk sensor data and keep the activity barcode specific to the instrumented shoes. *Walking* was segmented into locomotion periods of duration  $d < 30s$ ,  $30 < d < 120s$  and  $120 < d$ . For each locomotion period, the mean cadence was calculated in steps/min. The cadence was then segmented into  $cad < 50$ ,  $50 < cad < 80$ ,  $80 < cad < 140$  and  $140 < cad$ . The combinations of duration and cadence represent 12 numeric codes as shown in Table 4-1.

Table 4-1 – Coding activities based on duration and intensity thresholds; *d*: duration, *cad*: cadence

<i>Activity type</i>	<i>Activity duration</i>	<i>Activity intensity</i>	<i>Numeric code</i>
<i>Sitting/Lying</i>	-	-	1
<i>Standing</i>	-	-	2
<i>Walking</i>	<i>d &lt; 30s</i>	<i>cad &lt; 50</i>	3
		<i>50 &lt; cad &lt; 80</i>	4
		<i>80 &lt; cad &lt; 140</i>	5
		<i>140 &lt; cad</i>	6
	<i>30 &lt; d &lt; 120s</i>	<i>cad &lt; 50</i>	7
		<i>50 &lt; cad &lt; 80</i>	8
		<i>80 &lt; cad &lt; 140</i>	9
		<i>140 &lt; cad</i>	10
	<i>120 &lt; d</i>	<i>cad &lt; 50</i>	11
		<i>50 &lt; cad &lt; 80</i>	12
		<i>80 &lt; cad &lt; 140</i>	13
		<i>140 &lt; cad</i>	14

The entropy (complexity) of obtained barcodes was estimated using the Lempel-Ziv complexity metric [279], [280]. The correlation between the instrumented shoes and reference system complexities was calculated. The correlation between the Lempel-Ziv complexity evaluated from the instrumented shoes and gait parameters such as the stride velocity, stride length, max *HC* and min *TC*, as well as the duration of steady-state gait cycles was also calculated.

## 2.8 System comfort evaluation

Gathering feedback from the system users is important. Therefore, at the end of each data collection, the participants were asked the following question: “On a scale ranging between 0 “not comfortable at all” to 10 “very comfortable”, what score would you give to the system in terms of comfort during daily use?” Scores were recorded by the investigator retrieving the sensors at the end of the monitoring period.

## 3 Results

### 3.1 Activity Classification

A sample output of the event-based activity classification algorithm is shown in Figure 4-3. The data are selected from one subject and show a sequence of *walking*, *standing* and *sitting*. The 50%BW line is marked on the figure to show the distinction between *sitting* and *standing*. The *TO* instants used to classify *walking* are displayed in Figure 4-4, which is a zoom-in of the same *walking* period from Figure 4-3.



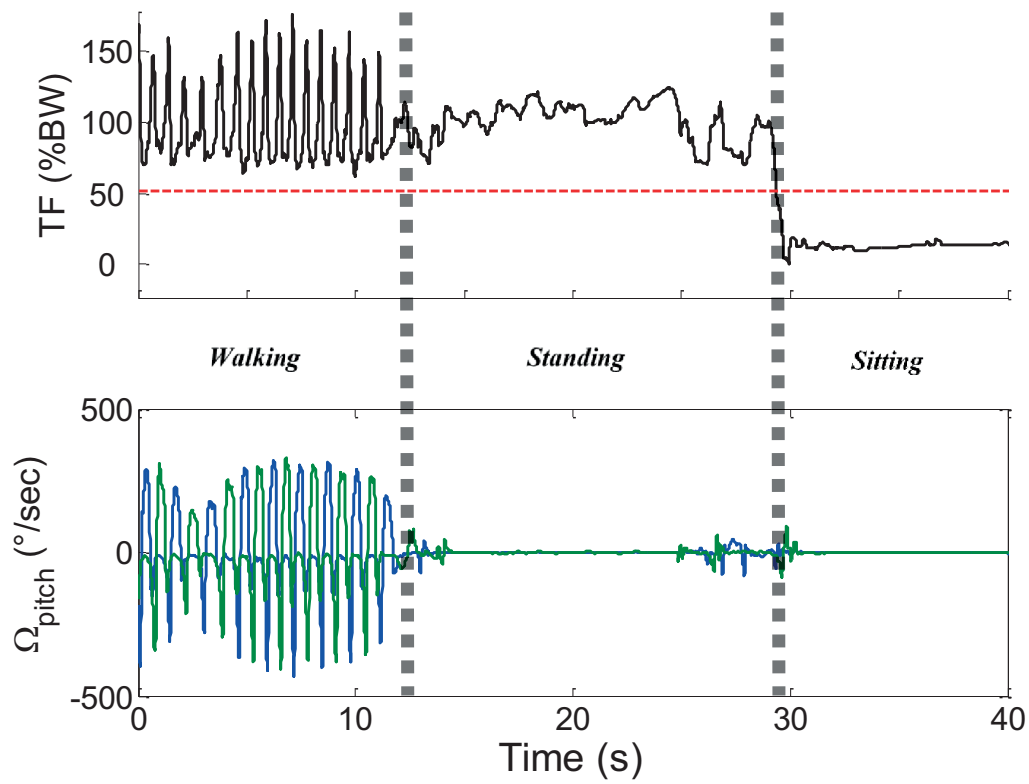


Figure 4-3 - Snapshot of classifier output from one participant (taken ~1h after the beginning of the recording). Top: plot of TF showing the 50% BW line (dashed red line). Bottom: pitch angular velocity: right foot (blue) and left foot (green). The vertical dashed bars represent different activity periods (walking, standing and sitting).

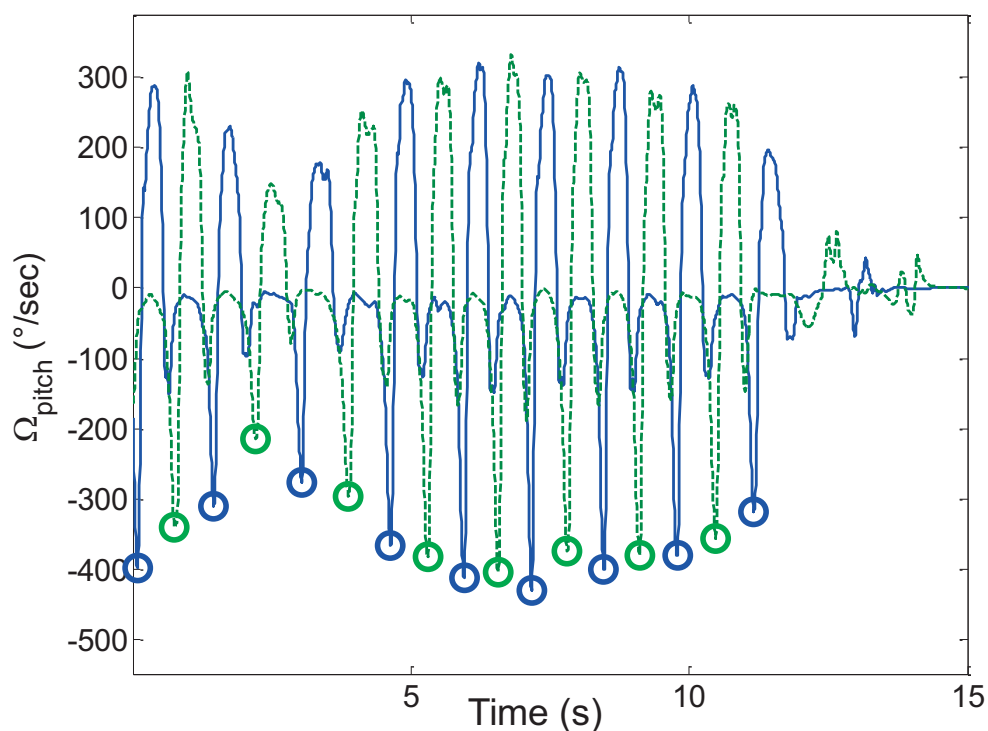


Figure 4-4 – Zoom-in on the walking period from Figure 4-3. The pitch angular velocity of the right foot is shown as a continuous line, and the left foot as a dashed line. TO instants are represented by circles.

Table 4-2 shows the confusion matrix and the classifier performances compared to reference activity. Sensitivity, specificity, precision and F-score were all 90% or higher for all activities except the sensitivity of *standing* (88%). Only 11 *sitting/lying* instances were predicted as *walking*, and one instance of *walking* were predicted as *sitting/lying*. Highest sensitivity was obtained for *sitting* (99%) and highest specificity for *walking* and *sitting/lying* (98 and 99%). A precision of 95% was achieved for *sitting/lying* as well as an F-score of 97%. The algorithm achieved a global accuracy of 93%.

Table 4-2 – Confusion matrix and classifier performance compared to reference activity. Each unit represents a 6 second activity epoch

<i>Predicted</i>	<i>Sitting/Lying</i>	<i>Standing</i>	<i>Walking</i>
<i>Reference</i>			
<i>Sitting/Lying</i>	9789	87	11
<i>Standing</i>	566	6788	402
<i>Walking</i>	1	420	3986
<i>Sensitivity</i>	0.99	0.88	0.90
<i>Specificity</i>	0.99	0.93	0.98
<i>Precision</i>	0.95	0.93	0.91
<i>F-score</i>	0.97	0.90	0.91

### 3.2 Gait analysis of locomotion periods

Mean cadence for every locomotion period with 3 or more steps is plotted as a histogram with a bin size of 1 step/min. A kernel smoothing fit is applied on this histogram as shown in Figure 4-5 (a). The two peaks of this fit correspond to a bimodal distribution with mode values of 83 and 93.5 steps/min. The separation of cadence distributions between locomotion periods of 20 or more steps and locomotion periods of less than 20 steps is also showed in Figure 4-5 (b) to better illustrate the hypothesis that cadence mode during short locomotion bouts is lower. This is done by obtaining the probability density function of each instantaneous cadence distribution per subject and calculating a mean  $\pm$  SD distribution. The distribution modes in this case are 90 steps/min (less than 20 steps) and 104 steps/min (20 steps or more). These values are somewhat different from the modes obtained for the entire distribution above because of the discrete separation of locomotion periods. The cumulative distribution of locomotion period durations (level and non-level) is shown on a semi-log plot, Figure 4-5 (c). The mean (thick line) and SD (shading) describe the locomotion period durations across all subjects. The longest continuous locomotion period was 432 seconds or 7.2 minutes. About 50% of locomotion periods lasted less than 7.4 seconds, and 94% were less than one minute.

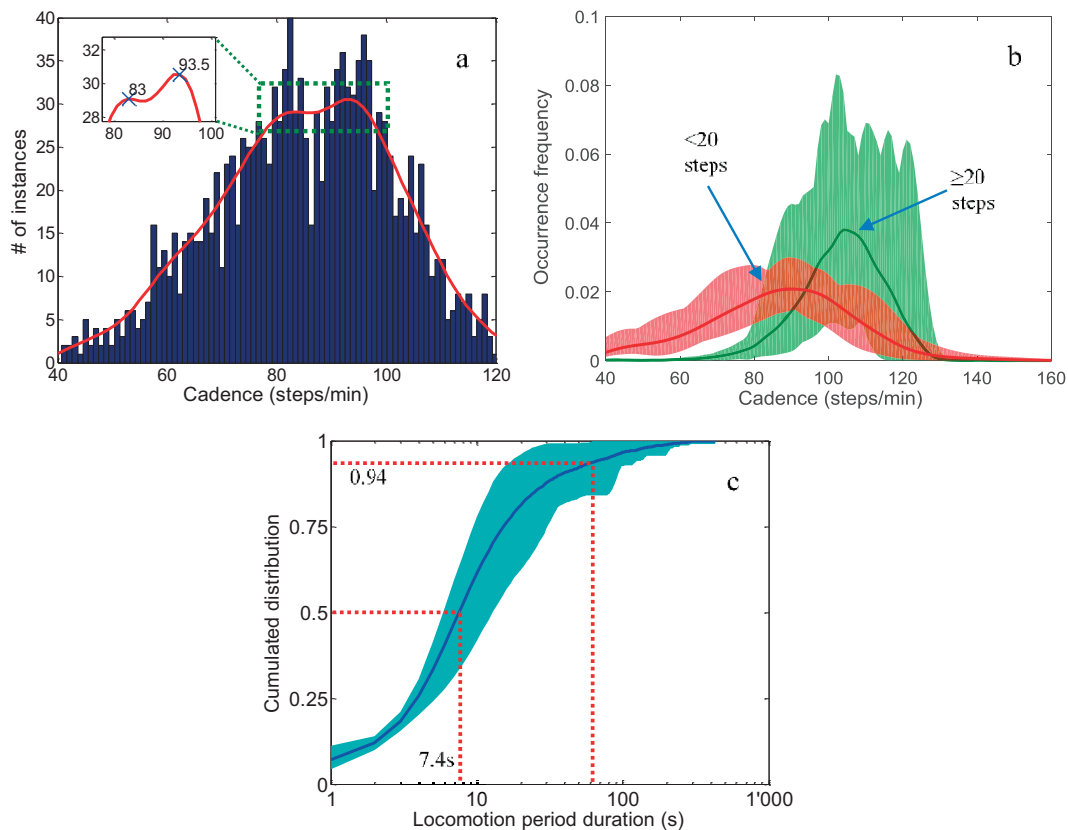


Figure 4-5 – a) Mean cadence distribution for all locomotion periods with 3 or more steps, b) Instantaneous cadence distribution for locomotion periods with 20 or more steps vs less than 20 steps, c) Cumulative distribution of locomotion period duration across all subjects (log scale for locomotion period duration axis). For b) and c): mean is represented by a thick line and SD by a shaded area.

Table 4-3 displays, for each participant, results of gait analysis during level locomotion over periods of 20 steps or more. Minimum, maximum, mean, and standard deviation of the duration of locomotion period are reported, as well as the number of bouts and analyzed gait cycles. The following gait parameters are shown as mean  $\pm$  standard deviation (SD): stride velocity, stride length, maximum heel clearance, minimum toe clearance, and gait cycle time variability. The total number of turning steps is also featured in this table.

Table 4-3 – Gait characterization from level walking periods of at least 20 steps. Reported values are mean  $\pm$  SD unless otherwise stated.

<i>ID</i>	<i>Duration (s) (min/max)</i>	<i>Duration (s)</i>	<i># Bouts</i>	<i># Gait cycles</i>	<i>Stride Velocity (m/s)</i>	<i>Stride length (m)</i>	<i>Heel Clearance (m)</i>	<i>Toe Clearance (m)</i>	<i>Variability (%)</i>	<i># Turning Steps</i>
1	13.86/190.48	56.73 $\pm$ 49.34	34	1419	1.07 $\pm$ 0.19	1.33 $\pm$ 0.15	0.28 $\pm$ 0.04	0.02 $\pm$ 0.01	8.19 $\pm$ 7.66	232
2	12.82/431.82	48.65 $\pm$ 73.74	34	1346	1.29 $\pm$ 0.20	1.43 $\pm$ 0.14	0.30 $\pm$ 0.04	0.03 $\pm$ 0.01	8.83 $\pm$ 11.05	240
3	14.59/284.61	94.80 $\pm$ 75.01	18	1284	0.97 $\pm$ 0.16	1.22 $\pm$ 0.12	0.27 $\pm$ 0.03	0.04 $\pm$ 0.02	6.56 $\pm$ 3.54	102
4	15.04/295.95	58.99 $\pm$ 63.54	50	2213	1.12 $\pm$ 0.20	1.32 $\pm$ 0.12	0.27 $\pm$ 0.02	0.03 $\pm$ 0.01	7.21 $\pm$ 6.11	390
5	12.97/60.54	24.36 $\pm$ 10.69	31	538	1.07 $\pm$ 0.34	1.22 $\pm$ 0.32	0.26 $\pm$ 0.05	0.04 $\pm$ 0.01	11.21 $\pm$ 10.12	176
6	10.68/130.64	35.07 $\pm$ 27.53	39	1082	1.28 $\pm$ 0.25	1.37 $\pm$ 0.22	0.25 $\pm$ 0.03	0.03 $\pm$ 0.01	9.69 $\pm$ 11.73	283
7	12.63/162.40	29.04 $\pm$ 38.67	14	307	1.47 $\pm$ 0.38	1.55 $\pm$ 0.26	0.27 $\pm$ 0.03	0.03 $\pm$ 0.01	9.51 $\pm$ 7.97	96
8	13.16/275.15	53.49 $\pm$ 64.30	60	2708	0.99 $\pm$ 0.16	1.07 $\pm$ 0.12	0.22 $\pm$ 0.02	0.03 $\pm$ 0.01	7.03 $\pm$ 6.30	345
9	12.97/368.34	49.77 $\pm$ 55.64	50	1939	1.37 $\pm$ 0.18	1.60 $\pm$ 0.16	0.31 $\pm$ 0.03	0.03 $\pm$ 0.01	7.85 $\pm$ 8.11	392
10	15.22/277.31	84.35 $\pm$ 96.03	11	735	1.06 $\pm$ 0.12	1.26 $\pm$ 0.10	0.22 $\pm$ 0.01	0.04 $\pm$ 0.01	8.79 $\pm$ 9.04	65

Table 4-4 shows the number of stairs and incline walking bouts (non-level locomotion), along with the total duration and number of steps taken during these walking activities.

Table 4-4 - Non-level locomotion periods. TD: total duration in seconds.

Participant	Upstairs			Downstairs			Uphill			Downhill		
	Bouts	TD (s)	Steps	Bouts	TD (s)	Steps	Bouts	TD (s)	Steps	Bouts	TD (s)	Steps
1	3	47.27	43	7	149.54	117	2	99.49	71	1	45.21	36
2	2	52.60	48	5	393.09	374	1	35.49	33	1	32.85	31
3	0	0	0	3	65.95	55	1	36.83	27	0	0	0
4	3	95.45	84	5	243.36	205	1	67.18	55	0	0	0
5	2	55.73	48	3	60.60	53	0	0	0	0	0	0
6	7	272.51	253	5	181.08	177	0	0	0	0	0	0
7	6	40.49	33	2	29.91	26	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0
9	11	193.77	162	14	168.33	150	2	16.39	16	0	0	0
10	3	96.05	76	1	21.08	17	0	0	0	0	0	0

To illustrate the range of walking performance, gait speed (stride velocity) and stride length profiles are shown in Figure 4-6. The cumulative distributions were obtained from the cumulated sum of the probability distributions of each subject. Subsequently, the average cumulative distribution (thick line) was calculated as the average of the cumulative distributions from each subject, and the shading represents the area between the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the cumulative distributions.

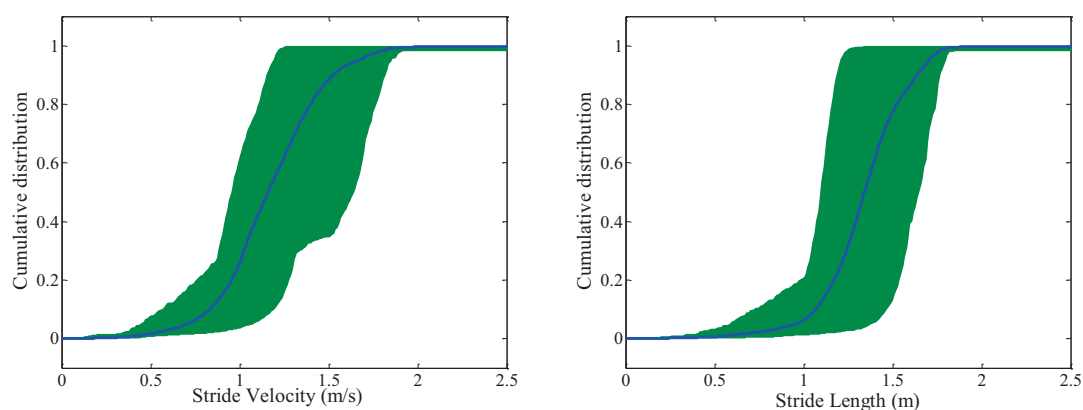


Figure 4-6 – Left: stride velocity distribution, right: stride length distribution as mean (thick line) and 5<sup>th</sup>/95<sup>th</sup> percentile shading across all subjects

Foot clearance is a novel parameter measured in daily life in this study. To highlight the importance of measuring this parameter, Figure 4-7 shows the relationship between stride velocity and maximum *HC*/minimum *TC*, respectively. Pearson's correlation coefficients reveal moderate positive correlation between *HC* and stride velocity ( $r = 0.50$ ;  $p < 0.001$ ) and weak negative correlation between *TC* and stride velocity ( $r = -0.18$ ;  $p < 0.001$ ).

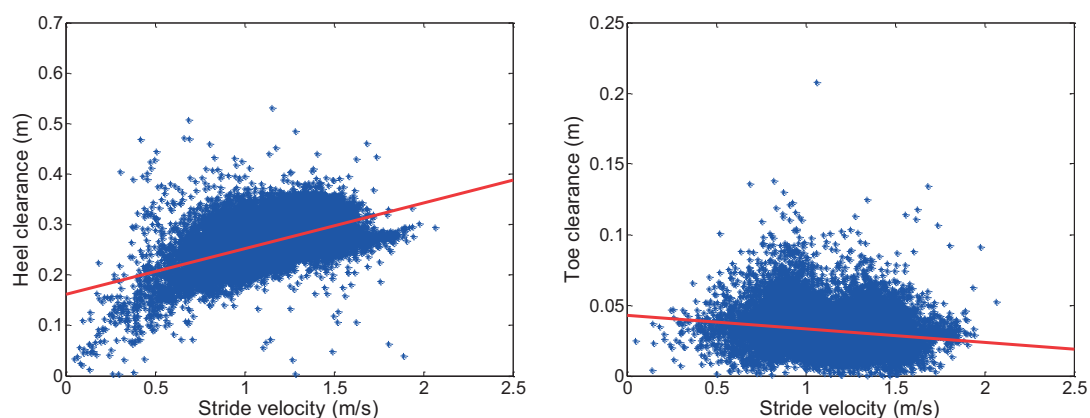


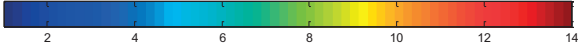










Figure 4-7 - Maximum *HC* (left) and minimum *TC* (right) as a function of stride velocity for all analyzed steps

### 3.3 Activity barcodes, complexity metric and activity distribution

Table 4-5 presents individual barcodes constructed for each participant and the corresponding Lempel-Ziv complexity obtained from the instrumented shoes and the reference system, respectively. The correlation between the reference and the instrumented shoes barcodes is considered as strong ( $r = 0.76$ ,  $p < 0.05$ ).

The correlation between complexity evaluated by instrumented shoes and relevant gait parameters was calculated to shed light on the complementarity of behavioral complexity and gait analysis. The Lempel-Ziv complexity showed little to no correlation with mean stride velocity ( $r = 0.02$ ,  $p = 0.96$ ), stride length ( $r = -0.12$ ,  $p = 0.75$ ), max *HC* ( $r = -0.05$ ,  $p = 0.88$ ) and min *TC* ( $r = -0.28$ ,  $p = 0.43$ ). However, this metric was strongly correlated to the number of gait bouts with more than 20 cycles ( $r = 0.91$ ,  $p < 0.001$ ) but not with the mean duration of these gait bouts ( $r = -0.24$ ,  $p = 0.50$ ) nor their maximum duration ( $r = 0.14$ ,  $p = 0.71$ ).

Table 4-5 - Subject specific activity barcodes. The scale on the right indicates the activity intensity, starting from 1: sitting, 2: standing, 3-14: walking with different cadences and locomotion period durations. Lempel-Ziv complexity values for each subject and for each activity monitoring system are shown

	Lempel-Ziv complexity		Activity barcodes from instrumented shoes
	Instrumented Shoes	Reference	Scale: 
P1	0.286	0.480	
P2	0.3	0.521	
P3	0.294	0.449	
P4	0.383	0.628	
P5	0.305	0.588	
P6	0.367	0.575	
P7	0.289	0.526	
P8	0.409	0.566	
P9	0.371	0.579	
P10	0.258	0.339	
			1                      2                      3                      4 Time (hours)

### 3.4 Evaluation of system comfort

A total of 9 scores from the 10 participants were collected. Missing data is due to the fact that assessment of comfort was introduced to the study protocol only after the first data collection. The scores are distributed as follows: 10, 9, 10, 10, 10, 8, 10, 10, 9, indicating good overall satisfaction (mean  $9.6 \pm 0.7$ ).

## 4 Discussion

This study presents evidence supporting the feasibility and validity of using an instrumented shoes system to monitor and classify activity during daily life in community-dwelling elderly subjects. Two algorithms were combined in order to provide both a coarse grained activity classification and fine-grained gait analysis towards a comprehensive evaluation of real-life physical behavior. Besides results of the system's validation, several metrics were proposed to characterize various aspects of daily life physical behavior. Those included postural allocations, locomotion bouts distribution, gait features such as foot clearance and velocity, as well as complexity of physical behavior.



## 4.1 Activity classification

The main validation outcome of this study pertains to the activity classification algorithm that performed with accuracy as high as 93% in real-life condition, a performance similar to the reference system used for its validation. This result compares favorably to those reported in previous studies on validation of activity classification in a real-life setting. Indeed, studies that used sensors on multiple body locations reported global accuracies ranging between 84-89% [44]–[46], whereas studies using single sensor systems reported accuracy from 76 to 80% [47], [49], [50]. These comparisons further emphasize the advantage of using combined inertial and pressure sensing at the foot level as a single location solution. In this study under real-world conditions, global accuracy of 93% was slightly lower than the 97% obtained with the semi-structured protocol validation [30]. This difference is negligible and appears congruent with similar worsened performance observed in previous studies when classification algorithms validated in lab or semi-structured conditions were applied to data collected under real-life conditions [46], [50], [51]. This disparity can be explained by the more limited range in both the type and intensity of structured activity assessed during these protocols, as shown in a previous study [281].

Lowest performances were observed for *standing* (88% sensitivity) periods. This slightly low sensitivity ensued mainly from misclassifications of *standing* as *sitting/lying*. Indeed, a couple of transitions from *sitting* to *standing* were not correctly detected and resulted in two relatively long periods of *sitting* classified as *standing*. A dedicated postural transition analysis can provide reliable information on the origin of such misclassifications. Furthermore, misclassifying *standing* into *walking* and vice-versa occurred for shortest locomotion periods (~3-5 steps), as well as from a small systematic difference between the two systems in defining start/end of locomotion periods. However, longer (i.e., 20 steps or more) locomotion periods were almost equally identified by both systems. The sensitivity and precision of *walking* were higher than 90%, reaching similar performance compared to that of the reference system [41].

*Sitting* and *lying* activities were combined into a single activity type. This limitation of the system is arguably relative since *lying* is an activity class that will rarely be observed by the system since people in their home environment would frequently remove their shoes before going to bed. A further relative limitation relates to the assumption we made that energy expenditure of *lying* and *sitting* are similar [282]. It could be hypothesized that during *lying*, the insole should measure negligible force under the feet, and this in turn could be used to classify *lying*. However this remains to be investigated.

## 4.2 Gait analysis

Instrumented shoes have been used in the past for gait analysis during locomotion tests in clinical or laboratory environment [84], [136], [167], [195]. This is, to the best of our knowledge, the first study combining activity monitoring and gait analysis using a single instrumented shoes system in daily life.

In terms of gait analysis, we showed the potential to provide reliable gait parameters for steady-state gait (periods with >20 steps). In this study, the mean stride velocity, stride length, maximum *HC* and minimum *TC* were similar to normative values obtained for an age matched cohort of healthy elderly subjects performing a 20m gait test in laboratory conditions [194]. Stride velocity, stride length and cadence measured during daily activity are significantly and prospectively associated with falls in elderly subjects as shown in a recent study [3]; instrumented shoes providing accurate estimation of these parameters could therefore be further used for fall prediction. Another original contribution of this study is to show the feasibility to record foot clearance parameters in daily life. To the best of our knowledge, these parameters have not yet been retrieved in other than clinical or gait lab settings, and never over extended periods such as performed in the current study. There is a major interest in obtaining clearance data from daily life especially since this parameter expresses the highest variance in gait data obtained from elderly subjects [195]. In the present study, clearance parameters were moderately (*HC*) and weakly (*TC*) correlated to stride velocity, a result similar to observations made in laboratory-based gait analysis over 20m in age- and health-matched older population [194]. Therefore, these parameters could provide new insights on a subject's performance in addition to stride velocity; while simultaneously playing a crucial role in obstacle negotiation and fall avoidance.

The cumulative distribution of locomotion periods provides a good illustration of a subject's overall mobility performance. In our study, this distribution varied substantially from one participant to another (Figure 4-5). A shift to the left of this sigmoid curve would indicate reduced occurrence of long periods of walking. Around 94% of locomotion periods were under one minute. The results vary somewhat compared to the literature; for example, Brodie et al. reported that almost 90% were less than a minute [275], whereas Orendurff et al. reported 81% of locomotion periods under one minute [54]. This is arguably due to the longer monitoring time in these two studies. However, the cadence distribution in the current study revealed a bimodal pattern that is similar to the result by Brodie et al. [275], even though the cadence peaks differ slightly (again, possibly due to monitoring time). Incidentally, when locomotion periods were separated by number of steps (<20 vs 20 or more steps), the cadence modes were similar to those reported in [275]. This result in itself is important because it underpins the hypothesis that locomotion strategies are different between short and long bouts of walking. Gini index [56] or Kolmogorov-Smirnov distance [283] between

distribution curves could be further used for the comparison of activity behaviors between subjects with different health conditions, as well as comparisons within the same individual over time to identify change in her/his activity level that could flag an underlying health problem

### **4.3 Physical behavior complexity**

The high correlation of Lempel-Ziv complexity values obtained from instrumented shoe barcodes with the reference system justifies the use of the instrumented shoes to assess physical behavior complexity. It should be noted that there is a slight discrepancy due to the few errors of activity classification between the two systems, mainly pertaining to misclassifications of *walking* into *standing* and vice-versa. A systematic underestimation of the Lempel-Ziv complexity metric by the instrumented shoes was observed. This could be explained by the lower number of states in the instrumented shoes barcodes (maximum of 14) compared to the reference system (maximum of 18). Still, results strongly suggest the potential application of instrumented shoes to assess physical behavior complexity in different populations of older persons. For instance, this system could be used to monitor progresses in patients undergoing rehabilitation. Another potential application could be to evaluate the potential positive or negative effects of a new medication regimen on mobility and activity over daytime periods.

Interestingly, there was no strong association between gait parameters (stride velocity, stride length, heel clearance and toe clearance) and the Lempel-Ziv complexity values. In contrast, this measure of complexity was highly correlated ( $r=0.91$ ,  $p<0.001$ ) with the number of steady-state locomotion bouts (i.e., 20 steps or more). This result strongly suggests the complementarity of activity pattern analysis and classical gait analysis. For example, participant 7 who achieved the highest average stride velocity had 14 steady-state locomotion bouts only whereas participant 8 who had the highest complexity value completed 60 bouts of steady-state locomotion but had a mean stride velocity lower than 1m/s. Thus, the complexity metric adds extra information to mobility assessment by quantifying physical behavior that cannot be achieved by looking at activity distribution, step counts, or spatio-temporal gait parameters.

### **4.4 System evaluation and drawbacks**

Participants gave highly positive feedback on the usability of the instrumented shoes in terms of comfort. Although the methodology used is subject to limitation (participants providing socially desirable answers, assessment not based on an exhaustive, previously validated questionnaire), these results can be considered as preliminary positive and encouraging from end-users of the instrumented-shoes system.

Additional investigation of other dimensions such as its easiness of use or end-users' concern about robustness or reliability will need to be considered in the future.

Some additional limitations of our study should be noted. The number of participants is limited and the recording time only covers 4 hours. All participants were fit and living independently, therefore results of this study do not reflect physical behavior and gait performance in frailer older persons who are the ultimate target population of this system. However, results of this feasibility study are sufficiently encouraging to further consider additional investigations such as including more participants from other populations (e.g., frail elderly or stroke patients), as well as performing longitudinal studies within the same individuals (e.g., monitoring of activity at baseline and at the end of rehabilitation). In our previous study it was also shown that stairs, ramps, and elevators can be recognized [276]. The validation of these events was not possible in the present study because the reference system used was minimized to lessen intrusiveness and therefore did not include an event marker to provide information on these activities as was the case in our previous validation study [276]. However, since the detection of elevation change depends mainly on barometric pressure variations, it would be possible to add the detection of such events in real life without compromising the accuracy of the classifier. These activities can be added to the activity barcode to enrich the complexity metric. In fact, non-level locomotion has different energy expenditure requirements compared to level walking and it would be extremely interesting to further compare barcodes in persons who frequently engage in such activities to those who rarely do.

## **5 Conclusions**

We presented and validated an instrumented shoes system for activity and gait monitoring of older adults in daily life. The activity classification algorithm proved to be highly accurate in identifying basic activities (sitting/lying, standing, and walking) and in distinguishing different types of locomotion (incline waling and stairs climbing). The feasibility of classifying daily life activity in elderly subjects was demonstrated and the system was capable of evaluating locomotion by performing highly detailed gait analysis on locomotion periods of sufficient durations. An additional important contribution of this study is to show that clinically relevant gait parameters such as stride velocity, stride length, cadence and their distribution during the period of recording can be extracted from instrumented shoes data. Moreover, some original gait parameters, such as foot clearance, were detected for the first time in daily life situation. The outcome measures from the instrumented shoes can also be accurately combined in an activity barcode embedding the complexity of daily life activity. This information on complexity appears to extend and enrich the type of information on physical behavior beyond what is usually assessed. The instrumented shoes were judged comfortable to use and did not hinder the movement of participants during daily life.

Overall, these results are promising to contemplate further applications of this system in more frail and diverse populations.

# Chapter 5

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## *Classification and characterization of postural transitions using instrumented shoes\**

### **Abstract**

Rising from a chair and sitting down are two frequent transitions occurring in daily life. The ability to perform postural transitions is a vital indicator of daily mobility since postural transitions require a high level of coordination and muscle strength. Furthermore, the duration of a transition can be relevant for fall risk assessment. The frequency and quality of postural transitions decrease with age; accurate classification and characterization of postural transitions in daily life of older adults is therefore needed. Wearable sensors provide the possibility of measuring different body segment movements and could inform about postural transitions. The trunk and the thigh have been the most predominant locations used to identify transitions. However, these locations require the attachment of sensors on the skin and provide little comfort in daily life. In this chapter, we propose to use instrumented shoes for postural detection and classification as well as the estimation of transition duration from the force signals of the insole. At a first stage, the transition duration is validated in laboratory conditions with healthy young and older adults. The potential to accurately estimate the total force under the feet is also revealed. Secondly, an algorithm for transition detection in daily life is validated against a wearable reference (inertial measurement unit on the thigh). Finally, the transition duration is compared to a trunk-based calculation. The instrumented shoes proved to measure the transition time with good accuracy compared to force plate. The detection and classification of postural transitions was achieved with excellent sensitivity and precision exceeding 90%. The comparison of duration estimation with the trunk revealed some variations that could be due to differences between lower body forces and upper body kinematics during the transition. In conclusion, the instrumented shoes were suitable for classifying and characterizing postural transitions in daily life conditions of healthy older adults.

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## **1 Introduction**

Sit-to-stand (SiSt) and stand-to-sit (StSi) are the most frequent postural transitions (PT) in daily life. The inability to perform such transitions results in substantial loss of independence and mobility [284]. Rising from a chair is an important but precarious action that challenges balance and stability and has therefore been associated with the risk of falling [285].

From a clinical perspective, efforts to better qualify and quantify PTs have led to the development of several clinical functional tests, such as the Five Times Sit-to-Stand Test (FTSST) [286], the thirty second (30s) chair stand [287], or the Timed Up and Go (TUG) [288]. For instance, the FTSST measures the time required for a person to perform 5 consecutive transition cycles (i.e. SiSt followed by StSi). Results of this test have been shown to predict the risk of falling in older adults [289]. Some of these tests have been instrumented in an attempt to provide more standardized measuring process enabling the quantification of parameters such as trunk tilt angles and movement smoothness [137], [290]–[292].

From a research perspective, traditional laboratory-based tools used for PTs' assessment consist of force plates and/or optoelectronic motion systems [293]–[295]. These systems provide accurate representations of full body kinematics and load measurements, thus allowing to split the transition movements into different phases and to fully characterize them. However, laboratory-based systems suffer from setup complexity, stationary setting, and high costs. In addition, PTs assessment in older persons within a lab-based, research setting, is a somewhat artificial reflection of their daily reality. Thus, ambulatory assessment of PTs (and indeed of daily physical activity) using body worn sensors has been investigated in recent years as an alternative, especially because such sensors can be used outside the laboratory setting and thus inform about real-life PTs.

Inertial measurement units (IMU) consisting of accelerometers and/or gyroscopes have been chiefly used for PT classification in laboratory settings because they can inform on the posture and orientation of a body segment during the task. The two most common sensor locations were the trunk or the thigh, since the SiSt consists of a trunk flexion followed by an extension that is associated with a simultaneous leg extension [296]. A PT model based on wavelets was developed to estimate the trunk orientation while removing integration drift from IMU data, achieving 93/82% sensitivity and 82/94% specificity for SiSt/StSi classification [285]. Fuzzy logic [297] and dynamic time warping [271] were used to improve the trunk-based wavelet algorithm. Vertical velocity estimates from de-drifted trunk acceleration integration were also used to classify PTs with 89/93% sensitivity and 94/82% specificity for SiSt and StSi, respectively [244]. A wavelet-based algorithm was also developed for an IMU placed at the waist [298]. Results showed that the order of positive and negative peaks in the acceleration signal reconstructed from wavelets could

identify transition type, but detailed results (i.e., sensitivity, specificity, accuracy) of this classification were not reported [298]. Recently, the addition of a barometric pressure sensor has been evaluated to increase the sensitivity and specificity of PT classification [299]. The change in trunk height measured by the barometer provides an additional confirmatory check on the occurrence of a PT and further defines in more detail its type. A uniaxial accelerometer placed at the thigh also showed the feasibility to detect PTs and appraise their type in lab under standardized conditions with healthy participants [300] and this has also been validated with high accuracy in children [301].

These evidence from in-lab PT classification using wearable sensors have channeled increasing interest in analyzing transitions in daily life, i.e., under real-world conditions. As in other clinical tests, performance over a temporary timescale in a controlled environment differs from behavior outside the lab. The underlying assumption is that, in most cases, in-lab performance does not reflect real-life behavior of a patient or even a healthy person. Interestingly, a recent review by Bohannon reports that to date, only a handful of studies investigated daily SiSt detection by ambulatory monitoring [302].

Among parameters characterizing the PT, the total duration (TD) of PTs is a crucial parameter in evaluating daily life mobility in older adults. Moreover, this parameter correlates well with the risk of falling [285]. Indeed, frail older adults who are at increased fall risk take longer to rise from a chair [303]. Several studies have been conducted to estimate PT durations in laboratory conditions using wearable sensors [298], [304]–[306] whereas only a few reported PT durations outside the lab [271], an observation that is congruent with the low number of studies that reported the amount of daily transitions [302].

The main body of research in PT classification so far mainly focused on sensors placed at the upper limb. To the best of our knowledge, there are no studies that investigated PT classification and characterization using wearable sensors placed at the foot, i.e. using pressure sensing insoles. Since such insoles are sensitive to load changes caused by body weight, they can distinguish sitting from standing. Furthermore, footwear offers enough space to integrate and protect electronics and batteries in order to keep instrumented shoes as conventional as possible and wearable during most daily activities. We previously reported results on sitting and standing detection in a larger activity classification framework but no dedicated algorithm for classification and evaluation of PT was proposed [276]. Also in [33], a highly accurate classification of sitting and standing was achieved using in-shoe pressure sensors but no details on transitions were provided. Zheng et al. used pressure sensing insoles and a thigh-worn IMU to detect SiSt transitions in laboratory conditions with a detection accuracy of 99.7%, but no standalone insole-based algorithm was presented [307].



From this overview, there is a clear need to have a wearable instrument able to classifying and characterizing PTs in real-life conditions. In a previous study, we developed instrumented shoes that combine pressure sensing insoles and IMUs to classify activities of daily life [276]. We found that it was possible to classify sitting and standing with excellent accuracy using the pressure sensing insole. In the present study, we extend the classification to PT and its characterization by performing the following studies:

- a) In-lab validation of TD and plantar force estimated from instrumented shoes using force plate as reference system
- b) Real-life validation of PT classification against a previously validated body worn IMU system [41]
- c) Comparison of TD estimated from instrumented shoes with existing body worn IMU system

## **2 Methods**

### **2.1 Measurement systems**

The instrumented shoes consist of a pressure sensing insole (IEE, LU) with 8 sensors under each foot connected to the Physilog® system (GaitUp, CH) through an electronic interface. The insole is placed inside the shoe and the Physilog® on top of the shoe, with electronics interface at the ankle, Figure 5-1. The Physilog® system contains the battery to power the insole and record its data, and an IMU not used in PT analysis, but crucial for activity classification and gait analysis [276]. Each participant was equipped with one pair of instrumented shoes with an adequate size insole (available size range: 38-45 EU). Two studies were performed to evaluate the performance of the instrumented shoes to detect the PT and estimate its duration. The first study aimed at validating the estimation of TD with the instrumented shoes in laboratory condition using force plate and comparing it to a validated system using body worn IMU. The second study was performed out of the lab in order to evaluate the performance of the instrumented shoes in real-life conditions.

In the first study, a force plate (Kistler, CH) was used to measure the reference ground reaction force and estimate the actual TD based on a model using the vertical force ( $F_z$ ). In the second study, a body worn IMU fixed on the right thigh was used to detect PT using an IMU and the TD was estimated using a second IMU fixed at sternum [41]. Data from all systems was sampled at 200 Hz. The force plate was electronically synchronized with the instrumented shoes and body worn IMU sensors via a separate device that could send synchronous pulses via an external trigger to all systems.

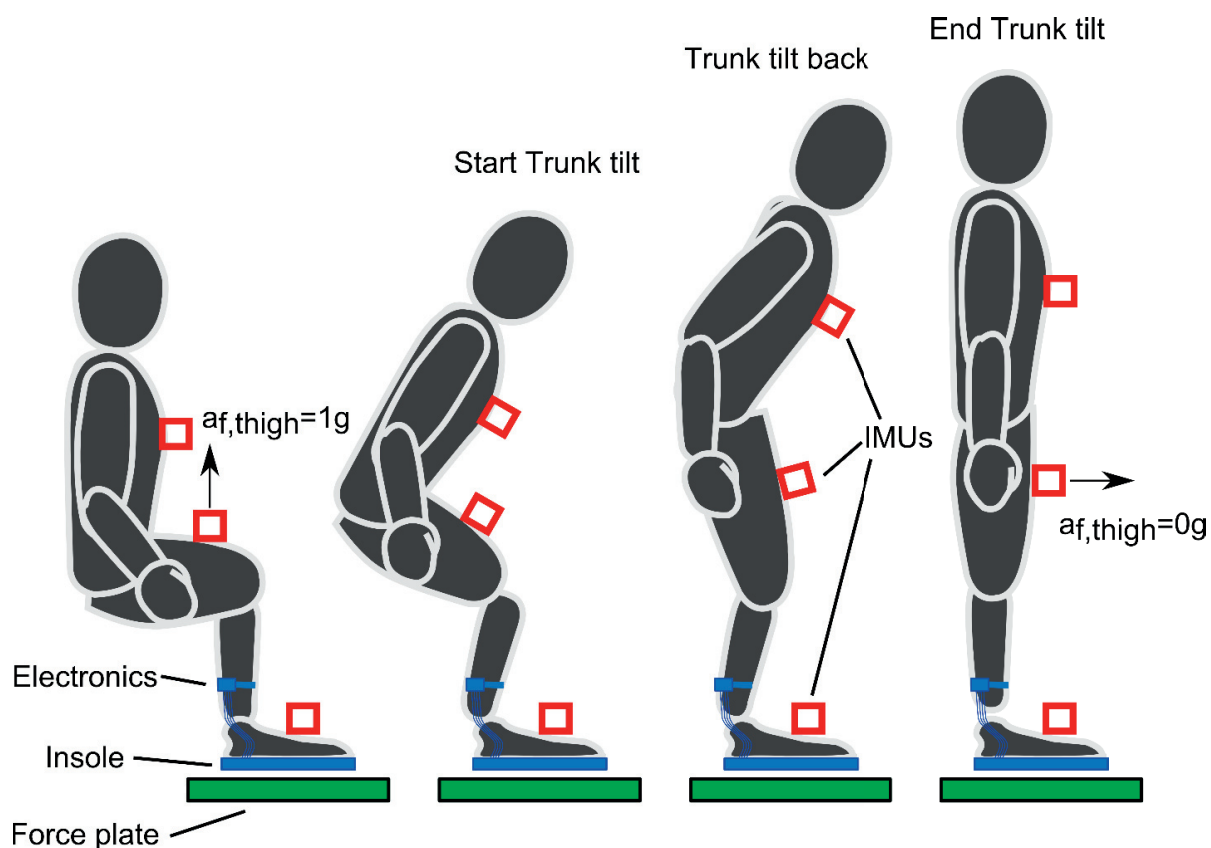


Figure 5-1 - Experimental setup showing the locations of the force plate, the instrumented shoes and body worn IMUs at sternum and thigh (represented by thick boxes). Force plate was used as reference for TD estimation, thigh IMU was used as reference to detect PT in real-life using thigh frontal acceleration ( $a_{f,thigh}$ ), sternum IMU was used to estimate TD for comparison with instrumented shoes.

## 2.2 Study 1: In-lab validation of TD and force estimation

### 2.2.1 Participants and protocol

Ten healthy, community-dwelling older adults and ten healthy young subjects participated in this study. Participants were asked to perform SiSt and StSi transitions from a chair while keeping their feet inside the force plate area and taking a minimum 3s break between consecutive transitions. Older adults performed a total of 10 transition cycles (SiSt followed by StSi) and young participants totaled 15 cycles. In addition to the instrumented shoes, elderly subjects all wore an IMU on trunk for comparison of TD with instrumented shoes.

All participants agreed to participate in the study by signing a consent form and the measurements were approved by the university's ethical committee: "Quantification of postural transitions using multimodal sensory input" under reference "EK 2012-N-32".

### **2.2.2 PT segmentation and TD estimation from force plate**

$F_z$  for each subject over the entire trial was smoothed by applying a moving-average filter with a 50 points window shifted by one sample at a time to reduce high frequency noise.  $F_z$  is then normalized between 0-100% body weight (BW). The estimated total force from the insoles ( $F_I$ ) is obtained as the sum of the 16 individual sensors from both insoles normalized between 0-100% BW for each subject independently.

Individual transitions were segmented using an algorithm inspired from the IEEE Standard for Transitions, Pulses, and Related Waveforms [264]. The method is summarized as in the following steps:

1. Identify the minimum and maximum of the signal
2. Split the signal into equal sized bins (1000 bins were used for this study, equivalent to the final resolution obtained after data preprocessing)
3. Count the number of data points falling inside each bin (histogram count)
4. Split the histogram in two based on a threshold (50% in this case)
5. The lower signal level  $L_{low}$  is then obtained as the mode of the first histogram, and the higher signal level  $L_{high}$  as the mode of the second histogram
6. A tolerance of 20% was applied to obtain the percent reference levels, i.e.  $L_{low} \pm 20\%$  and  $L_{high} \pm 20\%$
7. A transition is defined when the signal crosses  $L_{low} + 20\%$  followed by crossing  $L_{high} - 20\%$  for a SiSt, and vice-versa for StSi transition.
8. The mid-cross point is defined as the 50% reference level

For each transition, 500 samples before and after the mid-crossing sample were retained and thus the total retained time for each transition was 5 seconds (1001 samples). The same time instants were used to segment the insole and trunk IMU data.

The reference transition duration  $TD_F$  for a SiSt transition obtained from the force plate was based on the model from Lindemann et al. [262] with adaptations by Zijlstra et al. [305] (see Figure 5-2, a). For

each transition, steps 1-5 were applied again for an accurate estimation of  $L_{low}$  and  $L_{high}$ . The transition events were then obtained as follows:

- The starting sample ( $S_F$ ) occurs when  $F_z$  crosses 10% of  $L_{low}$  corresponding the feet weight before the trunk inclination
- The end sample ( $E_F$ ) occurs when  $F_z$  oscillates inside a band ranging  $\pm 2.5\%$  of  $L_{high}$  corresponding to BW after the occurrence of peak force (stable standing)
- $TD_F$  is the difference between these two time instants:

$$TD_F = E_F - S_F$$

### **2.2.3 TD calculation from trunk IMU**

The trunk angle ( $\theta_T$ ) was computed using the method described in [285]. This consisted of integrating the medio-lateral (pitch) gyroscope signal and applying a Coiflet order 5 wavelet to remove the drift by subtracting the 9<sup>th</sup> level approximation from the 5<sup>th</sup>, providing a frequency range of 0.04-0.68Hz. The following events (see Figure 5-2, b) were used to calculate transition duration from the trunk ( $TD_T$ ):

- The most prominent negative peak in ( $\theta_T$ ) was used for transition time occurrence detection. This corresponds to the subject starting to tilt back (Figure 5-1) for the upright position during SiSt and seated position during StSi
- The first positive peak before the transition time marked the start ( $S_T$ ), corresponding to the beginning of forward tilt (Figure 5-1) in both SiSt and StSi
- The first positive peak after the transition time marked the end ( $E_T$ ), corresponding to the end of backward tilt (Figure 5-1) in both SiSt and StSi
- $TD_T$  was calculated as:

$$TD_T = E_T - S_T$$

### **2.2.4 TD calculation from instrumented shoes**

The same approach was applied to identify the start sample ( $S_I$ ) from  $F_I$ . However, for the end sample, a stable standing phase was difficult to detect due to higher noise in the insole sensors. Instead, the first intersection between the lower range of the band of  $\pm 2.5\%$  BW, i.e. 97.5% BW, and  $F_I$  after the most negative peak before stabilization was taken as the end sample ( $E_I$ ) as shown in Figure 5-2, c.

A wavelet decomposition was applied to  $F_I$  in an attempt to enhance the signal and improve TD estimation from the raw insole data. A decomposition based on a Daubechies order 8 wavelet ( $db8$ ) was computed and the approximation at the 7<sup>th</sup> level was used. This corresponds to a frequency bandwidth of 0-0.78Hz corresponding to a minimum transition time of 1.28s. This estimated force is subsequently referred to as  $F_W$ . Moreover the derivative of  $F_W$  was considering by assuming that sudden changes in force could be better detected by its derivative,  $F_D$ . This way, the following events were added to the estimation of start/end times:

- The first negative ( $S_{W1}$ ) followed by a positive peak ( $S_{W2}$ ) before the mid-crossing instant were added as start events (Figure 5-2, d)
- The first positive ( $E_{W1}$ ) followed by a negative peak ( $E_{W2}$ ) after the mid-crossing instant were added as end events (Figure 5-2, d)
- The first negative ( $S_{D1}$ ) followed by a positive peak ( $S_{D2}$ ) before the highest positive peak in  $F_D$  were added as start events (Figure 5-2, e)
- The first negative ( $E_{D1}$ ) followed by a positive peak ( $E_{D2}$ ) after the highest positive peak in  $F_D$  were added as end events (Figure 5-2, e)

All  $TD_I$  were estimated as the difference between all the combinations of start and end samples from  $F_I$ ,  $F_W$  and  $F_D$ .

As for the StSi TD, there was no reference model proposed in the literature based on the force plate. However, by observing the force plate signals in this study, it could be assumed that the StSi transition is a mirror image of the SiSt and therefore the same analysis can be applied by flipping the StSi data from left to right. The event detection remains the same in this case for all signals of the force plate and insole. Zijlstra et al. [305] used a similar approach by adapting the SiSt model from [262].

For each valid transition, TD was calculated for each system and the difference between the force plate, the insole and the trunk IMU was reported.

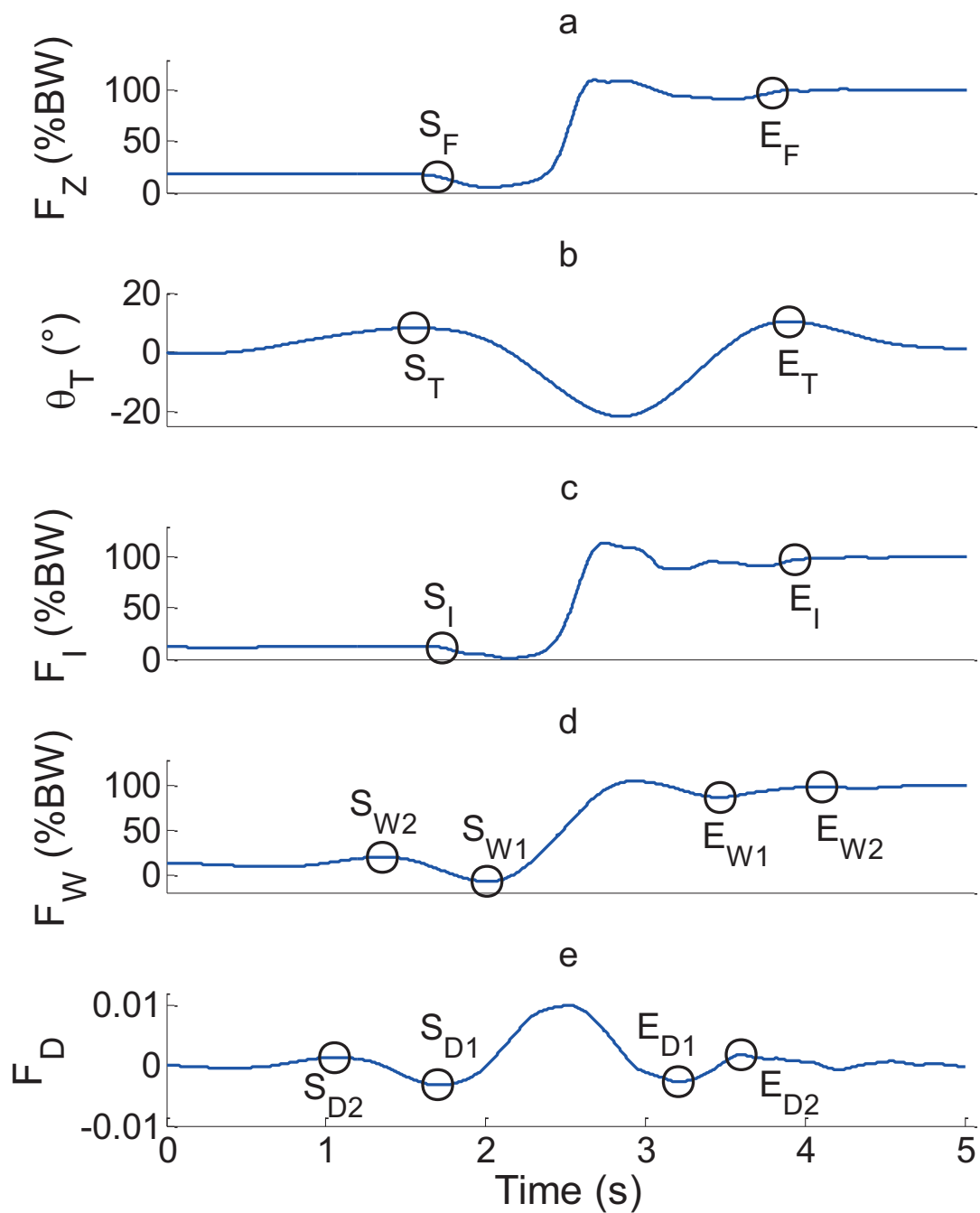


Figure 5-2 - Sit to stand transition example in an elderly subject. a) Force plate signal showing  $S_F$  and  $E_F$ , b) trunk angle showing the peaks of  $S_T$  and  $E_T$  c) raw insole signal with  $S_I$  and  $E_I$ , d) wavelet transform of raw insole signal with the detected peaks  $S_{W1}$ ,  $S_{W2}$ ,  $E_{W1}$ , and  $E_{W2}$ , e) derivative of the wavelet transform and the detected peaks  $S_{D1}$ ,  $S_{D2}$ ,  $E_{D1}$ , and  $E_{D2}$

### **2.2.5 Force estimation using instrumented insoles**

For each SiSt and StSi transition of length  $N$ , the absolute value of the difference between the 0-100% BW normalized  $F_z$  and  $F_l$  was estimated sample by sample:

$$err_{abs}(i) = abs(F_z(i) - F_l(i)), i = 1, \dots, N$$

Mean ( $\mu_F$ ) and SD ( $\sigma_F$ ) of  $err_{abs}$  for each participant (older adult and young) as well as global mean and SD were calculated to evaluate the potential of measuring plantar force using the proposed insole system.

## **2.3 Study 2: Postural transitions in real-life conditions**

### **2.3.1 PT detection and classification**

A novel method was applied to  $F_l$  data in this study to improve the detection of postural transitions in real-life conditions. The same wavelet transform described in section 2.2.4 was used to obtain  $F_w$ . This eliminates the high frequency locomotion content in  $F_l$  but maintains transitions since the low-pass cutoff is at 1.28s. The lowest and highest levels that represent sitting and standing, respectively, are obtained from the data distribution histogram of  $F_w$  over the entire measurement length as in section 2.2.4. The mid-crossing points between these two levels are then calculated similarly to section 2.2.4. A SiSt is labeled when this mid-crossing point instant is preceded by the lower level and followed by the high level; otherwise the transitions is labeled StSi. Since the sitting and standing levels may vary due to different loading conditions and sensor accuracy, a tolerance of 20% was applied on these levels for the detection of the mid-cross events.

Participants in this study were the same 10 older adults from Study 1 (described in section 2.2.1). As mentioned in section 2.1, in addition to the instrumented shoes, they wore an IMU at the thigh to reliably detect and identify PTs. They also wore an IMU at the trunk that was used to calculate the transition duration. The IMU system at the thigh was used as reference system for PT detection, based on a validated algorithm using the thigh frontal accelerometer data,  $a_{f,thigh}$ . During sitting, the steady-state value of  $a_{f,thigh}$  is 1g, whereas during standing it is 0g (Figure 5-1). This algorithm achieved above 99% sensitivity and specificity in classifying both SiSt and StSi transitions [41] and is therefore suitable to validate the performance of instrumented shoes for PT detection.

The results of PT classification are tabulated in a confusion matrix, Table 5-5. If both systems recorded a transition with a time range of 2.5 seconds of each other, the transition was validated. Otherwise,

the activity class classified by one system during a transition classified by the other system was reported in the confusion matrix.

### 2.3.2 TD calculation in real life conditions

Based on results from the first study, the best transition events described in section 2.2.4 and Figure 5-2 were used to calculate  $TD_I$  from the insole. In addition,  $TD_T$  was estimated from the trunk IMU as described in section 2.2.3. For each correctly classified transition, the difference  $TD_T - TD_I$  (best transition events included in  $TD_I$ ) was calculated, and the mean and standard deviation of this difference were obtained to compare both systems. The difference between in lab and at home transitions were highlighted by performing a non-parametric Wilcoxon Rank-sum test on the TD obtained from the trunk and the insole.

## 3 Results

### 3.1 Study 1: In-lab validation of TD and force estimation

Participant characteristics are shown in Table 5-1.

Table 5-1 - Participant characteristics

<i>Older adults</i>					<i>Young</i>				
<i>ID</i>	<i>Sex</i>	<i>Age</i>	<i>Weight (Kg)</i>	<i>Height (cm)</i>	<i>ID</i>	<i>Sex</i>	<i>Age</i>	<i>Weight (Kg)</i>	<i>Height (cm)</i>
1	M	75	72	175	1	M	25	73	170
2	M	72	80	172	2	M	22	68	178
3	M	68	88	168	3	M	28	70	180
4	M	66	92	184	4	F	21	61	170
5	M	68	114	183	5	M	27	67	174
6	M	73	62	162	6	M	26	85	180
7	M	65	73	178	7	M	31	73	179
8	F	71	70	158	8	M	27	60	170
9	M	71	75	174	9	F	24	54	170
10	F	70	75	163	10	F	21	52	164

One measurement in young subjects was not properly recorded on the SD card of the data logger so that subject (participant 7) was left out from further analyses. A total of 123 SiSt and 122 StSi out of 135 were retained for subsequent analysis in the young group. As for the older adults group, 96 SiSt and 82 StSi



were retained out of 104. For three older participants, trunk data were not available. Therefore  $TD_T$  and its difference with respect to force plate are based on 66 SiSt and 55 StSi transitions that were available for analysis.

### **3.1.1 TD calculation in laboratory conditions**

The differences in TD between force plate reference and instrumented shoes with all combinations of events presented in Figure 5-2 are shown in Table 5-2 for SiSt and Table 5-3 for StSi. TD estimations that have absolute combined mean $\pm$ SD inferior to 0.7s in elderly subjects are highlighted in both tables. Seven combinations fulfilled this criterion for the SiSt:  $E_{D1-SI}$ ,  $E_{W2-SW2}$ ,  $E_I-S_{W1}$ ,  $E_{W1-S_{W1}}$ ,  $E_{D2-S_{W1}}$ ,  $E_{W2-S_{D1}}$ , and  $E_{D1-S_{D1}}$ . These  $TD_I$  estimations were retained for further analyses in real-life conditions (study 2) because of their performance. As for  $TD_T$ , the mean error was relatively high (-0.44) but the SD error obtained (0.32) was lower than all  $TD_I$  combinations. This reveals a general overestimation of the transition duration from the trunk sensor.

The selected combinations did not always meet the performance criterion in the young group; only  $E_I-S_{W1}$  and  $E_{D2-S_{W1}}$  revealed errors  $< 0.7s$ . Other combinations did however perform well but were not retained for further analysis since only the older adult group was studied in real-life conditions.

As for the StSi, the following combinations performed best based on absolute combined mean $\pm$ SD errors $<0.7s$ :  $E_{W1-S_I}$ ,  $E_{D1-S_{W2}}$ ,  $E_{D2-S_{W1}}$ ,  $E_I-S_{D1}$ , and  $E_{D2-S_{D1}}$ . Errors for  $TD_T$  were  $-0.17\pm 0.41$ , with the SD error also lower than  $TD_I$  combinations. Similarly to SiSt results, there was a general tendency to overestimate TD by the trunk sensor but less marked for the StSi (mean error -0.17s) compared to SiSt (mean error -0.44s).

Table 5-2 - Transition duration of SiSt in young and old subject groups obtained from instrumented shoes ( $TD_I$ ) using all combinations of start and end samples.  $TD$  obtained from the trunk IMU ( $TD_T$ ) is also reported. Mean $\pm$ SD difference of error compared to actual transition duration obtained from force plate ( $TD_F$ ) are listed. Combinations with errors $<$ 0.7 are highlighted

	$TD$		$Differences with respect to TD_F (mean\pmSD)$		
	Young	Older Adults	Young	Older Adults	ALL
$TD_F$	1.92 $\pm$ 0.37	1.77 $\pm$ 0.29	-	-	-
$TD_T$	-	2.26 $\pm$ 0.24	-	-0.44 $\pm$ 0.32	-
$E_I-S_I$	2.09 $\pm$ 0.50	2.09 $\pm$ 0.51	-0.16 $\pm$ 0.44	-0.32 $\pm$ 0.55	-0.23 $\pm$ 0.50
$E_{W2}-S_I$	1.44 $\pm$ 0.41	1.43 $\pm$ 0.42	0.49 $\pm$ 0.48	0.34 $\pm$ 0.48	0.42 $\pm$ 0.49
$E_{W1}-S_I$	1.90 $\pm$ 0.40	1.96 $\pm$ 0.44	0.03 $\pm$ 0.45	-0.19 $\pm$ 0.51	-0.07 $\pm$ 0.49
$E_{D1}-S_I$	1.56 $\pm$ 0.35	1.63 $\pm$ 0.41	0.37 $\pm$ 0.38	0.14 $\pm$ 0.48	0.27 $\pm$ 0.44
$E_{D2}-S_I$	1.95 $\pm$ 0.46	2.04 $\pm$ 0.49	-0.03 $\pm$ 0.49	-0.27 $\pm$ 0.57	-0.13 $\pm$ 0.54
$E_I-S_{W2}$	2.67 $\pm$ 0.44	2.60 $\pm$ 0.46	-0.75 $\pm$ 0.49	-0.83 $\pm$ 0.51	-0.78 $\pm$ 0.50
$E_{W2}-S_{W2}$	2.02 $\pm$ 0.45	1.94 $\pm$ 0.42	-0.10 $\pm$ 0.62	-0.17 $\pm$ 0.49	-0.13 $\pm$ 0.56
$E_{W1}-S_{W2}$	2.48 $\pm$ 0.45	2.46 $\pm$ 0.43	-0.56 $\pm$ 0.60	-0.69 $\pm$ 0.51	-0.62 $\pm$ 0.57
$E_{D1}-S_{W2}$	2.15 $\pm$ 0.40	2.13 $\pm$ 0.40	-0.22 $\pm$ 0.54	-0.36 $\pm$ 0.48	-0.28 $\pm$ 0.52
$E_{D2}-S_{W2}$	2.54 $\pm$ 0.52	2.54 $\pm$ 0.51	-0.61 $\pm$ 0.63	-0.77 $\pm$ 0.59	-0.68 $\pm$ 0.62
$E_I-S_{W1}$	1.94 $\pm$ 0.37	1.90 $\pm$ 0.37	-0.02 $\pm$ 0.46	-0.13 $\pm$ 0.44	-0.07 $\pm$ 0.45
$E_{W2}-S_{W1}$	1.29 $\pm$ 0.36	1.24 $\pm$ 0.31	0.63 $\pm$ 0.57	0.53 $\pm$ 0.41	0.59 $\pm$ 0.51
$E_{W1}-S_{W1}$	1.75 $\pm$ 0.35	1.77 $\pm$ 0.33	0.17 $\pm$ 0.55	0.00 $\pm$ 0.44	0.10 $\pm$ 0.51
$E_{D1}-S_{W1}$	1.41 $\pm$ 0.27	1.44 $\pm$ 0.27	0.51 $\pm$ 0.47	0.33 $\pm$ 0.41	0.43 $\pm$ 0.45
$E_{D2}-S_{W1}$	1.80 $\pm$ 0.42	1.84 $\pm$ 0.42	0.12 $\pm$ 0.57	-0.07 $\pm$ 0.52	0.03 $\pm$ 0.56
$E_I-S_{D1}$	2.20 $\pm$ 0.44	2.18 $\pm$ 0.37	-0.28 $\pm$ 0.52	-0.41 $\pm$ 0.44	-0.34 $\pm$ 0.49
$E_{W2}-S_{D1}$	1.55 $\pm$ 0.40	1.52 $\pm$ 0.33	0.38 $\pm$ 0.59	0.25 $\pm$ 0.42	0.32 $\pm$ 0.53
$E_{W1}-S_{D1}$	2.01 $\pm$ 0.39	2.05 $\pm$ 0.34	-0.09 $\pm$ 0.57	-0.28 $\pm$ 0.45	-0.17 $\pm$ 0.53
$E_{D1}-S_{D1}$	1.67 $\pm$ 0.30	1.72 $\pm$ 0.29	0.25 $\pm$ 0.49	0.05 $\pm$ 0.41	0.16 $\pm$ 0.47
$E_{D2}-S_{D1}$	2.06 $\pm$ 0.42	2.13 $\pm$ 0.42	-0.14 $\pm$ 0.58	-0.36 $\pm$ 0.52	-0.24 $\pm$ 0.56
$E_I-S_{D2}$	2.83 $\pm$ 0.55	2.80 $\pm$ 0.43	-0.90 $\pm$ 0.59	-1.03 $\pm$ 0.46	-0.96 $\pm$ 0.54
$E_{W2}-S_{D2}$	2.18 $\pm$ 0.49	2.14 $\pm$ 0.41	-0.25 $\pm$ 0.64	-0.37 $\pm$ 0.47	-0.30 $\pm$ 0.57
$E_{W1}-S_{D2}$	2.64 $\pm$ 0.49	2.67 $\pm$ 0.42	-0.71 $\pm$ 0.62	-0.90 $\pm$ 0.49	-0.80 $\pm$ 0.57
$E_{D1}-S_{D2}$	2.30 $\pm$ 0.40	2.34 $\pm$ 0.37	-0.38 $\pm$ 0.53	-0.57 $\pm$ 0.45	-0.46 $\pm$ 0.50
$E_{D2}-S_{D2}$	2.69 $\pm$ 0.49	2.75 $\pm$ 0.46	-0.77 $\pm$ 0.61	-0.98 $\pm$ 0.54	-0.86 $\pm$ 0.59

Table 5-3 - Transition duration of StSi in young and old populations obtained from instrumented shoes ( $TD_I$ ) using all combination of start and end samples.  $TD$  obtained from the trunk IMU ( $TD_T$ ) is also reported. Mean $\pm$ SD difference of error compared to the actual value ( $TD_F$ ) from force plate, are listed. Combinations with errors $<$ 0.7 are highlighted

	$TD$		<i>Differences with respect to <math>TD_F</math> (mean<math>\pm</math>SD)</i>		
	<i>Young</i>	<i>Older Adults</i>	<i>Young</i>	<i>Older Adults</i>	<i>All</i>
$TD_F$	2.13 $\pm$ 0.37	2.32 $\pm$ 0.38	-	-	-
$TD_T$	-	2.27 $\pm$ 0.39	-	-0.17 $\pm$ 0.41	-
$E_I-S_I$	2.29 $\pm$ 0.47	2.48 $\pm$ 0.53	-0.15 $\pm$ 0.40	-0.16 $\pm$ 0.59	-0.16 $\pm$ 0.48
$E_{W2}-S_I$	1.71 $\pm$ 0.45	1.68 $\pm$ 0.35	0.42 $\pm$ 0.50	0.64 $\pm$ 0.49	0.51 $\pm$ 0.50
$E_{W1}-S_I$	2.31 $\pm$ 0.50	2.39 $\pm$ 0.40	-0.17 $\pm$ 0.53	-0.07 $\pm$ 0.50	-0.13 $\pm$ 0.52
$E_{D1}-S_I$	1.85 $\pm$ 0.40	1.97 $\pm$ 0.32	0.28 $\pm$ 0.47	0.35 $\pm$ 0.46	0.31 $\pm$ 0.47
$E_{D2}-S_I$	2.42 $\pm$ 0.51	2.65 $\pm$ 0.42	-0.29 $\pm$ 0.55	-0.33 $\pm$ 0.50	-0.30 $\pm$ 0.53
$E_I-S_{W2}$	2.53 $\pm$ 0.42	2.71 $\pm$ 0.47	-0.40 $\pm$ 0.42	-0.39 $\pm$ 0.53	-0.40 $\pm$ 0.47
$E_{W2}-S_{W2}$	1.96 $\pm$ 0.41	1.91 $\pm$ 0.35	0.17 $\pm$ 0.52	0.41 $\pm$ 0.47	0.27 $\pm$ 0.51
$E_{W1}-S_{W2}$	2.55 $\pm$ 0.47	2.62 $\pm$ 0.40	-0.42 $\pm$ 0.56	-0.30 $\pm$ 0.49	-0.37 $\pm$ 0.53
$E_{D1}-S_{W2}$	2.10 $\pm$ 0.36	2.20 $\pm$ 0.34	0.04 $\pm$ 0.50	0.12 $\pm$ 0.46	0.07 $\pm$ 0.48
$E_{D2}-S_{W2}$	2.67 $\pm$ 0.47	2.88 $\pm$ 0.40	-0.53 $\pm$ 0.57	-0.56 $\pm$ 0.47	-0.54 $\pm$ 0.53
$E_I-S_{W1}$	1.99 $\pm$ 0.39	2.11 $\pm$ 0.46	0.14 $\pm$ 0.38	0.21 $\pm$ 0.54	0.17 $\pm$ 0.45
$E_{W2}-S_{W1}$	1.42 $\pm$ 0.36	1.31 $\pm$ 0.27	0.72 $\pm$ 0.48	1.01 $\pm$ 0.45	0.83 $\pm$ 0.49
$E_{W1}-S_{W1}$	2.01 $\pm$ 0.43	2.03 $\pm$ 0.33	0.12 $\pm$ 0.52	0.29 $\pm$ 0.45	0.19 $\pm$ 0.50
$E_{D1}-S_{W1}$	1.55 $\pm$ 0.31	1.60 $\pm$ 0.25	0.58 $\pm$ 0.46	0.72 $\pm$ 0.43	0.64 $\pm$ 0.45
$E_{D2}-S_{W1}$	2.12 $\pm$ 0.44	2.28 $\pm$ 0.35	0.01 $\pm$ 0.54	0.04 $\pm$ 0.46	0.02 $\pm$ 0.51
$E_I-S_{D1}$	2.05 $\pm$ 0.40	2.23 $\pm$ 0.48	0.08 $\pm$ 0.39	0.09 $\pm$ 0.56	0.08 $\pm$ 0.47
$E_{W2}-S_{D1}$	1.48 $\pm$ 0.45	1.42 $\pm$ 0.34	0.65 $\pm$ 0.55	0.90 $\pm$ 0.50	0.75 $\pm$ 0.54
$E_{W1}-S_{D1}$	2.07 $\pm$ 0.50	2.14 $\pm$ 0.40	0.06 $\pm$ 0.58	0.18 $\pm$ 0.52	0.11 $\pm$ 0.56
$E_{D1}-S_{D1}$	1.62 $\pm$ 0.40	1.72 $\pm$ 0.32	0.51 $\pm$ 0.53	0.61 $\pm$ 0.48	0.55 $\pm$ 0.51
$E_{D2}-S_{D1}$	2.19 $\pm$ 0.53	2.39 $\pm$ 0.39	-0.05 $\pm$ 0.62	-0.07 $\pm$ 0.50	-0.06 $\pm$ 0.58
$E_I-S_{D2}$	2.35 $\pm$ 0.53	2.53 $\pm$ 0.60	-0.22 $\pm$ 0.53	-0.21 $\pm$ 0.68	-0.22 $\pm$ 0.60
$E_{W2}-S_{D2}$	1.78 $\pm$ 0.62	1.73 $\pm$ 0.52	0.35 $\pm$ 0.70	0.59 $\pm$ 0.65	0.45 $\pm$ 0.69
$E_{W1}-S_{D2}$	2.37 $\pm$ 0.66	2.45 $\pm$ 0.56	-0.24 $\pm$ 0.72	-0.13 $\pm$ 0.66	-0.20 $\pm$ 0.70
$E_{D1}-S_{D2}$	1.92 $\pm$ 0.58	2.02 $\pm$ 0.50	0.22 $\pm$ 0.68	0.30 $\pm$ 0.62	0.25 $\pm$ 0.66
$E_{D2}-S_{D2}$	2.49 $\pm$ 0.68	2.70 $\pm$ 0.55	-0.35 $\pm$ 0.75	-0.38 $\pm$ 0.64	-0.36 $\pm$ 0.71

The agreement with the force plate reference for the seven selected  $TD_I$  estimates for the SiSt as well as the  $TD_T$  is shown on separate Bland-Altman plots including SiSt transitions from elderly participants,

(Figure 5-3). These plots reveal the overall good agreement between selected  $TD_I$  and  $TD_T$ , as well as the overestimation bias of  $TD_T$ .

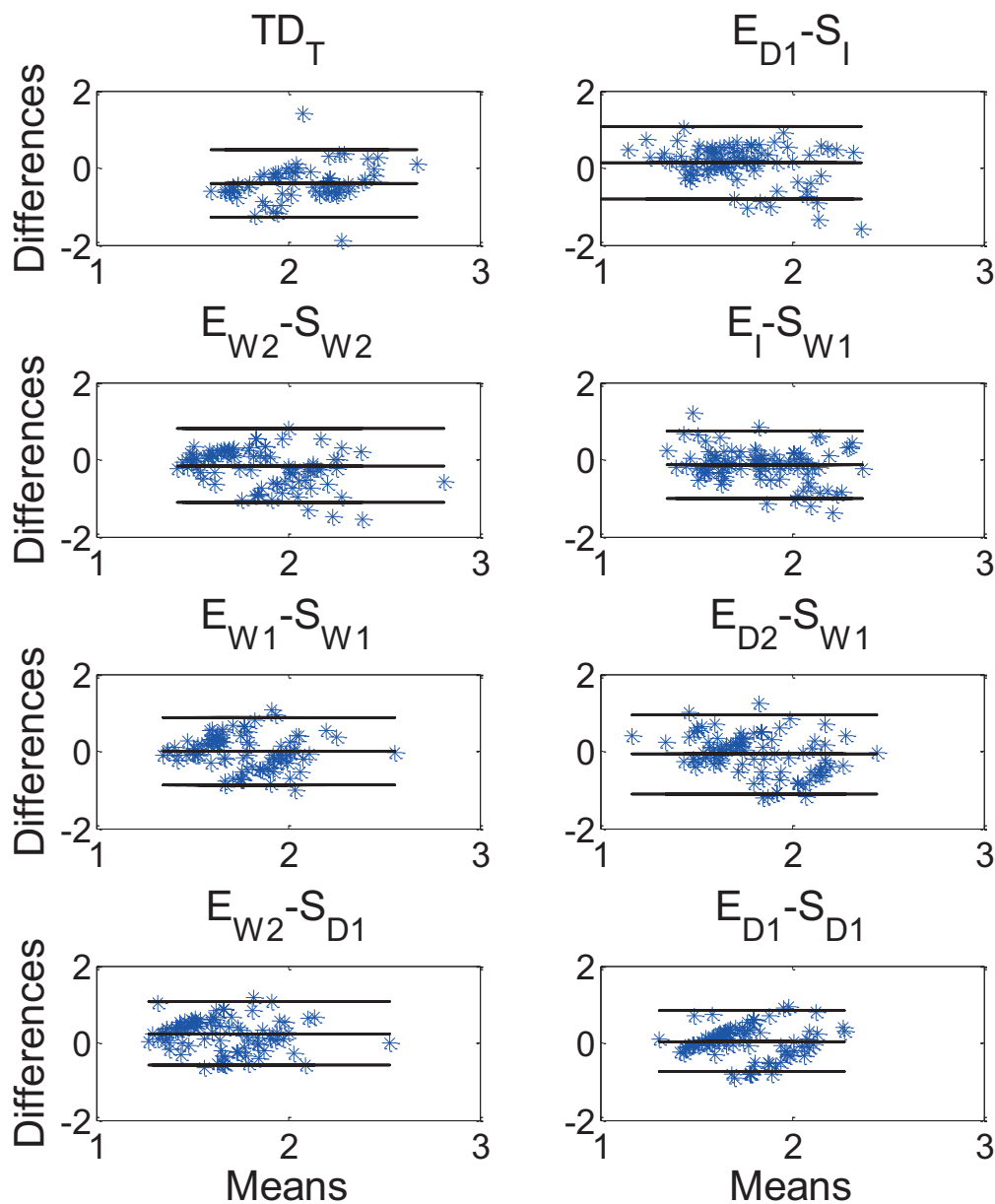


Figure 5-3 - Bland-Altman plots for the best performing SiSt estimated  $TD_I$  and  $TD_T$ .

### 3.1.2 Force estimation using instrumented insoles

The force estimation errors ( $\mu_F$ ,  $\sigma_F$ ) between instrumented insoles and force plate reference are shown in Table 5-4. All young subjects exhibited errors below 10%BW and the mean population error was  $6.3 \pm 7.9$ . The error was also inferior to 10% in 8 out of 10 older adults, with a mean population error of  $9.1 \pm 8.5$ .

Table 5-4 - Mean ( $\mu_F$ ) and SD ( $\sigma_F$ ) of force estimation error from instrumented shoes compared to force plate reference. Values are expressed as %BW and reported for each subject and averaged for all the population.

<b>Young</b>			<b>Older adults</b>		
	$\mu_F$	$\sigma_F$		$\mu_F$	$\sigma_F$
<b>P1</b>	5.7	6.6	<b>P1</b>	4.8	5.3
<b>P2</b>	3.1	5.4	<b>P2</b>	5.5	3.8
<b>P3</b>	8.4	9.9	<b>P3</b>	6.6	5.5
<b>P4</b>	4.7	5.8	<b>P4</b>	16.2	8.1
<b>P5</b>	4.8	5.8	<b>P5</b>	6.9	7.2
<b>P6</b>	3.4	4.5	<b>P6</b>	14.9	11.5
<b>P7</b>	N/A	N/A	<b>P7</b>	6.1	4.2
<b>P8</b>	9.3	9.7	<b>P8</b>	8.9	5.7
<b>P9</b>	9.4	9.3	<b>P9</b>	8.9	8.4
<b>P10</b>	7.5	8.3	<b>P10</b>	9.3	11.1
<b>All</b>	6.3	7.9	<b>All</b>	9.1	8.5

## 3.2 Study 2: Transitions in real-life conditions

### 3.2.1 PT detection and classification

Table 5-5 shows the confusion matrix of SiSt and StSi classification with respect to other performed activities across all 10 older adult participants. A sensitivity of 90% and precision of 93% were achieved for both SiSt and StSi detection.

Table 5-5 - Confusion matrix for SiSt and StSi transitions in real-life conditions.

<i>Reference</i> \ <i>Predicted</i>	<i>SiSt</i>	<i>StSi</i>	<i>Sitting</i>	<i>Standing</i>	<i>Walking</i>	<i>Sensitivity</i>
<i>SiSt</i>	103	0	0	12	0	0.90
<i>StSi</i>	0	104	1	10	1	0.90
<i>Sitting</i>	4	3				
<i>Standing</i>	4	4				
<i>Walking</i>	0	1				
<i>Precision</i>	0.93	0.93				

Only 1 instance of StSi was detected as walking and vice-versa. All other misclassifications were related to sitting or standing.

### 3.2.2 TD calculation in real-life conditions

The best  $TD_I$  estimations obtained in section 3.1.1 for elderly subjects were used for evaluation in real-life conditions. Table 5-6 summarizes the results and also the differences between  $TD_T$  and the selected  $TD_I$ . The StSi differences are shown in Table 5-7.

Table 5-6 - SiSt in real-life conditions:  $TD_I$  estimation from selected combinations compared to  $TD_T$ 

	$TD_T$	$ED1-SI$	$EW2-SW2$	$EI-SW1$	$EW1-SW1$	$ED2-SW1$	$EW2-SD1$	$ED1-SD1$
<b>TD</b>	$2.31 \pm 0.3786$	$1.95 \pm 0.90$	$3.58 \pm 0.81$	$3.36 \pm 1.05$	$2.02 \pm 0.54$	$1.93 \pm 0.47$	$3.07 \pm 0.70$	$1.81 \pm 0.35$
<b>Difference</b>	-	$0.37 \pm 0.94$	$-1.3 \pm 0.83$	$-1.05 \pm 1.15$	$0.31 \pm 0.61$	$0.39 \pm 0.55$	$-0.75 \pm 0.73$	$0.52 \pm 0.45$

Total duration varied substantially between the trunk and the insole estimations. Combinations including raw ( $E_{D1-SI}$  and  $E_{I-SW1}$ ) insole features revealed the largest SD in duration estimation and in the differences compared to the trunk. Three combinations exhibited relatively lower differences with respect to others:  $E_{W1-SW1}$ ,  $E_{D2-SW1}$ , and  $E_{D1-SD1}$ .

Table 5-7 - SiSt in real-life conditions:  $TD_I$  estimation from selected combinations compared to  $TD_T$ 

	$TD_T$	$E_{W1-SI}$	$E_{D1-SW2}$	$E_{D2-SW1}$	$E_{I-SD1}$	$E_{D2-SD1}$
<b>TD</b>	$2.40 \pm 0.48$	$2.41 \pm 1.25$	$2.15 \pm 0.76$	$2.15 \pm 0.74$	$3.77 \pm 1.22$	$2.46 \pm 0.37$
<b>Difference</b>	-	$-0.02 \pm 1.23$	$0.25 \pm 0.89$	$0.25 \pm 0.87$	$-1.37 \pm 1.35$	$-0.05 \pm 0.61$

Finally, transition durations in the lab and at home life were compared in a box plot, Figure 5-4. For comparison purposes, only the  $E_{W1-SW1}$  combination was selected. Significant differences between the lab

and home durations were observed for both  $TD_T$  and  $E_{W1}-S_{W1}$  (p-values of  $<0.001$  and  $0.003$ , respectively, from Wilcoxon Rank-sum test).

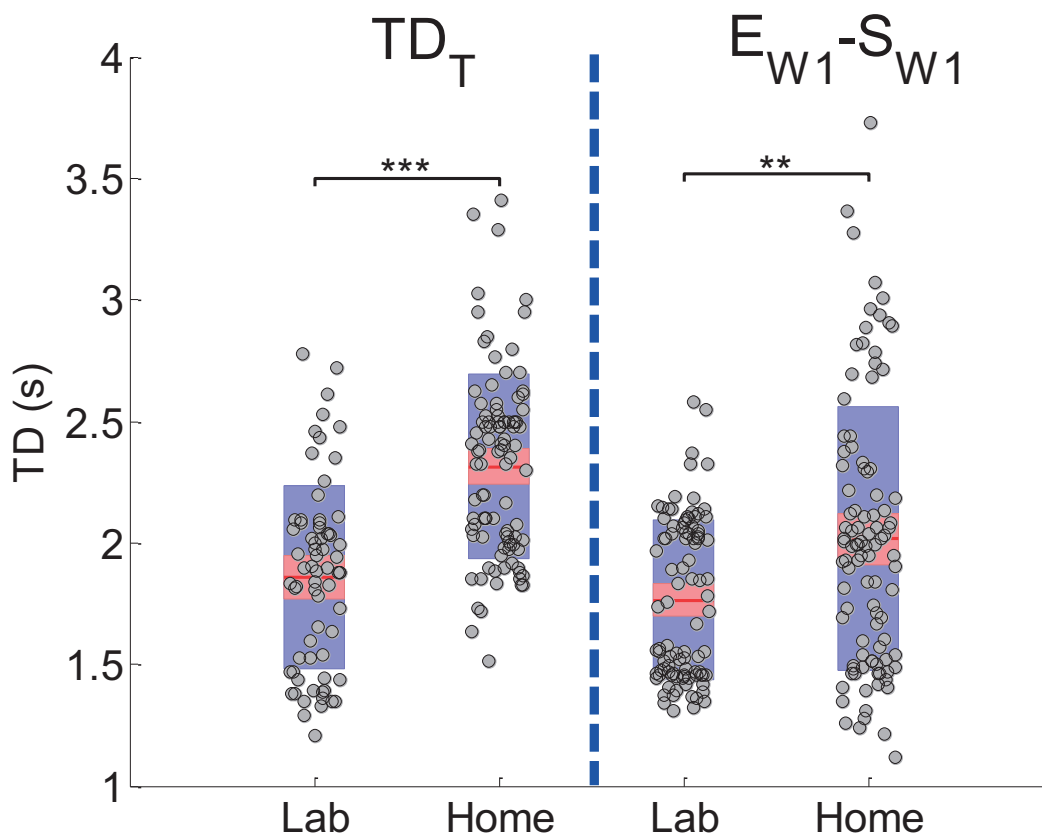


Figure 5-4 - Box plot of TD in lab and at home for the trunk and the  $E_{W1}-S_{W1}$  estimation.

## 4 Discussion

This study evaluated the agreement between an instrumented insole and force plate reference to estimate the TD and total plantar force in laboratory conditions among young and older persons, as well as PT classification and TD estimation compared to a wearable IMU system in real-life conditions in older persons. Results showed high agreement between reference values and estimated values from instrumented shoes, as well as excellent classification results and low error in force estimation.

#### **4.1 TD calculation in laboratory conditions**

Results from the laboratory-based TD estimation with the insole are very good, especially with the use of events from the wavelet approximation of the insole forces. The trunk IMU systematically overestimated the SiSt duration but achieved a slightly lower SD than the insole that could indicate better repeatability. As for the StSi, there were fewer combinations that matched the error criterion. This could well be expected since the StSi transition involves a somewhat different mechanism. For example, subjects tend to turn slightly to check the position of their seat before sitting down, and this could have an effect on both the trunk tilt and the loading of the insole. In this study, participants were free to perform the movement as they liked. It would be interesting to perform similar experiments while imposing some constraints such as that the hands remain crossed over the sternum to identify any potential effect from upper body movement. Despite these observations, current results indicate the overall suitability of calculating postural transition durations using the instrumented insole with acceptable errors. Furthermore, the TDs reported in this study in laboratory conditions are similar to values from the literature in healthy subjects and, similarly, did not show any significant difference between healthy young and healthy older adults [294].

#### **4.2 Force estimation using instrumented insoles**

The possibility to measure plantar force from the proposed instrumented insoles was demonstrated with overall errors of less than 10% BW in both studied groups. However, a prior dynamic calibration of each individual sensor in the insole would still be desirable to obtain accurate force measurements. In fact, some differences were observed in error values between sitting and standing phases. This could be remedied by individual calibration or linear regression to estimate real force values from a platform reference based on individual sensor inputs from the insole. A detailed study of the error during the transition phases, with an emphasis on the error of peak force estimation, could be interesting for a future evaluation of the instrumented insoles. It should also be noted that while the insoles and the force plate are both measuring plantar force, the force are more likely to be altered in the insole due to sensor quality, covering material (neoprene layer in this case), contact surface between insole and the foot as well as the shoe type (e.g. narrow or wide). For example, even in non-supporting phase of the foot the insole could measure some force just because the shoe is too tight. The evaluation of the force estimation error during gait would also be important to evaluate the insole performance during dynamic activity.



### 4.3 **PT detection and classification**

The direct detection and characterization of PTs in real-life conditions using wearable insole data has not been examined previously in the literature. Insoles have been used in previous studies to classify postures without looking at transition events [307], [308]. The present study is therefore the first to report robust detection and classification of PTs in real-life conditions as shown by sensitivity and precision of 90% and 93%, respectively, for both SiSt and StSi transitions. Moreover, there were no errors in misclassifying a SiSt as a StSi, and only one instance in which a StSi was classified as walking and vice versa. An in-depth look at the misclassifications of PTs into sitting/standing revealed the presence of some confounding events when the thigh remains straight but the load under the feet decreases considerably (this could be an event where the participant leaned against a wall/table) or when the thigh reveals a change in posture but the insoles still measure a high load (this could be a period of crouching/squatting or tying shoes, for example). Indeed, a participant told the study investigators that he performed in-home exercises and data from this patient revealed misclassifications similar to crouching. These types of misclassifications were rare and would arguably be inexistent in population at-risk for falls. A future investigation on confounding movements could slightly improve the performances of our PT detection algorithm.

Considering the total number of SiSt transitions (103) over the 4 hour monitoring period of 10 participants, an average of 62 transitions per day can be extrapolated. This is similar to other studies reported in the review by Bohannon [302] in older adults living independently, suggesting excellent congruency with the instrumented insoles and other systems such as IMU placed on the thigh or trunk in detecting postural transitions for long term monitoring.

An interesting observation from this study on real-life transitions is unsuccessful transition attempts, as shown in Figure 5-5. This attempt was not detected as a true transition which is a correct classification as compared to the thigh where no movement is observed on the bottom plot. However, a trunk tilt can be seen on the top plot confirming the attempt. The identification of such events in a long-term force signal can be extremely informative in terms of mobility as well as frailty occurrence, and has been associated to increased fall risk in older adults [285].

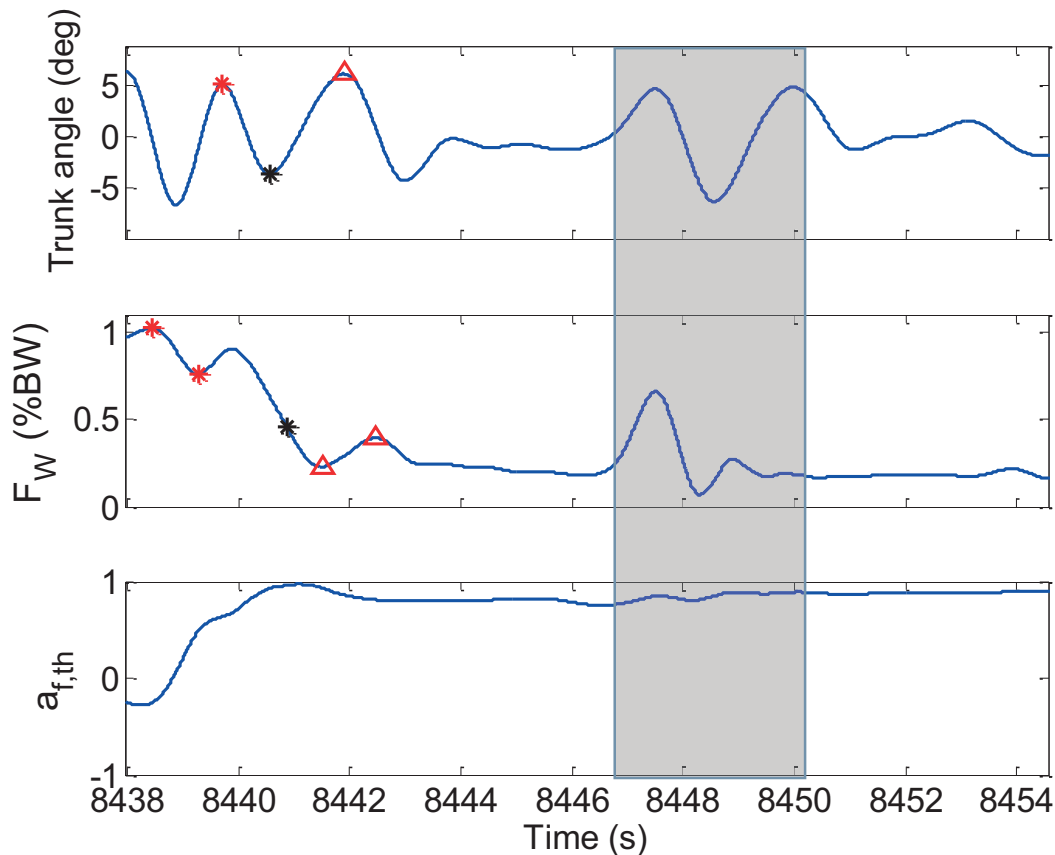


Figure 5-5- Example of an unsuccessful transition attempt (shaded area). At time 8440, a correct transition is shown with detected events for FW and the trunk angle are shown.

#### 4.4 TD calculation in real-life conditions

The TD estimated at home revealed some inconsistencies compared to laboratory measurements. Firstly, the features from the raw insole data exhibited large SD in transition duration calculation as well as in comparison with the trunk estimation. It is highly probable that quiet sitting in real-life occurs without placing weight on the feet: e.g. sitting with feet on a stool, or with ankles on the ground and feet pointing upwards. In this case  $S_1$  detection becomes problematic, since the lower level of the transition does not correspond to the feet weight level. As for the end event, several transitions could also occur where the person starts walking immediately after standing, without achieving a quiet standing phase. This resulted in an overestimation of  $E_1$ . The wavelet approximation was necessary to improve the detection in such cases and emphasize pertinent transition events. The cutoff frequency of the wavelet corresponding to a minimum

of 1.28s TD is suitable for this estimation since it is lower than observations in healthy young and older adult persons reported in the literature [294].

The combinations that were retained from the in-lab study based on the wavelet transform did not compare well to  $TD_T$  in real-life. This could be due to the different strategies of PTs in real-life and to the existence of frequent Sit-to-walk or walk-to-Sit (with turning) transitions that do not mirror in-lab, controlled transitions. However, it should also be noted that TD from the trunk is affected by upper body sway. The overestimation of TD by the trunk IMU could be due to the tilt starting before the load is transferred to the feet. It could be of interest to use another sensor that is less sensitive to sway (e.g. IMU on the thigh) to estimate TD and compare the performances to insole-based estimations since both sensors would be on the lower limb and the TD differences (especially the SD) could be smaller.

The accurate classification and characterization of PTs can provide information about activity behavior. Older adults were significantly slower in performing transitions at home. This result illustrates very well the importance to monitor activity in real-life conditions as performance can be differ substantially from those measured during the more controlled and potentially stimulating in lab environment. Indeed, this result further support previous observation that participants tend to perform better in constrained environments when performing clinical tests in the presence of an observer. Furthermore, the posture of a subject can be accurately obtained using the instrumented shoes. This provides crucial information on sedentary behavior of subjects and in turn can help break down long periods without movement, which has shown several benefits [309].

## **4.5 Study limitations**

This study has some drawbacks. Firstly, sample size was limited and both participant groups consisted of only healthy, able-bodied persons. The application of the PT classification and characterization using instrumented insoles would provide valuable parameters for at-risk populations such as frail older adults or stroke patients. This would ultimately be the main purpose of the proposed algorithm. Secondly, the characterization of PTs from plantar force data can only inform about the duration and the different phases of a transition. Additional analyses would be required to evaluate the potential of estimating more parameters such as movement smoothness or the number of attempts at performing a transition. Combining instrumented insoles and a trunk IMU can be extremely powerful in clinical PT analysis by making power calculations possible. Thirdly, sit-to-walk and walk-to-sit transitions were not included in the protocol. These transitions are relevant for clinical mobility tests such as the TUG and could better reflect daily life transitions.

## **5 Conclusion**

The proposed instrumented insole system was validated for estimating transition durations and accurately classifying postural transitions in daily life. This system was also validated for activity monitoring and gait analysis in daily life. The combination of activity classification in terms of postures and detailed characterization of gait/transitions offers an “all-in-one” assessment tool that can provide crucial information about activity pattern and behavior in at-risk subjects. In turn, this information could help clinicians in better tailoring individual interventions as well as in providing useful feedback to patient to promote increased mobility and activity to improve their quality of life. The instrumented shoes are comfortable and unobtrusive and provide the possibility of concealing the sensors in footwear to avoid stigmatization. This is an advantage with respect to other systems for postural transition characterization such as IMU on the trunk or the thigh that are sometimes difficult to conciliate with real-life activities.

## Chapter 6

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### *Outcome evaluation of elderly inpatients during rehabilitation after hip fracture using instrumented shoes*

#### **Abstract**

Measurement of recovery in post-surgery hip fracture patients is crucial for clinicians to assign an appropriate discharge date. Hip fracture patients walk very soon after surgery to regain functional mobility and therefore a detailed analysis of their activity behavior as well as their gait is important. This is usually assessed by standardized clinical test scores that rely on clinical observation and functional tests. However, these tests give no information about daily behavior of patients. In this chapter, instrumented shoes are used to monitor one day of activity in post-surgery hip fracture patients as soon as they are able to walk and two weeks later. Patients follow a rehabilitation program between these monitoring days and its effects are evaluated using the Tinetti clinical score as well as objective metrics from instrumented shoes in four categories: activity, load, gait, and complexity. Results revealed improvements in the expected direction as revealed by the Tinetti test for almost all objective metrics, especially load, complexity, and maximum locomotion duration. Objective metrics proved to be complementary to the clinical score since they revealed changes in subjects whose scores did not improve much, whereas they followed the Tinetti score well in subjects whose improvement was substantial.

## **1 Introduction**

Hip fracture is associated with high mortality and morbidity rates [310], [311]. Mortality rates one year post hip fracture in geriatric population have exceeded 20%, and it appears that this number has not significantly decreased over the past 30-40 years [312]. Cooper et al. [313] projected that more than 6 million annual hip fracture cases will occur in the world by the year 2050. The consequences of hip fracture on daily life mobility in older adults are drastic. Between 32-80% of hip fracture survivors develop a permanent disability even after hospitalization, and 6-60% need long-term professional care [314]. The two main treatments of hip fracture are hip fracture surgery (i.e. bone fixation) and total hip replacement, the former having higher mortality rates than the latter [315]. The goal of these treatments remains to restore mobility of patients to pre-fracture levels. At the clinic, patients who walk in the first two days after surgery benefit more than patients who walk later on in terms of overall mobility [316]. In a prospective follow-up study up to 2 years after hip fracture, Alarcón et al. [317] found that activities such as grooming and feeding have higher rates of improvement, whereas transferring from a chair and negotiating stairs had improvement probabilities of less than 70% after 2 years. This overview highlighted the importance of behavior monitoring in post-surgery hip fracture patients at the clinic and at home to better understand the rehabilitation process and possibly improve it.

Wearable activity monitoring has found relevant applications in mobility assessment of older adults [93]. Sensors consisting of accelerometers and/or gyroscopes (known as Inertial Measurement Units or IMUs) have been predominantly employed and mostly placed on the sternum, waist, thigh, shank, and wrists. However, relatively few wearable sensor systems have been used for the evaluation of post-surgery hip fracture patients. Accelerometers were used in conjunction with force plate to evaluate balance post operatively [318]. Activity counts obtained from wrist- and ankle-attached accelerometers correlated well with a patient participation score evaluated by the therapist during physiotherapy sessions [319]. In terms of daily life assessment, Taraldsen et al. [320] used a uniaxial accelerometer placed on the thigh to monitor activity for 24 hours at 4 days after surgery. They showed that time spent in upright posture after a comprehensive geriatric care (including early mobilization) that was purposefully developed for hip fracture rehabilitation was higher than that after traditional orthopedic care and physiotherapy. The study was followed by at-home monitoring 4 and 12 months post-surgery and showed similar results for time spent upright based on treatment type [321]. Accelerometers were also used to monitor hip fracture inpatients for 5 days and activity count outcomes were shown to correlate well with a rehabilitation participation measure evaluated by therapists, and higher activity levels during these 5 days were associated with better mobility recovery at 3 and 6 months postoperative follow-up [322]. Posture was evaluated using a thigh-based accelerometer and showed that post-surgery hip fracture patients spend ~99% of the time in sitting/lying

posture, ~1% standing and 0.05% walking, resulting in an average of 35 steps per day [323]. Benzinger et al. [324] performed a longitudinal study with post-surgery hip fracture inpatients and monitored one day of activity at baseline and 2-week follow-up using a trunk-worn IMU. They revealed improvements in time spent walking and upright, as well as significant correlations of these two parameters with clinical tests such as the Timed Up and Go and the 5-Chair-rise.

It is evident, from this overview of wearable assessment of hip fracture, that time spent in different postures is important. However, there are other potential outcomes that could be highly associated with rehabilitation such as gait parameters and foot loading obtained during daily activity. We have already validated the use of instrumented shoes for activity classification, postural transition detection, gait analysis, load evaluation, and complexity assessment in older adults in Chapters 3-5. In this study, we use all the aforementioned outcomes to evaluate the rehabilitation outcome of geriatric post-surgery hip fracture inpatients in a prospective study. We hypothesize that the rehabilitation process will improve the mobility of the patient and this improvement can be perceived by objective metrics derived from instrumented shoes expressing various aspects of mobility, like activity profile, gait performance, load distribution, and behavioral complexity. With this objective information, we expect that clinicians could better evaluate various rehabilitation aspects and therefore propose tailored treatment to improve the rehabilitation in hip fracture.

## **2 Methods**

### **2.1 Participants and measurements**

Post-surgery hip fracture patients admitted to the rehabilitation center of the university hospital (CHUV) were recruited for this study. Inclusion criteria were:

- Unilateral hip fracture admitted to post-acute care rehabilitation
- Ability to walk 20m (with or without cane/walker)
- Shoe size 38-45 (imposed by the available insole sizes)

Exclusion criteria were:

- Important symptomatic mood disorder (clinical assessment)

- Cognitive impairment (MMS<sup>1</sup> < 18)
- Ongoing delirium (CAM<sup>2+</sup>)
- Uncontrolled pain (VAS<sup>3</sup> > 6) during mobilization
- Assistance of a person for walking
- Limited life expectancy (<6 months)

In total, eight patients, four men and four women, were enrolled in the study. All patients signed informed consent and the protocol was accepted by the cantonal ethical committee. Patients were screened shortly after their admission to the rehabilitation center. The first measurement took place as soon as possible (1 day in most cases) after consent and inclusion and the second measurement 14 days later, before discharge from the rehabilitation center (Figure 6-1). During these 14 days, patients followed an interdisciplinary and individualized rehabilitation program with the goal to preserve autonomy, quality of life, and to prevent falls or adverse events stemming from falls. During physiotherapy, treatment is tailored to improve joint mobility, muscle force, equilibrium and cardiovascular endurance through individual as well as group sessions. Adaptation to walking aids is also performed. In the morning on each monitoring day, the participants' shoes were equipped with the monitoring system described in section 2.2. Patients were free to keep their own shoes or to use hospital shoes if they were more comfortable. They then performed a 20m walking test in the presence of a physiotherapist to assess gait parameters in a supervised setting over a relatively long path. This test was completed in the corridor of the floor where the patients were residing. Afterwards, patients were asked to keep on their instrumented shoes during the day for at least 8 hours, after which a study investigator removed the monitoring system. A bed protection was placed in case participants wanted to lie down with their shoes on in the day. At the end of each monitoring day, the data collected from the monitoring system was downloaded on a computer and stored anonymously for post-processing. Additionally, the Tinetti test score was available for each patient at baseline and follow-up as a clinical mobility score. This test consists of balance and gait assessment with 17 items ranked over 28 points [325].

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<sup>1</sup> Mini Mental State examination

<sup>2</sup> Confusion assessment method

<sup>3</sup> Visual analog scale pain assessment



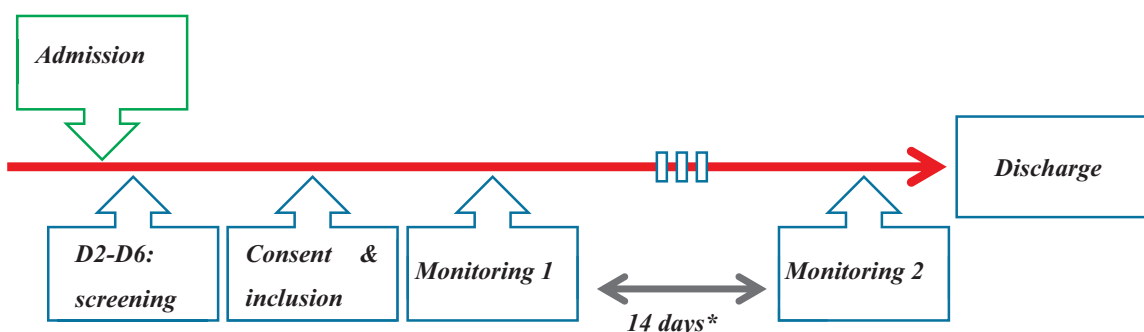


Figure 6-1 - Flowchart of the study protocol with intermediate steps from admission to discharge for participants. \*the decision to have 14 days between measurements is based on a median hospitalization time of 25 days (interquartile range 18-35) for geriatric hip fracture rehabilitation obtained from the geriatric service yearly statistics.

## 2.2 Instrumented shoe system

The monitoring system included an inertial measurement unit or IMU (Physilog®, GaitUp, CH) and a pressure sensing insole (Smart Insole, IEE, LU). The IMU measures 3D acceleration, 3D angular velocity and barometric pressure and functions as data logger and power unit. The insole measure plantar force at 8 locations under the foot, namely the heel (medial and lateral), the arch (lateral), the metatarsals (1<sup>st</sup>, 3<sup>rd</sup> and 5<sup>th</sup>) and the toes (hallux and the remaining toes). Converting electronics that perform digitization and amplification of the insole signals were strapped to each patient’s ankles. Insoles were inserted into each foot and the IMUs were placed on the dorsal aspect of each foot. The system components are shown in Figure 6-2. The sampling frequency was set at 200Hz for all sensors, allowing an autonomy of up to 16 hours.

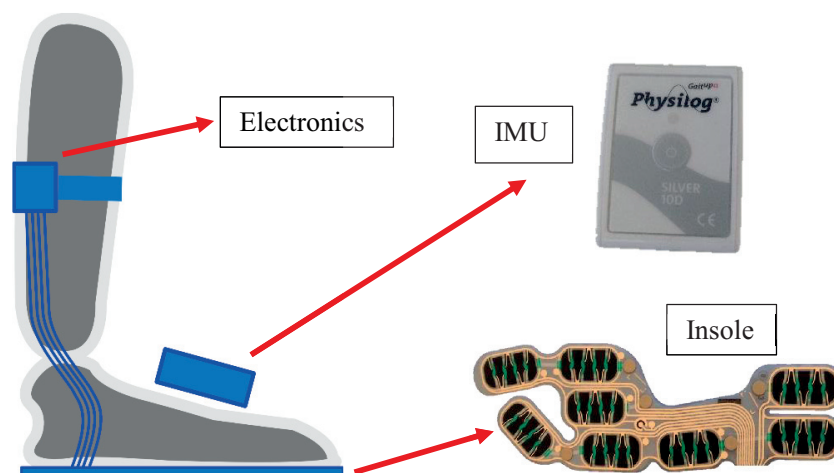


Figure 6-2 - Instrumented shoe system: Physilog® inertial sensor placed on the shoe, insole inserted inside the shoes and converting electronics placed above the ankle.

## 2.3 Outcome analysis

There were four main outcome measures in this study: activity profile, foot loading, gait performance, and behavioral complexity. Each outcome is described separately below.

### 2.3.1 Activity profile

The sensor data obtained from the instrumented shoes system were fed into the activity classifier previously described in Chapters 3, 4, and 5. In summary, the classifier detected the Toe Off instants from the pitch (mediolateral) gyroscope signal enhanced by wavelet decomposition. These instants were then used to detect locomotion. The total force ( $TF$ ), under the feet was calculated as the sum of all 16 sensors from both insoles and normalized to body weight (0-100%). The low and high levels of  $TF$  were estimated using a histogram and transitions from low to high level were recognized as sit to stand (SiSt) and high to low level as stand to sit (StSi). Activity preceding a SiSt was labeled as sitting, and following a SiSt as standing. For each patient and each monitoring day, the percentage of time spent in each of these three basic activities (i.e. sitting, standing and walking) was calculated. The number of locomotion periods and their durations were also retrieved, as well as the total number of postural transitions and their duration.

### 2.3.2 Foot loading

Load symmetry was evaluated based on the total plantar force measured from the insoles. In order to have an estimate of loading value under each foot, the sum of all sensors from each left (L) and right (R) foot was obtained ( $TF_{L,R}$ ) by considering the entire monitoring duration. Then a histogram was applied ( $hist(TF_{L,R}, bin)$ ) and the median value of  $TF_{L,R}$  ( $TF_{L,R med}$ ) was estimated to separate loading range ( $TF_{L,R} > TF_{L,R med}$ ). The loading of each foot ( $Load_{L,R}$ ) corresponded to the value of  $TF_{L,R}$  with the highest probability in the loading range:

$$Load_{L,R} = \max\left(hist(TF_{L,R}, bin)\right), TF_{L,R} > TF_{L,R med}. \quad (\text{eq. 1})$$

This level was then used to estimate the loading on the affected and unaffected side ( $Load_{affected}$ ,  $Load_{unaffected}$ ) and loading symmetry index ( $LSI$ ), defined as:

$$LSI = abs\left(\frac{Load_{affected} - Load_{unaffected}}{Load_{affected} + Load_{unaffected}}\right) \quad (\text{eq. 2})$$

Hence, a decrease in  $LSI$  would indicate improvement in loading symmetry.

### 2.3.3 Spatio-temporal gait analysis

The analysis of locomotion periods is similar to that of Chapter 4. For locomotion bouts of more than 20 steps spatio-temporal parameters were obtained based on the following references [126], [136], [137], [141]. These parameters were separated into three types: performance, symmetry, and variability as detailed below:

- Performance: stride velocity ( $SV$ ), stride length ( $SL$ ), cadence ( $cad$ ), heel clearance ( $HC$ ), toe clearance ( $TC$ ), %stride, number of turning steps per bout ( $\#Turning/bout$ ), i.e. steps with axial turning angle  $> 20^\circ$
- Symmetry: symmetry index ( $SI$ ) of maximum heel clearance ( $HC$ ), minimum toe clearance ( $TC$ ), percent stance time:

$$SI = abs\left(\frac{Parameter_{affected} - Parameter_{unaffected}}{Parameter_{affected} + Parameter_{unaffected}}\right) \quad (\text{eq. 3})$$

- Variability: mean and SD of  $GCT$  inter-stride variability calculated from the coefficient of variation ( $CV$ ):

$$CV = 100 \times \frac{\sigma_{GCT}}{\mu_{GCT}} \quad (\text{eq. 4})$$

Where  $\sigma_{GCT}$  is the standard deviation of gait cycle time ( $GCT$ ) and  $\mu_{GCT}$  the mean of  $GCT$  over one walking bout. All parameters were also calculated for the 20m walking test to compare the capacity of patients during the clinical test and their performance in daily life.

Finally, a fourth category was defined as the gait profile: for any locomotion period with 3 or more detected steps, the duration of each gait cycle ( $GCT$ ) was estimated and converted to Instantaneous Cadence or  $Icad$  (eq. 5) and its histogram was estimated for the whole recording.

$$Icad = 120/GCT \quad (\text{eq.5})$$

For each parameter, the analysis was conducted on the mean value for each subject as well as the 90<sup>th</sup> percentile to evaluate the improvement of extreme parameter values.

### 2.3.4 Behavioral complexity

Complexity was evaluated similarly to Chapter 4. For each patient and monitoring day, activity barcodes were constructed from the activity type (sitting, standing and walking) as well as the intensity (duration of walking period and cadence). The complexity metric for each barcode was then calculated using the Lempel-Ziv ( $LZ$ ) definition of the Kolmogorov complexity [280].

### 2.3.5 Comparative analysis

For each of the aforementioned parameters, statistical significance was evaluated between baseline and follow-up monitoring days using the Wilcoxon Rank-sum non-parametric test. For each tested variable, the significance is mentioned at the 5% level (\*), 1% level (\*\*) and 0.1% level (\*\*\*).

An effect size descriptor was used in this study to evaluate parameters with low sample size. This descriptor was Cliff's delta, a measure of how many values at baseline are larger than values at follow-up for a given parameter. It is calculated using eq. 4:

$$Cliff's\ delta = \frac{\#(P_{B,i} > P_{F,i}) - \#(P_{B,i} < P_{F,i})}{N(P_B) \times N(P_F)} \quad (\text{eq. 6})$$

Where  $P_{B,i}$  and  $P_{F,i}$  are the elements of the parameter at baseline and follow-up, respectively,  $N(P_B)$  and  $N(P_F)$  the total number of elements of the parameter at baseline and follow-up, respectively. This measure is also non-parametric in the sense that it does not need the data to follow any pre-assumed distribution. Cliff's delta represents the percentage of non-overlap between the baseline and follow-up vectors for each parameter and can range between -1 to +1. The sign is an indicator of the trend direction: negative sign for an increasing trend and positive sign for a decreasing trend. A higher absolute value of

this descriptor indicates a high effect size i.e. low overlap between baseline and follow-up. Three thresholds are available effect size, low:  $0.147 < \text{Cliff's delta} < 0.33$ , moderate:  $0.33 < \text{Cliff's delta} < 0.474$  and high:  $0.474 < \text{Cliff's delta}$  [326].

In addition to effect size the relative improvement (%change) of each patient was calculated for each selected parameter and clinical score by eq. 5:

$$\%change = \frac{P_F - P_B}{P_B} \quad (\text{eq. 7})$$

For parameters with several values per subject (i.e. transition duration and gait parameters), results are shown for the mean and 90<sup>th</sup> percentile obtained for each subject.

### 3 Results

Patient characteristics are shown in Table 6-1. The Tinetti test results reveal an improvement in all patients except for ID 7 whose score remained the same. The change of Tinetti score at follow-up was significant ( $p < 0.001$ ) compared to baseline.

Table 6-1 - Patient characteristics with MMS and Tinetti scores

<i>ID</i>	<i>Age</i>	<i>Gender</i>	<i>Affected side</i>	<i>MMS</i>	<i>Tinetti (baseline)</i>	<i>Tinetti (follow-up)</i>
<i>1</i>	<i>92</i>	<i>Female</i>	<i>Left</i>	<i>22</i>	<i>18</i>	<i>20</i>
<i>2</i>	<i>83</i>	<i>Male</i>	<i>Left</i>	<i>28</i>	<i>15</i>	<i>23</i>
<i>3</i>	<i>90</i>	<i>Female</i>	<i>Right</i>	<i>19</i>	<i>18</i>	<i>20</i>
<i>4</i>	<i>69</i>	<i>Male</i>	<i>Right</i>	<i>30</i>	<i>18</i>	<i>21</i>
<i>5</i>	<i>90</i>	<i>Female</i>	<i>Right</i>	<i>27</i>	<i>17</i>	<i>20</i>
<i>6</i>	<i>80</i>	<i>Female</i>	<i>Right</i>	<i>27</i>	<i>18</i>	<i>22</i>
<i>7</i>	<i>92</i>	<i>Male</i>	<i>Right</i>	<i>29</i>	<i>21</i>	<i>21</i>
<i>8</i>	<i>93</i>	<i>Male</i>	<i>Right</i>	<i>28</i>	<i>15</i>	<i>23</i>
<i>Mean±SD</i>					<i>17±2</i>	<i>21±1</i>

#### 3.1 Activity profile

The percentage time of each activity during the 8 hours monitoring is shown in Figure 6-3. Based on the Wilcoxon Rank-sum test, no significant differences between baseline and Follow-up were determined for sitting ( $p = 0.08$ ), standing ( $p = 0.10$ ) nor walking ( $p = 0.07$ ). However, the p-values are small and close to the 5% significance level. Furthermore, a trend could be seen in the data confirming that less time is spent sitting and more time is accumulated for standing and walking, indicating improvement in overall mobility.

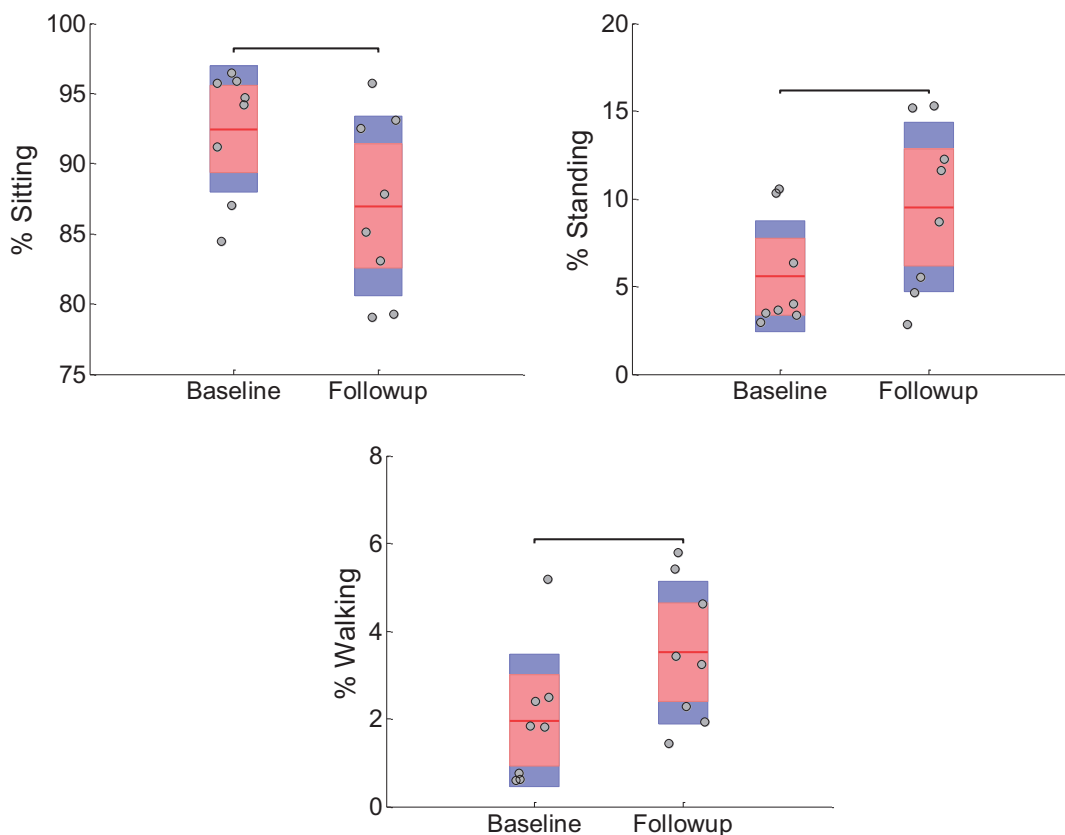


Figure 6-3 - Percent of time spent in each basic posture: sitting (top left), standing (top right), and walking (bottom). No significant changes were determined but a trend of improvement can be observed.

Patients performed  $21 \pm 11$  sit-to-stand and  $21 \pm 11$  stand-to-sit transitions at baseline compared to  $26 \pm 13$  sit-to-stand and  $26 \pm 13$  stand-to-sit at follow-up. The number increased but not significantly ( $p = 0.45$  for both). The transition duration at baseline was  $2.49 \pm 0.79$  compared to  $2.53 \pm 0.66$  at follow-up with no significant change ( $p = 0.30$ )

The analysis of locomotion periods is presented in Table 6-2. Total, maximum, and mean duration as well as the total number of locomotion bouts all showed improving trends, but only the maximum walking duration was significantly higher at follow-up.

Table 6-2 - Locomotion period characterization shown as mean±SD for all subjects at baseline and follow-up

<i>Parameter</i>	<i>Baseline (mean±SD)</i>	<i>Follow-up (mean±SD)</i>	<i>p-value</i>
<i>Total duration (min)</i>	<i>9.20±7.22</i>	<i>15.42±6.41</i>	<i>0.083</i>
<i>Maximum duration (sec)</i>	<i>51.75±18.26</i>	<i>77.67±35.39</i>	<i>0.028*</i>
<i>Mean duration (sec)</i>	<i>13.33±3.16</i>	<i>14.23±3.59</i>	<i>0.57</i>
<i>Total number (bouts)</i>	<i>41.50±26.75</i>	<i>70.50±35.68</i>	<i>0.10</i>

The empirical cumulative distribution of locomotion bout durations is shown in Figure 6-4. The curves are practically superimposed until ~1.5min. The follow-up distribution goes further until ~2.6min, confirming the significant change in maximum duration rather than mean or total locomotion bout duration.

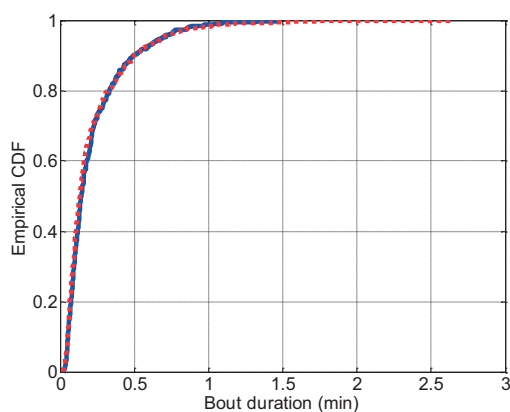


Figure 6-4 - Empirical cumulative distribution function for locomotion bout duration. Solid line: baseline, dashed line: follow-up

### 3.2 Load evaluation

Figure 6-5 shows the load symmetry evaluation using *LSI* defined in section 2.3.2 of this chapter. *LSI* revealed significant improvements in loading symmetry as demonstrated by the Wilcoxon Rank-Sum test ( $p = 0.01$ ) with values of  $0.22 \pm 0.12$  at baseline and  $0.10 \pm 0.06$  at follow-up.

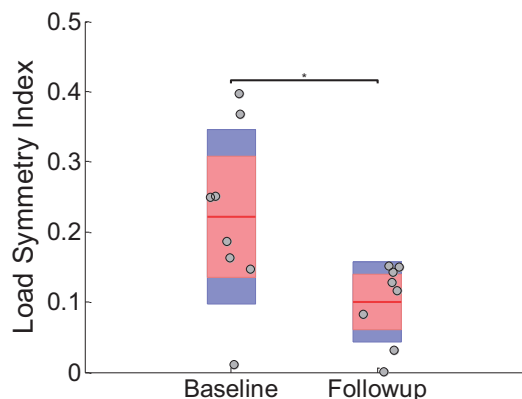


Figure 6-5 - Load symmetry obtained from the load symmetry index. Significant difference at the 5% significance level was observed between baseline and follow-up.

An example of the *LSI* is shown in Figure 6-6. The level obtained from the histogram improved drastically for the affected side (right). It is also noticeable that the maximum peaks are closer between both sides at follow-up. Interestingly, a drastic improvement in cadence can be seen between baseline and follow-up as well.

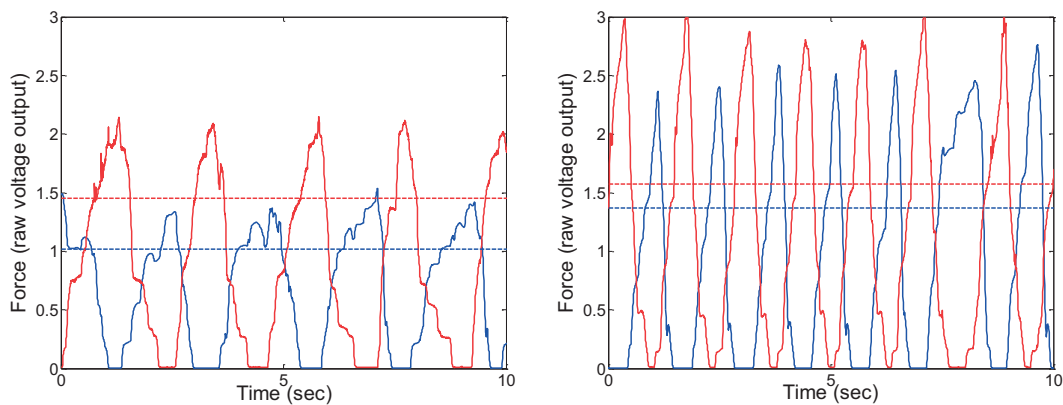


Figure 6-6 - Load symmetry example from subject 4 with a 10 second snapshot of walking at baseline (left panel) and follow-up (right panel). Blue: right foot, red: left foot. Dashed lines: blue, right load level and red, left load level.



### 3.3 Spatio-temporal gait parameters

#### 3.3.1 Daily life gait

The gait performance metrics are shown in Table 6-3. These values represent the mean±SD for the mean and 90<sup>th</sup> percentile of each parameter obtained from each subject. All parameters improved in the expected direction but none significantly, except for the 90<sup>th</sup> percentile of cadence which did not improve.

Table 6-3 - Gait performance metrics for baseline and follow-up. Values are mean±SD of the mean value and 90<sup>th</sup> percentile of each subject and p-values are shown for each metric

<i>Performance</i>	<i>Baseline</i>	<i>Follow-up</i>	<i>p-value</i>
<i>SV (m/s) mean</i>	<i>0.31±0.11</i>	<i>0.38±0.09</i>	<i>0.23</i>
<i>SV (m/s) 90<sup>th</sup> percentile</i>	<i>0.40±0.14</i>	<i>0.50±0.11</i>	<i>0.16</i>
<i>SL (m) mean</i>	<i>0.58±0.21</i>	<i>0.63±0.17</i>	<i>0.44</i>
<i>SL (m) 90<sup>th</sup> percentile</i>	<i>0.73±0.25</i>	<i>0.77±0.16</i>	<i>0.57</i>
<i>Cad (steps/min) mean</i>	<i>68.22±16.50</i>	<i>73.71±14.07</i>	<i>0.38</i>
<i>Cad (steps/min) 90<sup>th</sup> percentile</i>	<i>86.54±17.16</i>	<i>86.22±16.74</i>	<i>0.96</i>
<i>#Turning/bout (steps)</i>	<i>3.18±1.57</i>	<i>2.87±1.70</i>	<i>0.59</i>

The instantaneous cadence distribution obtained from all locomotion bouts is shown in Figure 6-7. The distribution at baseline is unimodal with peak cadence mode of 66.2steps/min, whereas the distribution at follow-up exhibits a shift to the right indicating increasing peak cadence mode at 82.5steps/min. A second, lower mode can be observed at 62.5steps/min. At baseline, *Icad* means were 73.62±16.79 and 90<sup>th</sup> percentile 94.03±17.52, whereas means at follow-up were 77.79±13.79 and 90<sup>th</sup> percentile 99.66±14.24 with p-values of 0.65 and 0.27, respectively.

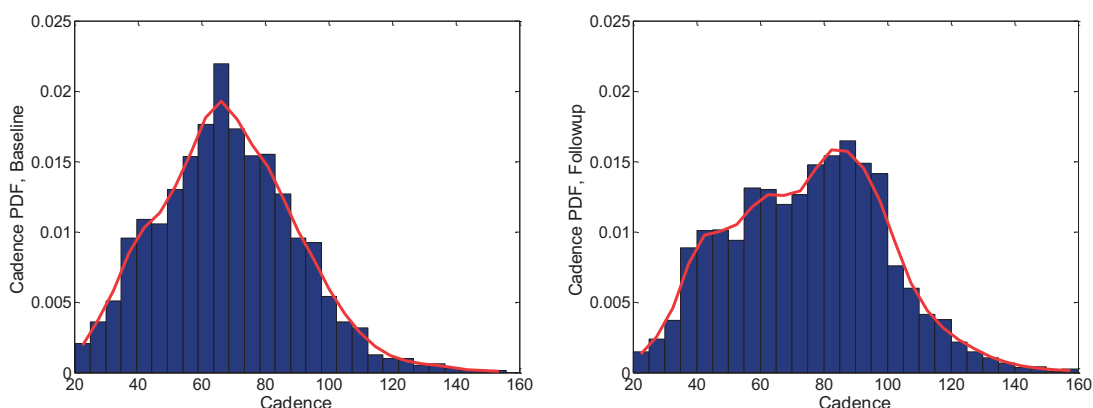


Figure 6-7 - Instantaneous cadence (*Icad*) distribution (probability density function: PDF) at baseline (left) and follow-up (right)

Symmetry metrics are summarized in Table 6-4. Heel clearance and %*stance SI* improved in the expected direction, whereas mean *TC SI* did not improve and 90<sup>th</sup> percentile *TC SI* worsened. None of the changes were significant.

Table 6-4 – Clearance (*HC*, *TC*) and stance parameters (%*stance*) for affected and unaffected hip with their symmetry index (*SI*) at baseline and follow *p*-values indicate significant changes between *SI* at baseline and follow-up. Baseline and follow-up columns show unaffected/affected mean±SD for each parameter

<i>Parameter</i>	<i>Baseline</i>	<i>Follow-up</i>	<i>SI</i> <i>Baseline</i>	<i>SI</i> <i>follow-up</i>	<i>p</i> - <i>value</i>
<i>HC (m) mean</i>	0.15±0.05/0.20±0.07	0.17±0.03/0.22±0.04	0.28±0.16	0.17±0.10	0.10
<i>HC (m) 90<sup>th</sup> percentile</i>	0.22±0.06/0.26±0.06	0.23±0.03/0.27±0.04	0.51±0.25	0.32±0.12	0.10
<i>TC (m) mean</i>	0.03±0.01/0.02±0.01	0.03±0.01/0.03±0.01	0.17±0.13	0.17±0.10	0.62
<i>TC (m) 90<sup>th</sup> percentile</i>	0.03±0.01/0.03±0.01	0.04±0.01/0.03±0.01	0.28±0.17	0.37±0.21	0.38
<i>%Stance (mean)</i>	68.42±9.53/74.64±6.12	66.46±6.53/71.55±5.45	0.08±0.04	0.07±0.04	0.28
<i>%Stance (90<sup>th</sup> percentile)</i>	76.46±9.80/82.66±5.50	74.00±7.20/78.45±5.21	0.16±0.08	0.13±0.08	0.19

Gait cycle time variability was 14±19 at baseline and decreased to 12±9 at follow-up but the change was not significant (*p* = 0.1).

### 3.3.2 20m gait test

The gait performances for the 20m test are shown in Table 6-5. Stride velocity, length, and cadence all increased but none significantly.

Table 6-5 - Gait performances over 20m test

<i>Performance</i>	<i>Baseline</i>	<i>Follow-up</i>	<i>p-value</i>
<i>SV (m/s) mean</i>	<i>0.41±0.16</i>	<i>0.49±0.17</i>	<i>0.44</i>
<i>SV (m/s) 90<sup>th</sup> percentile</i>	<i>0.46±0.17</i>	<i>0.55±0.18</i>	<i>0.51</i>
<i>SL (m) mean</i>	<i>0.69±0.20</i>	<i>0.74±0.17</i>	<i>0.72</i>
<i>SL (m) 90<sup>th</sup> percentile</i>	<i>0.76±0.19</i>	<i>0.83±0.19</i>	<i>0.65</i>
<i>Cad (steps/min) mean</i>	<i>70.74±21.32</i>	<i>77.88±15.60</i>	<i>0.57</i>
<i>Cad (steps/min) 90<sup>th</sup> percentile</i>	<i>76.68±21.81</i>	<i>87.94±13.66</i>	<i>0.28</i>

The symmetry parameters for the 20m gait tests are shown in Table 6-6. *HC* and *%stance* symmetry improved, but *TC* symmetry increased. None of the parameters changed significantly. It is interesting to note, however, that *HC* and *%stance* of both affected and non-affected sides improved in the expected direction.

Table 6-6 - Symmetry parameters for 20m test, Baseline and Follow-up show affected/non-affected values

<i>Parameter</i>	<i>Baseline</i>		<i>Follow-up</i>		<i>p-value</i>
	<i>SI</i>	<i>SI</i>	<i>SI</i>	<i>SI</i>	
<i>HC (m) mean</i>	<i>0.18±0.07</i>	<i>0.20±0.06</i>	<i>0.19±0.04</i>	<i>0.21±0.03</i>	<i>0.28</i>
<i>HC (m) 90<sup>th</sup> percentile</i>	<i>0.22±0.07</i>	<i>0.23±0.05</i>	<i>0.22±0.07</i>	<i>0.24±0.03</i>	<i>0.13</i>
<i>TC (m) mean</i>	<i>0.03±0.01</i>	<i>0.03±0.00</i>	<i>0.03±0.01</i>	<i>0.03±0.00</i>	<i>0.71</i>
<i>TC (m) 90<sup>th</sup> percentile</i>	<i>0.03±0.01</i>	<i>0.03±0.00</i>	<i>0.03±0.01</i>	<i>0.03±0.01</i>	<i>0.62</i>
<i>%Stance (mean)</i>	<i>65.70±8.24</i>	<i>72.17±5.32</i>	<i>64.71±4.76</i>	<i>68.25±5.18</i>	<i>0.65</i>
<i>%Stance (90<sup>th</sup> percentile)</i>	<i>71.51±7.95</i>	<i>77.43±6.51</i>	<i>69.71±5.97</i>	<i>72.49±6.21</i>	<i>0.65</i>

Gait cycle time variability for the 20m test was 9±5 at baseline and 9±6 at follow up with  $p = 0.83$  indicating no statistical difference.

### 3.4 Complexity analysis

The LZ complexity calculated at baseline and follow-up is shown on the box plot, Figure 6-8. The Wilcoxon Rank-Sum test revealed a significant difference between baseline and follow-up ( $p = 0.04$ ).

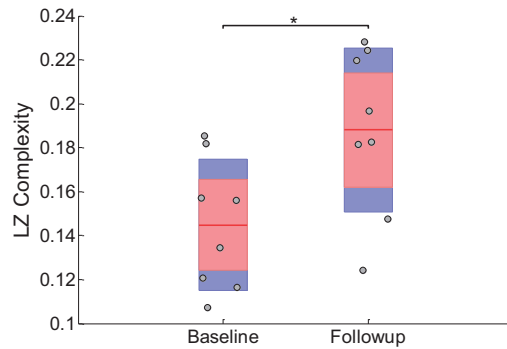


Figure 6-8 – Box plot of the LZ complexity metric for baseline and follow-up for all 8 patients

Barcodes of all patients are shown in Figure 6-9. It is evident from the plots that baseline barcodes are less rich in both the number of changes from one activity to another and in the presence of higher intensity activities revealed by the warmer colors, compared to follow-up barcodes.

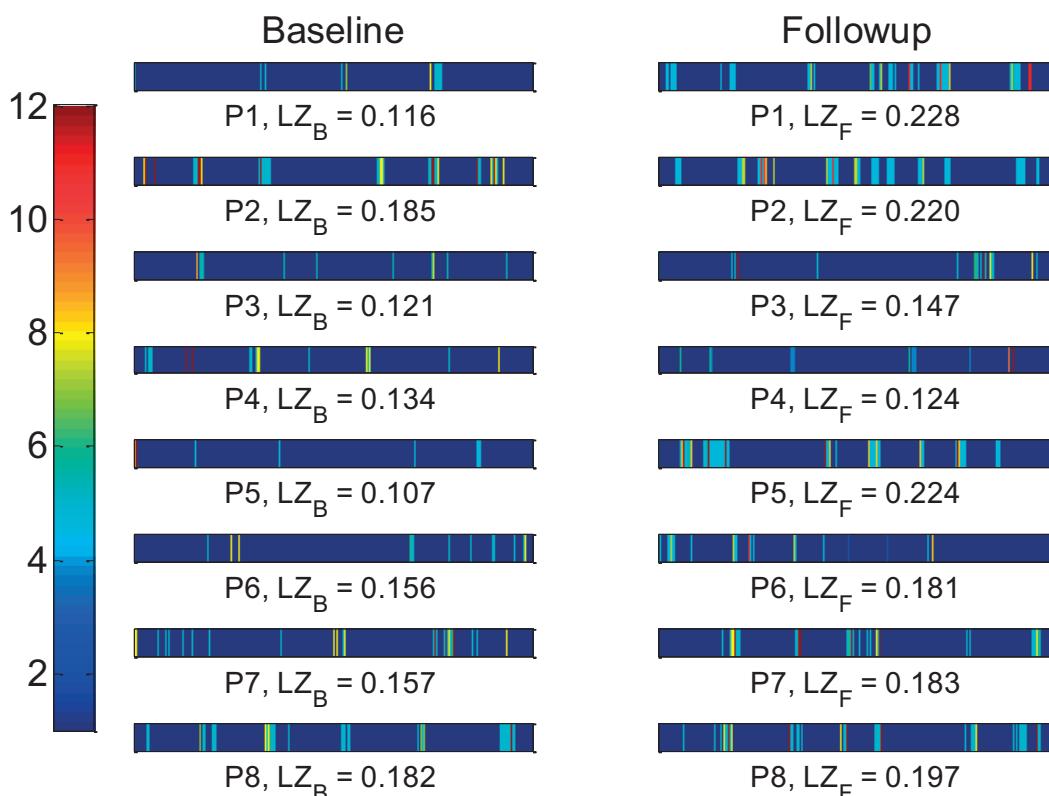


Figure 6-9 - Activity barcodes for all patients at baseline (left) and follow-up (right) showing the values of the LZ complexity. The color code represents the different activity intensities explained in Chapter 4.  $LZ_B$  and  $LZ_F$  refer to baseline and follow-up complexity values, respectively.

### 3.5 Comparative analysis

The sensitivity to change and effect size of each metric is shown in Table 6-7. Besides the Tinetti clinical test, the following objective metrics revealed high effect sizes: %sit, %stand, %walk, total locomotion duration, maximum locomotion duration, total number of locomotion bouts, LZ complexity, load SI and HC SI (both mean and 90<sup>th</sup> percentile). Table 6-8 shows the values at baseline and follow-up as well as the percent change (highlighted) for each subject of all parameters with high effect size highlighted in Table 6-7.

Table 6-7 - Percent change and Cliff's delta for all parameters. Parameters with Cliff's delta higher than 0.474 are highlighted

<i>Clinical tests</i>	<i>%change (mean±SD)</i>	<i>Cliff_delta</i>
<i>Tinetti***</i>	<i>23.18±19.72</i>	<i>-0.88</i>
<i>Activity &amp; Complexity metrics</i>		
<i>% sit</i>	<i>-5.84±6.53</i>	<i>0.53</i>
<i>% stand</i>	<i>102.66±153.41</i>	<i>-0.50</i>
<i>% walk</i>	<i>214.80±325.83</i>	<i>-0.56</i>
<i>Total duration (min)</i>	<i>179.92±247.03</i>	<i>-0.53</i>
<i>Maximum duration* (sec)</i>	<i>59.51±71.51</i>	<i>-0.66</i>
<i>Mean duration (sec)</i>	<i>10.45±32.72</i>	<i>-0.19</i>
<i>Total number (bouts)</i>	<i>194.47±309.36</i>	<i>-0.50</i>
<i>#transitions</i>	<i>30.92±54.99</i>	<i>-0.23</i>
<i>TD (mean)</i>	<i>-0.36±23.52</i>	<i>0</i>
<i>TD (90<sup>th</sup> percentile)</i>	<i>-0.63±24.87</i>	<i>0.09</i>
<i>LZ complexity*</i>	<i>34.87±42.87</i>	<i>-0.63</i>
<i>Load and Gait metrics</i>		
<i>Load SI*</i>	<i>105.24±459.58</i>	<i>0.72</i>
<i>SV (mean)</i>	<i>30.62±35.33</i>	<i>-0.38</i>
<i>SV (90<sup>th</sup> percentile)</i>	<i>32.10±35.15</i>	<i>-0.44</i>
<i>SL (mean)</i>	<i>11.48±13.36</i>	<i>-0.25</i>
<i>SL (90<sup>th</sup> percentile)</i>	<i>9.76±17.08</i>	<i>-0.19</i>
<i>Cad (mean)</i>	<i>14.31±23.00</i>	<i>-0.28</i>
<i>Cad (90<sup>th</sup> percentile)</i>	<i>13.06±16.46</i>	<i>-0.22</i>
<i>Icad (mean)</i>	<i>8.84±21.77</i>	<i>-0.16</i>
<i>Icad (90<sup>th</sup> percentile)</i>	<i>7.24±12.60</i>	<i>-0.34</i>
<i>HC, SI (mean)</i>	<i>-29.18±39.80</i>	<i>0.50</i>
<i>HC, SI (90<sup>th</sup> percentile)</i>	<i>-25.11±44.20</i>	<i>0.50</i>
<i>TC, SI (mean)</i>	<i>-1.81±36.87</i>	<i>-0.14</i>
<i>TC, SI (90<sup>th</sup> percentile)</i>	<i>23.13±50.81</i>	<i>-0.23</i>
<i>%stance, SI (mean)</i>	<i>-22.69±20.15</i>	<i>0.34</i>
<i>%stance, SI (90<sup>th</sup> percentile)</i>	<i>-23.66±16.62</i>	<i>0.41</i>
<i>Variability (mean)</i>	<i>-5.65±62.68</i>	<i>0.28</i>
<i>Variability (90<sup>th</sup> percentile)</i>	<i>-3.72±79.12</i>	<i>0.31</i>
<i>#Turning/bout</i>	<i>15.23±77.81</i>	<i>0.17</i>

Table 6-8 - Clinical score and relevant outcome metrics at baseline and follow-up with their percentage of change (%) for each subject highlighted

ID		1	2	3	4	5	6	7	8
Tinetti	B	18.00	18.00	17.00	18.00	21.00	15.00	18.00	15.00
	F	20.00	21.00	20.00	22.00	21.00	23.00	20.00	23.00
	%	11.11	16.67	17.65	22.22	0.00	53.33	11.11	53.33
%sit	B	95.70	94.73	96.47	94.16	91.16	87.06	95.88	84.49
	F	93.09	95.76	79.04	92.54	87.86	85.14	83.11	79.28
	%	-2.73	1.08	-18.07	-1.72	-3.62	-2.20	-13.32	-6.17
%stand	B	3.67	3.46	2.94	4.00	6.35	10.54	3.37	10.32
	F	4.64	2.81	15.18	5.54	8.71	11.63	12.27	15.30
	%	26.19	-18.79	415.95	38.27	37.07	10.33	264.07	48.20
%walk	B	0.63	1.81	0.59	1.84	2.49	2.40	0.75	5.19
	F	2.27	1.43	5.78	1.93	3.43	3.23	4.62	5.42
	%	263.02	-20.84	881.01	4.67	37.87	34.53	513.60	4.52
Total duration	B	2.79	8.53	2.72	8.57	11.65	11.18	3.54	24.65
	F	10.80	6.71	18.81	8.97	16.20	15.03	21.24	25.58
	%	286.41	-21.26	592.95	4.78	38.97	34.40	499.33	3.76
Max duration	B	32.48	52.03	46.48	35.96	62.30	58.36	38.04	88.38
	F	68.26	157.98	60.51	63.15	93.89	70.78	42.47	64.38
	%	110.16	203.62	30.19	75.60	50.71	21.27	11.66	-27.16
Total number (bouts)	B	15.00	39.00	9.00	54.00	48.00	65.00	17.00	85.00
	F	38.00	19.00	76.00	52.00	69.00	71.00	123.00	116.00
	%	153.33	-51.28	744.44	-3.70	43.75	9.23	623.53	36.47
Complexity	B	0.12	0.13	0.11	0.16	0.16	0.18	0.12	0.19
	F	0.15	0.12	0.22	0.18	0.18	0.20	0.23	0.22
	%	22.35	-7.42	109.01	16.27	16.09	8.14	96.05	18.48
Load SI	B	0.16	0.40	0.19	0.25	0.01	0.15	0.37	0.25
	F	0.13	0.00	0.03	0.14	0.15	0.08	0.12	0.15
	%	-20.82	-99.94	-83.47	-43.35	1240.84	-43.21	-68.45	-39.66
HC SI (mean)	B	0.45	0.14	0.11	0.33	0.57	0.17	0.20	0.29
	F	0.11	0.10	0.15	0.20	0.25	0.08	0.11	0.36
	%	-76.21	-27.38	37.66	-41.40	-56.00	-50.15	-44.31	24.37
HC SI (90 <sup>th</sup> percentile)	B	0.96	0.30	0.21	0.62	0.72	0.41	0.39	0.47
	F	0.22	0.24	0.33	0.38	0.43	0.15	0.25	0.52
	%	-77.22	-20.17	62.99	-39.15	-39.86	-62.35	-35.52	10.42

All subjects except for subject 2 decreased sitting and increased standing/walking time. Incidentally, subject 2 was the only one whose complexity decreased. All subjects increased their maximum walking bout duration except for subject 8. Subject 5 had an increasing *LSI* due to very low baseline value, but the follow-up value is close to the range of other subjects. Subjects 3 and 8 had an increase in *HC SI*.

## **4 Discussion**

This study aimed at showing the sensitivity of the instrumented shoes to health improvements. The study was designed in order to produce a significant clinical change in the mobility of post-surgery elderly patients through a 2 weeks rehabilitation program and to show that this clinical change is objectively assessed by metrics provided by the instrumented shoes. The four analysis dimensions were globally sensitive to mobility improvements between baseline and follow-up monitoring days and corroborate the use of instrumented shoes as monitoring tool for clinical rehabilitation analysis.

### **4.1 Activity profile**

The amount of time spent in each posture showed that patients were more active and less sedentary at follow-up. Sitting (including lying as detailed in Chapter 4) time decreased whereas both walking and standing time increased. These results are congruent with a similar longitudinal study where trunk IMU was used for activity monitoring at baseline and 2-week follow-up [324]. Patients completed more postural transitions at follow-up as well. Total, mean, and maximum walking duration increased and so did the total number of walking bouts. Interestingly, only the maximum walking duration exhibited a statistically significant change at the 5% level, indicating a notable improvement in the maximum rather than the mean of walking bout duration. It should be noted that since the study was conducted in a rehabilitation center, long walking periods are limited to the indoor space available, especially straight corridors. The fact that the maximum walking duration increased significantly could mean that patients needed less breaks when negotiating the longest paths during the day, and this is a good indicator of reduced walking fragmentation.

The increase in number of transitions is crucial even though it was not statistically significant. Postural transitions put substantial stress on lower and upper body muscles and their increase shows both a gain in muscle function and postural stability. Furthermore, this could have future implications on the behavior at home after discharge of these patients, since the ability to perform transitions is linked with betted movement independence and lower fall risk.



The sample size of 8 patients remains low to draw conclusions upon statistical significance, but it is evident that all activity metrics obtained from the instrumented shoes exhibited changes in the direction of mobility improvement, and are thus highly encouraging for use in rehabilitation.

## **4.2 Load evaluation**

The loading symmetry is a crucial indicator of improvement in post hip fracture assessment. In this study, the loading symmetry was evaluated by the symmetry index, showing a significant decrease. This means that patients put significantly more weight on their affected side and this could be a clear indicator of rehabilitation success for a clinician. To the best of our knowledge, this is the first time such a parameter is evaluated using instrumented shoes in daily life. Besides the *LSI*, an interesting observation from Figure 6-6 is that peak forces during walking increased for affected and unaffected sides, therefore more total force was exerted during walking. This could be a result of the patient relying less on the walking aid (walker) to support themselves. Therefore, another potential parameter to be measured using the instrumented shoe system could be the improvement of weight bearing percentage using walking aids.

## **4.3 Spatio-temporal gait parameters**

Gait parameters were separated into four categories: performance, symmetry, variability, and profile. The performance metrics exhibited improvement in terms of both mean and 90<sup>th</sup> percentile values. Even though results did not exhibit significant changes, it was previously reported that a minimum change of 0.04 to 0.06 m/s is required for stride velocity changes to be clinically significant [327], and therefore the mean stride velocity change in this study from  $0.31 \pm 0.11$  m/s at baseline to  $0.38 \pm 0.09$  m/s at follow-up is clinically relevant.

During the 20m test, all metrics again changed in the expected direction of improvement (no significant changes were revealed though). However, compared to real-life patients were capable of higher velocities and stride lengths at both baseline and follow-up. This reasserts the importance of real life monitoring since clinical tests could reflect higher capacity due to the test conditions (i.e. confined environment, presence of an observer) that is ultimately not performed in daily life. It should also be noted that all patients had walking aids (either a walker or a cane) at both baseline and follow-up. This could have potentially limited the stride velocity and stride length [328]. Additionally, the clinical setting does not present many opportunities for higher gait speeds nor the need to walk faster. The number of turning steps per bout also decreased; this could be linked to an improved gait performance by extrapolating that less turning steps were required to change direction during gait.

*HC* symmetry improved at follow-up whereas *TC* symmetry did not. This might not be entirely unexpected, since *TC* is already a rather small value (2-5cm) and there would be no direct reason to increase it in daily life if it weren't for obstacle negotiation. Both the improved *HC* symmetry and the increase in *HC* for affected and non-affected sides indicate a shift from shuffling-like walking towards more normal walking, since the foot is lifted higher from the ground. The %*stance* time *SI* decreased as well. This meant that patients not only put more load on their affected side, but they were able to better distribute the loading time at follow-up. The symmetry results tendency is concordant with the 20m gait test albeit with better performances during the 20m gait test. This could again reflect the different mechanisms involved in negotiating a straight walk during a test in the presence of an observer and more complex, free walks in daily life. The symmetry results demonstrate the importance of evaluating gait parameters in daily life during rehabilitation as they can provide important insights for clinicians on gait performance.

Gait cycle time variability was high at baseline and follow-up for both daily life and 20m test. Even a slight decrease was noticed in daily life at follow-up, this was not statistically significant. This indicates that patients still have irregular walking. However the fact that patients have a cane could have an impact on this high variability, a similar result was shown in [328]. In fact, persons with walking aids had significantly lower stride velocity and length than age-matched persons without walking aids, and this could be an additional explanation to the low gait performance of the patients in our study.

Finally, the change in *Icad* distribution revealed a substantial increase in peak cadence mode indicating improvement in that area. Whereas the cadence distribution at baseline exhibited a unimodal shape, the distribution at follow-up resembled the bimodal distribution that was obtained for healthy participants in Chapter 4 (albeit with lower cadence modes), and this could point out an initial restoration of usual walking mechanisms where longer walking periods have different cadence compared to shorter bouts.

#### **4.4 Complexity analysis**

The *LZ* complexity increased significantly between baseline and follow-up at the 5% level. This metric proved to be more sensitive to mobility change than classical posture metrics (i.e. percent time spent in each posture). This is an innovative and important result, demonstrating that the activity pattern is more relevant than the quantity of activity, and that the richness of activity barcodes can be used further as an objective clinical outcome for rehabilitation.

## 4.5 Comparative analysis

This analysis was intended for comparing the percent change and effect size (percent non-overlap) of Tinetti test score and objective metrics. Even though most objective metrics did not reveal statistically significant changes, several had large effect sizes and were highly sensitive to change. In particular, the percent time spent in each posture revealed extremely high changes. Locomotion descriptors such as total duration and number of bouts also revealed high changes and effect sizes, confirming the good progress of locomotion in the studied population. Load and complexity had the highest effect sizes for objective metrics and were close to the effect size of the Tinetti score. In terms of gait parameters, only heel clearance symmetry had a high effect size. Stride velocity was close to the 0.474 threshold (Cliff's delta of -0.44 for the 90<sup>th</sup> percentile of velocity). The 90<sup>th</sup> percentile exhibited larger changes in all gait parameters except stride length and mean cadence. While this is not a conclusive result because of the low sample size, it could still assert the fact that extreme values exhibit higher changes and therefore are more suitable to describe rehabilitation than mean values, in line with the findings of Rispen et al. [329].

All subjects improved their %time spent in each posture except for subject 2 (Table 6-8). This subject was the only one to exhibit a decrease in complexity. Interestingly, based on the Tinetti score, the only subject (patient 5) whose load *SI* did not improve had an equal score for baseline and follow-up, showing that this effect is potentially due to an already low *LSI* at baseline or measurement day variability. Individual changes of Tinetti score did not always match the changes in objective metrics. For example, subjects 6 and 8 with the highest change in Tinetti score did not exhibit the highest change in activity or complexity metrics. Furthermore, subject 8 improved more than subject 6 in terms of activity and complexity, but had a reduction in the longest walking period. Therefore the Tinetti test indicating an equal change in both patients was unable to characterize this change. Subject 5, whose Tinetti score did not increase, did improve in all metrics except for *LSI*. This emphasizes the fact that objective metrics are capable of showing complementary improvement dimensions compared to standardized tests

In summary, the four analysis dimensions were complementary in revealing improvements after rehabilitation of hip fracture patients. Activity profile and locomotion bout analysis showed tendencies in the direction of recovery, even though not all parameters changed significantly. Gait analysis revealed the potential capacity of patients at follow-up that was not completely retained in daily life performance possibly because of the clinical environment. Nevertheless gait symmetry as well as load symmetry improved significantly at follow-up. Finally, complexity values that embed activity and locomotion patterns showed

significant progress. This could eventually suggest that recovery in terms of complexity occurs before full gait recovery.

#### **4.6 Study limitations**

The first and foremost limitation of this study is the low number of participants. However, the study is ongoing and up to 20 patients are expected to be enrolled for the final outcome analysis. The results are encouraging, notwithstanding. The monitoring duration was limited to one day; this was mainly due to the measurement logistics. In fact, a study investigator had to place the system in the morning and retrieve it in the evening of the monitoring day. Since autonomy was ~16 hours, the devices needed to be recharged nightly and therefore could not be given to patients for more than a day. It could be expected that in the future a miniaturized prototype of the instrumented shoes could be handed to the patients and worn for more than one day with minimal interference from a study investigator. The analysis was limited to the clinical milieu; it would be interesting in the future to evaluate the behavior of post hip fracture patients outside the clinic to see if they retain the mobility improvements they gain after rehabilitation. One clinical aspect that was not dealt with in this study was fear of falling. It would be highly relevant to obtain such data and correlate with mobility metrics to evaluate the impact of rehabilitation on patients. A factor analysis could reveal the effect of underlying parameters or associations between the parameters presented in this study. However, due to the relatively low sample number, this analysis was not available. Factor analysis could highlight whether a combination of parameters could better explain the rehabilitation outcomes compared to single parameter values and ultimately reduce the parameter set to a minimal number or even a clinical score that could be used by the clinician to evaluate global recovery.

### **5 Conclusion**

This study demonstrated the clinical validity of instrumented shoes in rehabilitation assessment of post hip fracture patients. The four proposed analysis dimensions (activity, load, gait, and complexity) are complementary and reveal different mobility outcomes that can be related to recovery strategies of patients. Even though the sample size was small, at least one metric of each dimensions i.e. maximum duration of walking, loading symmetry, cadence and *LZ* complexity showed significant improvement at follow-up. All dimensions revealed to be congruent with standard clinical evaluation and displayed diverse and relevant parameters that are not routinely measured in daily life. These metrics should be taken into consideration by clinicians in order to improve the rehabilitation process and tailor it to each patient according to their individual mobility limitation. The results in clinical setting are highly encouraging towards further studies at home outside the hospital.

## Chapter 7

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### *Outcome evaluation of post stroke inpatients during rehabilitation using instrumented shoes*

#### **Abstract**

Recovery after stroke is highly dependent on the condition severity and the impairments caused by the event. Mobility could be drastically affected and rehabilitation programs usually focus on the recovery of each aspect of impairment. Several clinical scores exist for the assessment of stroke patients before and after a rehabilitation program. However, these scores do not necessarily reflect the daily life mobility of patients and could therefore be complemented by objective metrics. In this study, stroke patients were monitored for two days using the instrumented shoes: one day at baseline once they were able to walk and another day at follow-up before discharge. The activity, load, gait, and complexity metrics revealed several parameters that could describe the recovery, notably complexity, percent time spent sitting, and total number of walking bouts. These metrics evolved with similar effect size compared to clinical scores. Objective metrics were also capable of showing improvements in patients whose clinical scores improved marginally, further asserting their complementarity to observation-based scores. The instrumented shoes were thus shown to be greatly useful in rehabilitation monitoring of stroke inpatients.

## **1 Introduction**

The incidence of stroke in Switzerland is roughly 16,000 yearly [330], i.e. ~2 in 1000 subjects are affected. Stroke accounts for 0.4% of all chronic diseases in persons aged 15 or older in Switzerland, and remains the principal cause of non-congenital disability in adults [331], as well as the third most frequent death cause in developed countries [332]. Eighty percent of stroke survivors suffer from hemiparesis: one side of their body is usually affected and the control of this side (especially the arm, leg and face) is reduced, leading to motor impairment [332]. Since this impairment affects the daily function of stroke survivors, rehabilitation programs are oriented towards restoring mobility [333]. Recovery often occurs several months after incidence, and is maintained 6 months after effective rehabilitation especially in terms of activities of daily living [334]. A smaller recovery rate was also observed up to two years after a stroke. However, patients discharged too early or without an appropriate rehabilitation program exhibited worsening mobility. Hence, it is essential to monitor the motor function of post-stroke patients both at the clinic before discharge and at home in order to identify rehabilitation progress and act accordingly to improve individual mobility of patients.

The assessment of impaired motor function in stroke patients is mainly based on clinical examination through validated tests as well as patients' logs of daily activity [62]. These measures while sensitive to rehabilitation, are mainly based on observation and qualitative assessment and provide little to no objective information on daily life mobility. Furthermore, their application is limited to the clinic and to short activity bouts that do not reflect the performance of individuals in their own environment. Activity monitoring can be a powerful alternative to provide objective measures of motor function without the need of visual assessment. Recent progresses in wearable sensors have allowed the recording of patient movements in an effort to profile the activity over a day and characterize the different activity dimensions. In the particular case of stroke survivors, relatively few studies have been conducted to monitor the daily activity of this patient group, in clinical environment or at home. A uniaxial accelerometer placed on the shank was used for step and activity counts to monitor stroke patients before and after discharge showing improvements mainly in total daily activity and bout length [335]. Activity counts were also obtained using a hip-worn 3D accelerometer during three days of community dwelling stroke patients, revealing good consistency for the sensor placement at the paretic and non-paretic side [336]. Accelerometer and gyroscopes attached to the sternum were used to determine walking and upright time in stroke patients at admission and two weeks follow-up, demonstrating significant improvements [337]. In a recent study, an inertial measurement unit placed at the sternum including a barometer was used to monitor stroke patients at home and revealed significant differences between their daily activity parameters and those of an

age-matched older adult healthy group [338]. GPS has also been used in conjunction with accelerometers to monitor target locations for stroke patients [339].

In terms of shoe-based activity monitoring, some algorithms to recognize activity and analyze the gait of stroke patients were proposed using an instrumented shoe [124], [340]–[342]. These algorithms revealed high accuracies similar to what we presented in Chapter 3. However, none of these studies evaluated the daily activity of stroke patients and were limited to structured protocols with the intention of training and validating activity classifiers/gait analysis algorithms.

In conclusion, there is an apparent lack of information on daily activity profiles of stroke patients. Therefore, the main objective of this study is to monitor daily activity of stroke patients during rehabilitation at the clinic and perform detailed gait and activity analysis using the instrumented shoes. We hypothesize that when the rehabilitation process improves the mobility of the patient, this improvement can be estimated through objective metrics derived from instrumented shoes and expressing complementary aspects of mobility, such as activity profile, gait performance, load distribution, and behavioral complexity. Improvements in activity performance are evidenced and comparisons between objective metrics and standard clinical tests are made to verify if there are similarities between both measures.

## **2 Methods**

### **2.1 Participants and measurements**

Post stroke patients admitted to the rehabilitation center of Kliniken Valens-Switzerland, were recruited for this study. In total eight patients were enrolled. All patients signed informed consent and the protocol was accepted by the cantonal ethical committee. Patients were screened shortly after their admission to the rehabilitation center. The first measurement took place as soon as possible after the stroke occurrence and the second measurement before discharge. The time between these days varied depending on the patients and the stroke severity. In between these measurement days patients followed a rehabilitation program during which they received individualized rehabilitation therapy, depending on their disabilities and rehabilitation goal. The training may include physical therapy, occupational therapy, language therapy, balance training, different kinds of water therapy, hippo therapy (on horses) or medical training therapy (including weights in a fitness room under therapist supervision). An average training day consisted of 5-7 therapy hours. The training duration and intensity were patient-tailored with weak or elderly patients receiving less therapy, and younger, highly motivated patients receiving more (and more intense) therapy.

In the morning of each monitoring day, the participant shoes were equipped with the monitoring system describes in section 2.2. Patients were asked to keep their shoes on during the day for at least 8 hours, after which a study investigator removed the monitoring system. At the end of each monitoring day, the data collected from the monitoring system was downloaded on a computer and stored anonymously for post-processing. Additionally, the clinical scores described in section 1 were available for each patient at baseline and follow-up. The study protocol also includes measurements at home after discharge and at 6 months (roughly 5 months after discharge) follow-up, Figure 7-1.

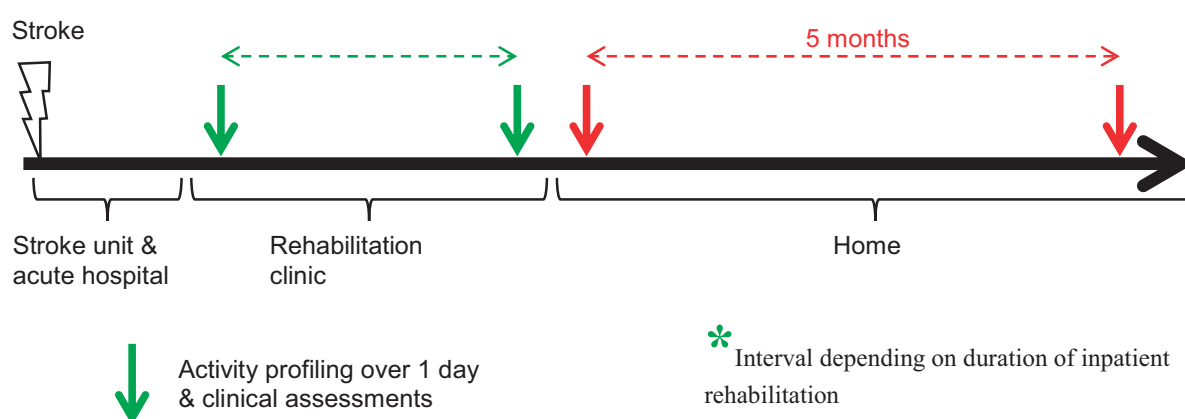


Figure 7-1 - Flowchart of the study protocol with intermediate steps from admission to discharge for participants. Vertical arrows represent monitoring days, with green arrows for the clinical monitoring days included in this thesis and red arrows for monitoring days at home (data collection in progress)

The following clinical tests were performed for each patient at baseline and follow-up:

- NIHSS (National Institute of Health Stroke Scale)<sup>1</sup>: it is a 15-item neurologic examination scale measuring psychological and physiological variables. It is performed by a trained observer and each item is scored 0 to 5 with 0 as normal.
- MAL-30 (Motor Activity Log 30): it is a 30-item examination evaluating the use of the paretic upper limb and movement quality for typical activities occurring in daily life [343].

<sup>1</sup> <http://www.nihstrokescale.org/> (accessed 26.05.2016)



- mRS (modified Rankine Scale): it is a measure of independence i.e. the ability to perform activities without assistance, scored from 0 (no symptoms) to 5 (complete inability to perform activities without assistance) [344]
- EBI (Extended Barthel Index): it is a measure of independence with several items based on activities of daily living and is scored from 0-100 (100 meaning complete independence in performing activities) [345]
- Fugl-Meyer test: it is an upper limb motor function test with several items including stability, coordination and range of motion, scored from 0-66 with 66 meaning full mobility of the upper limb [346]
- ARAT (Action Research Arm Test): it is a test of upper limb mobility with 19 items including fine activities such as grasping and pinching. It is scored from 0-3 with 3 describing normal movement. It requires additional equipment to be performed [347]
- BBS (Berg Balance Scale): it is a test of static and dynamic balance including 14 items scored 0-4 each (4 being the highest score for independent movement). It is the most commonly used test in stroke rehabilitation assessment [348].
- TUG (Timed Up and Go over 3m): it is a functional mobility test where the time to rise from a chair, walk 3m, turn around a fixed point, walk back and sit down is measured [349].

## **2.2 Instrumented shoe system**

The monitoring system included an inertial measurement unit or IMU (Physilog®, GaitUp, CH) and a pressure sensing insole (Smart Insole, IEE, LU). The IMU measures 3D acceleration, 3D angular velocity and barometric pressure and functions as data logger and power unit. The insole measure plantar force at 8 locations under the foot, namely the heel (medial and lateral), the arch (lateral), the metatarsals (1<sup>st</sup>, 3<sup>rd</sup> and 5<sup>th</sup>) and the toes (hallux and the remaining toes). Converting electronics that perform digitization and amplification of the insole signals were strapped to each patient's ankles. Insoles were inserted into each foot and the IMUs were placed on the dorsal aspect of each foot. The system components are shown in Figure 7-2. The sampling frequency was set at 200Hz for all sensors, allowing an autonomy of up to 16 hours.

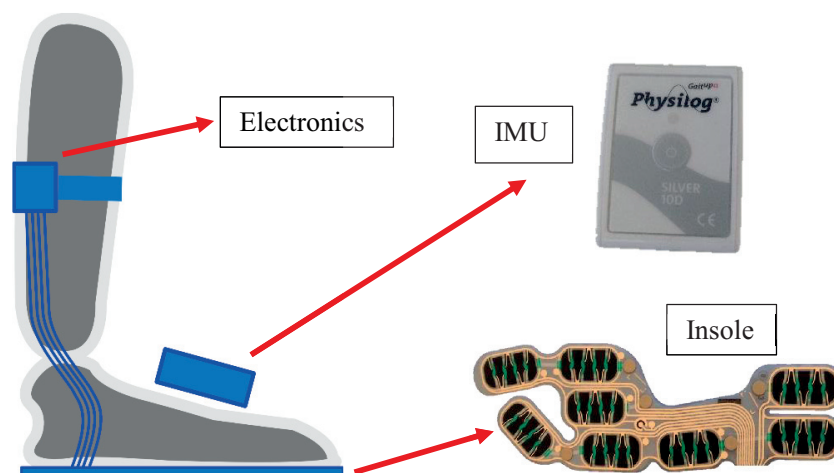


Figure 7-2 - Instrumented shoe system: Physilog® inertial sensor placed on the shoe, insole inserted inside the shoes and converting electronics placed above the ankle.

## 2.3 Outcome analysis

Similar to Chapter 6, the main outcome measures in this study were: activity profile and behavioral complexity, foot loading, gait performance, and effect size comparison. Each outcome is briefly described below.

### 2.3.1 Activity profile and behavioral complexity

Locomotion was labeled from the detection of Toe Off instants based on the pitch angular velocity, and sitting/standing were identified using the total force under the feet obtained from the insoles (Chapter 6, section 2.3.1). The percentage of time spent in each of these three basic activities (i.e. sitting, standing and walking) was calculated. The number of locomotion periods and their durations were also retrieved, as well as the total number of postural transitions and their duration.

For each patient and monitoring day, activity barcodes were constructed from the activity type (sitting, standing and walking) as well as the intensity (duration of walking period and cadence). The complexity metric for each barcode was then calculated using the Lempel-Ziv (*LZ*) definition of the Kolmogorov complexity [280].

### 2.3.2 Foot loading and spatio-temporal gait analysis

Load symmetry was evaluated based on the plantar force measured from the insoles. The sum of all sensors from each foot was obtained and then a histogram was applied to identify a global high level (*Load*) for the entire monitoring duration. The *Load* level was estimated for the affected and unaffected side then used to calculate load symmetry index (*LSI*), eq. 1 defined as:

$$LSI = abs\left(\frac{Load_{affected} - Load_{unaffected}}{Load_{affected} + Load_{unaffected}}\right) \quad (\text{eq. 1})$$

Hence, a decrease in *LSI* would indicate improvement in loading symmetry.

Spatio-temporal parameters of gait were separated into four categories and obtained based on the references [126], [136], [137], [141]. For each locomotion bout of 20 steps and more:

- Performance: mean and standard deviation (SD) of stride velocity (*SV*), stride length (*SL*), cadence (*cad*), number of turning steps (*#Turning*, steps with axial turning angle > 20°)
- Symmetry: mean and SD of symmetry index (*SI*) of maximum heel clearance (*HC*), minimum toe clearance (*TC*), percent stance time (*%stance*):

$$SI = abs\left(\frac{Parameter_{affected} - Parameter_{unaffected}}{Parameter_{affected} + Parameter_{unaffected}}\right) \quad (\text{eq. 3})$$

- Variability: mean and SD of *GCT* inter-stride variability calculated from the coefficient of variation (*CV*):

$$CV = 100 \times \frac{\sigma_{GCT}}{\mu_{GCT}} \quad (\text{eq. 4})$$

Where  $\sigma_{GCT}$  is the standard deviation of *GCT* and  $\mu_{GCT}$  the mean of *GCT* over one walking bout.

for any locomotion period with 3 or more detected steps:

- Gait profile: the duration of each gait cycle (*GCT*) was estimated and converted to Instantaneous Cadence (*Icad*, eq. 5) and its histogram was estimated for the whole recording.

$$Icad = 120 / GCT \quad (\text{eq.5})$$

### 2.3.3 Comparative analysis

For each clinical score and parameters extracted from instrumented shoes, statistical significance was evaluated between baseline and follow-up monitoring days using the Wilcoxon Rank-sum non-parametric test. The significance is mentioned at the 5% level (\*), 1% level (\*\*) and 0.1% level (\*\*\*)

An effect size descriptor was used in this study to evaluate parameters with low sample size. This descriptor was Cliff's delta, a measure of how many values at baseline are larger than values at follow-up for a given parameter. It is calculated using eq. 4:

$$Cliff's\ delta = \frac{\#(P_{B,i} > P_{F,i}) - \#(P_{B,i} < P_{F,i})}{N(P_B) \times N(P_F)} \quad (eq. 4)$$

Where  $P_{B,i}$  and  $P_{F,i}$  are the elements of the parameter at baseline and follow-up, respectively,  $N(P_B)$  and  $N(P_F)$  the total number of elements of the parameter at baseline and follow-up, respectively. This measure is also non-parametric in the sense that it does not need the data to follow any pre-assumed distribution. Cliff's delta represents the percentage of non-overlap between the baseline and follow-up vectors for each parameter and can range between -1 to +1. The sign is an indicator of the trend direction: negative sign for an increasing trend and positive sign for a decreasing trend. A higher absolute value of this descriptor indicates a high effect size i.e. low overlap between baseline and follow-up. Three thresholds are available effect size, low:  $0.147 < Cliff's\ delta < 0.33$ , moderate:  $0.33 < Cliff's\ delta < 0.474$  and high:  $0.474 < Cliff's\ delta$  [326].

In addition to effect size the relative improvement (%change) of each patient was calculated for each selected parameter and clinical score by eq. 5:

$$\%change = \frac{P_F - P_B}{P_B} \quad (eq. 5)$$

## 3 Results

Patient characteristics are shown in Table 7-1. The score for each clinical test at baseline and follow-up is also shown, as well as the mean±SD and the p-value from Wilcoxon Rank-sum test. Four out of the eight tests improved significantly: NIHSS, mRS, EBI and BBS.

Table 7-1 - Patient characteristics and clinical test scores at baseline and follow-up (B-F). Fugl-Meyer and ARAT are shown for the paretic limb only. TUG is over 3m and the values shown are in seconds. Mean, SD and p-values for comparison between baseline and follow-up are shown as well. Gender: M for Male and F for Female, paretic side: R for Right and L for Left

ID		1	2	3	4	5	6	7	8		
Age		45	85	49	38	40	70	61	55		
Gender		M	F	M	F	M	M	F	M		
Paretic Side		L	L	R	L	L	R	R	L	Mean±SD	p-value
NIHSS	B	6	3	2	11	2	1	9	2	4.5±3.5	0.05*
	F	0	3	1	11	0	0	0	1	2±3.54	
MAL-30	B	0.15	3.63	4.76	0	2.62	4.8	1.71	2.6	2.53±1.74	0.34
	F	2.42	4.34	4.9	0	2.83	5	4.7	2.69	3.36±1.61	
mRS	B	3	3	2	4	3	1	4	3	2.88±0.93	0.03*
	F	2	2	1	3	2	1	2	2	1.88±0.6	
EBI	B	43	37	59	36	54	55	34	40	4.5±3.5	0.003**
	F	63	55	64	51	64	64	64	59	2±3.54	
Fugl-Meyer	B	4	57	63	4	57	61	42	61	43.63±23.66	0.18
	F	41	59	66	5	64	60	65	62	52.75±19.52	
ARAT	B	0	47	57	0	57	57	50	57	40.63±23.72	0.69
	F	47	50	57	0	57	57	57	57	47.75±18.42	
BBS	B	46	48	56	42	54	48	7	33	41.75±14.72	0.04*
	F	50	51	56	49	56	52	54	50	52.25±2.59	
TUG (sec)	B	20.47	10.21	4.41	16.25	8.47	10.15	0	19.44	11.18±6.71	0.08
	F	6.85	9.19	4.08	10.8	5.6	9.82	7.75	12	8.26±2.51	

### 3.1 Activity profile

Patients spent 85±10% of monitoring time sitting, 9±7% standing, and 6±5% walking for the baseline measurement. On the follow-up monitoring day, they spent 77±8% sitting, 14±6% standing, and 10±5% walking, indicating an increase in upright and decrease in resting time, Figure 7-3. These differences were not statistically significant (p-value range: 0.13-0.19). At baseline, patients completed 26±13 sit-to-stand and 26±13 stand-to-sit, compared to 30±15 sit-to-stand and 30±14 stand-to-sit at follow-up, an increase that was not statistically significant (p = 0.62). Transition duration was 2.18± 0.57s at baseline and decreased to 2.13± 0.63s at follow-up, with p = 0.13.

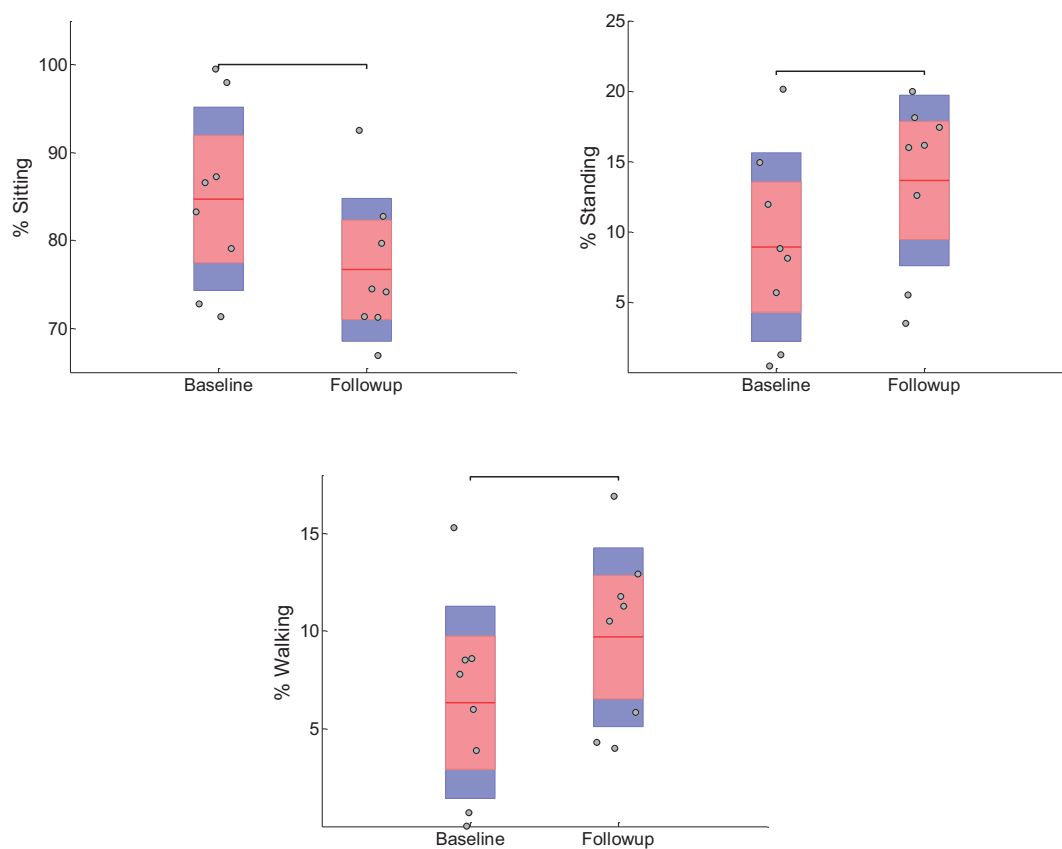


Figure 7-3 - Percent time spent in each activity type at baseline and follow-up.

The analysis of locomotion periods is presented in Table 7-2. Total, maximum, and mean duration as well as the total number of locomotion bouts all showed improving trends but not significantly.

Table 7-2 - Locomotion period characterization shown as mean±SD for all subjects at baseline and follow-up

Parameter	Baseline (mean±SD)	Follow-up (mean±SD)	p-value
Total duration (min)	33.09±22.86	50.70±21.19	0.19
Maximum duration (sec)	215.24±261.36	324.03±439.54	0.65
Mean duration (sec)	17.57±11.74	18.43±9.39	0.80
Total number (bouts)	108.63±74.88	179.13±58.40	0.09

### 3.2 Load evaluation

Figure 7-4 shows the load symmetry index for all subjects across all load data. A slight trend of improvement could be observed, but no significant difference was found ( $p = 0.69$ ). An attempt at separating the *LSI* for walking and standing was also made but still revealed no significant changes ( $p = 0.19$  for walking and  $p = 0.72$  for standing).

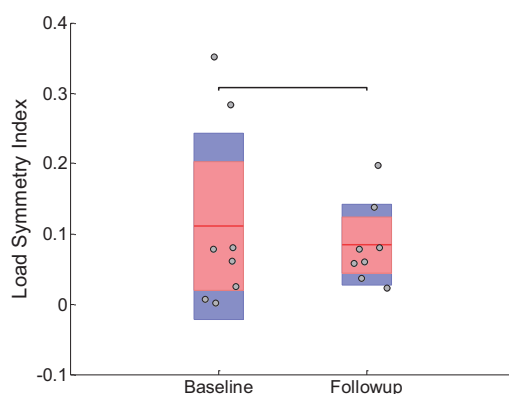


Figure 7-4 - Load symmetry obtained from the load symmetry index (LSI).

### 3.3 Spatio-temporal gait parameters

The gait performance metrics are shown in Table 7-3Table 6-3. All parameters improved in the expected direction but none significantly. A notable increase in 90<sup>th</sup> percentile of stride velocity can be seen, from  $0.95 \pm 0.36$  m/s to  $1.16 \pm 0.35$  m/s ( $p = 0.19$ ).

Table 7-3 - Gait performance metrics for baseline and follow-up. Values are mean±SD across all analyzed gait cycles from all subjects. p-values are shown for each metric

<i>Performance</i>	<i>Baseline</i>	<i>Follow-up</i>	<i>p-value</i>
<i>SV (m/s) mean</i>	<i>0.74±0.26</i>	<i>0.91±0.27</i>	<i>0.23</i>
<i>SV (m/s) 90<sup>th</sup> percentile</i>	<i>0.95±0.36</i>	<i>1.16±0.35</i>	<i>0.19</i>
<i>SL (m) mean</i>	<i>1.01±0.24</i>	<i>1.11±0.27</i>	<i>0.46</i>
<i>SL (m) 90<sup>th</sup> percentile</i>	<i>1.20±0.27</i>	<i>1.32±0.28</i>	<i>0.40</i>
<i>Cad (steps/min) mean</i>	<i>86.40±16.12</i>	<i>95.13±14.55</i>	<i>0.23</i>
<i>Cad (steps/min) 90<sup>th</sup> percentile</i>	<i>97.09±18.34</i>	<i>107.00±18.16</i>	<i>0.23</i>
<i>#Turning/bout (steps)</i>	<i>6.85±2.65</i>	<i>8.30±2.82</i>	<i>0.61</i>

The instantaneous cadence distribution obtained from all locomotion bouts is shown in Figure 7-5. Both distributions exhibit bimodal behavior, with modes at 52 and 96 steps/min at baseline, 72 and 111 steps/min at follow-up. The increase in both modes indicates a substantial improvement in cadence. Mean *Icad* was 80.59±12.05steps/min at baseline and 89.88±13.08steps/min at follow-up ( $p = 0.19$ ), 90<sup>th</sup> percentile was 115.55±17.58steps/min at baseline and 111.21±15.99steps/min at follow-up ( $p = 0.72$ ).

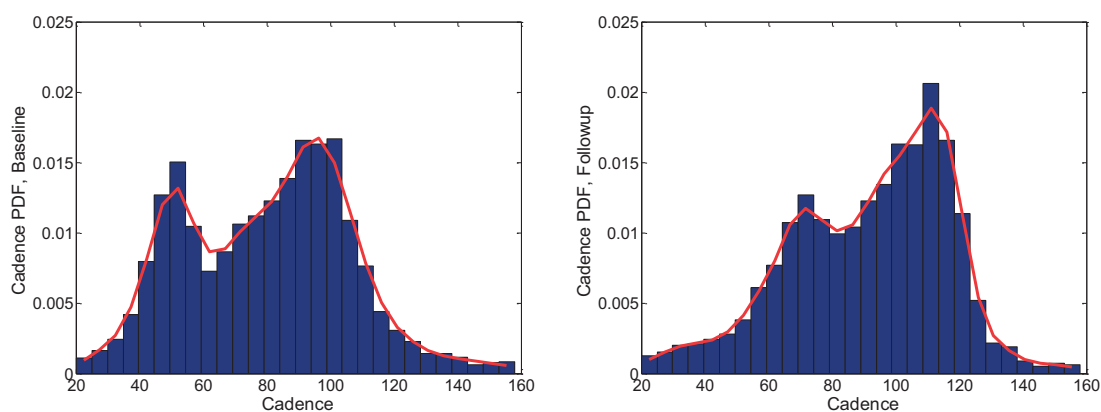


Figure 7-5 - Instantaneous cadence distribution (probability density function, PDF) at baseline (left) and follow-up (right)

Symmetry metrics are summarized in Table 7-4. Interestingly, *SI* for *HC* and *TC* worsened (except for mean *HC*), and only a slight improvement was shown for *%stance*.



Table 7-4 - Symmetry parameters compared at baseline and follow-up using the symmetry index.

<i>Parameter</i>	<i>Baseline</i>	<i>Follow-up</i>	<i>SI</i> <i>Baseline</i>	<i>SI</i> <i>follow-up</i>	<i>p-value</i>
<i>HC (m) mean</i>	<i>0.23±0.06/0.23±0.03</i>	<i>0.25±0.04/0.24±0.04</i>	<i>0.10±0.08</i>	<i>0.09±0.06</i>	<i>0.96</i>
<i>HC (m) 90<sup>th</sup> percentile</i>	<i>0.27±0.06/0.27±0.04</i>	<i>0.33±0.15/0.27±0.03</i>	<i>0.19±0.10</i>	<i>0.22±0.16</i>	<i>0.87</i>
<i>TC (m) mean</i>	<i>0.03±0.01/0.03±0.01</i>	<i>0.03±0.02/0.03±0.01</i>	<i>0.17±0.04</i>	<i>0.25±0.09</i>	<i>0.07</i>
<i>TC (m) 90<sup>th</sup> percentile</i>	<i>0.04±0.01/0.05±0.02</i>	<i>0.04±0.01/0.04±0.01</i>	<i>0.35±0.08</i>	<i>0.46±0.14</i>	<i>0.07</i>
<i>%Stance (mean)</i>	<i>61.65±5.84/66.58±3.81</i>	<i>61.99±5.23/65.82±2.51</i>	<i>0.06±0.05</i>	<i>0.06±0.05</i>	<i>0.87</i>
<i>%Stance (90<sup>th</sup> percentile)</i>	<i>66.58±5.98/72.20±5.72</i>	<i>67.48±7.22/70.02±3.48</i>	<i>0.10±0.06</i>	<i>0.09±0.05</i>	<i>0.87</i>

Gait cycle time variability was  $9\pm 8$  at baseline and increased to  $11\pm 11$  at follow-up but the change was not significant ( $p = 0.84$ ).

### 3.4 Behavioral complexity

The LZ complexity metric calculated for baseline and follow-up is shown on the box plot, Figure 7-6. Even though the complexity trend was towards improvement, the p-value of 0.065 was not statistically significant. However, this value was the closest of all activity metrics (see section 3.1) to the 5% significance level. Therefore, as was the case for the hip-fracture patient population, complexity seems to explain improvements after rehabilitation better than the time spent in different activities or locomotion period analysis.

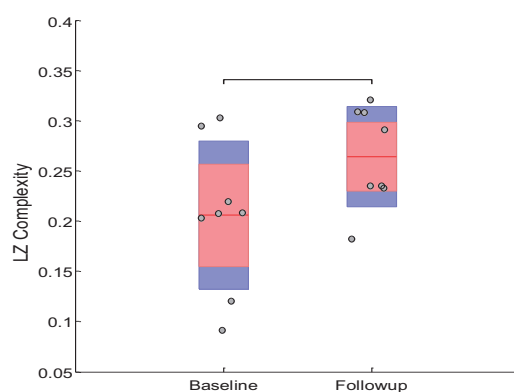


Figure 7-6 – Box plot of the LZ complexity metric for baseline and follow-up for all 8 patients

Barcodes of all patients are shown in Figure 7-7 at baseline and follow-up. Barcodes appear to be richer in terms of both activity intensity and the number of changes between states at follow-up. It is worth mentioning that there were two subjects for which the complexity decreased (P6 and P8), and this could be visually observed by looking at their barcodes which were richer at baseline.

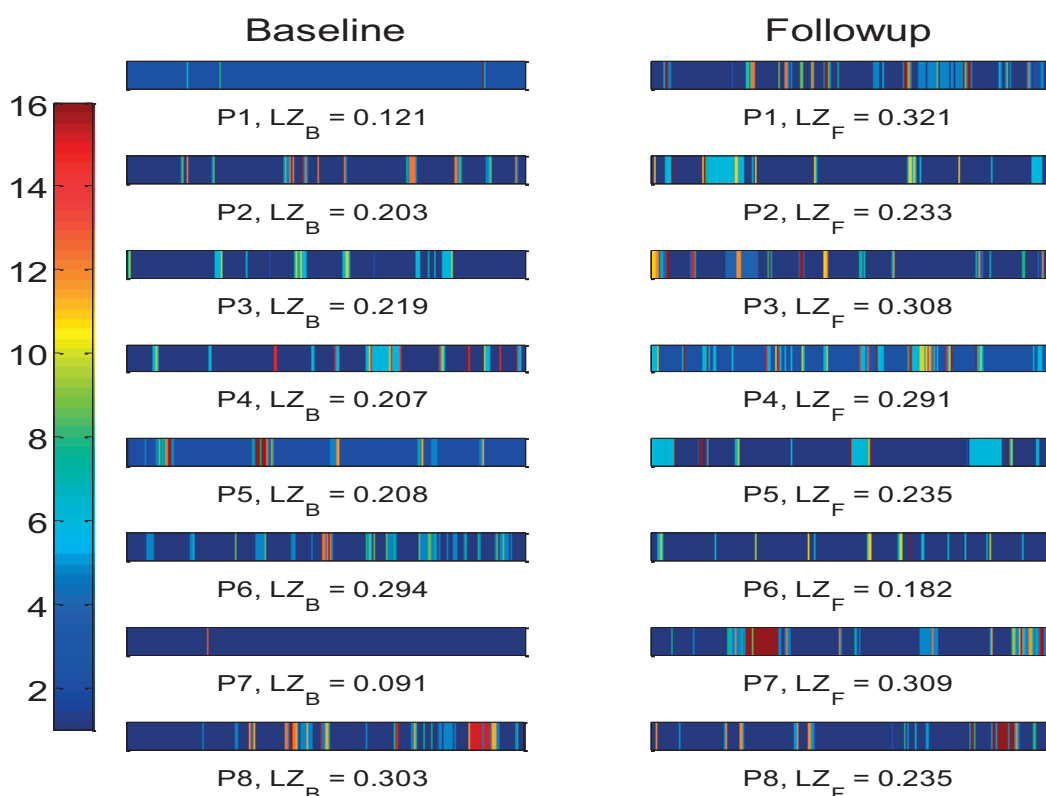


Figure 7-7 - Activity barcodes for all patients at baseline (left) and follow-up (right) showing the values of the LZ complexity. The color code represents the different activity intensities explained in Chapter 4.

### 3.5 Comparative analysis

The effect size measured by Cliff's delta and relative change are shown for each clinical test and outcomes metrics in Table 7-5. Among the clinical tests, the NIHSS, mRS, EBI and BBS showed significant improvements at follow-up. In terms of Cliff's delta, all these tests had a high effect size. As for the activity metrics, the LZ complexity exhibited a Cliff's delta higher than 0.474 in absolute value reflecting a high effect size. Cliff's delta for the percent time spent in each posture are close to this threshold as well, indicating little overlap between baseline and follow-up measures. The high percent change in some activity

and locomotion parameters is due to the fact that patient 2 performed extremely low amounts of standing and walking at baseline and therefore the improvements at follow-up were drastic.

Table 7-5 - Percent change and effect size for clinical tests and objective metrics. Highlighted metrics have absolute Cliff delta larger than 0.474

<i>Clinical tests</i>	<i>%change (mean±SD)</i>	<i>Cliff_delta</i>
<b>NIHSS*</b>	<b>-62.50±44.32</b>	<b>0.59</b>
<i>MAL-30</i>	<i>246.62±562.06</i>	<i>-0.23</i>
<b>mRS*</b>	<b>-32.29±15.71</b>	<b>0.61</b>
<b>EBI**</b>	<b>39.49±25.40</b>	<b>-0.84</b>
<i>Fugl-Meyer</i>	<i>128.16±322.50</i>	<i>-0.41</i>
<i>ARAT</i>	<i>N/A (infinite)</i>	<i>-0.16</i>
<b>BBS*</b>	<b>95.82±233.14</b>	<b>-0.61</b>
<i>TUG 3m</i>	<i>-27.57±22.41</i>	<i>0.41</i>
<i>Activity metrics</i>		
<b>%sit</b>	<b>-7.47±20.47</b>	<b>0.47</b>
<i>% stand</i>	<i>643.96±1267.65</i>	<i>-0.41</i>
<i>% walk</i>	<i>21316.28±59675.14</i>	<i>-0.41</i>
<i>Total duration (min)</i>	<i>7424.84±20337.51</i>	<i>-0.41</i>
<i>Maximum duration (sec)</i>	<i>3244.64±9054.87</i>	<i>-0.16</i>
<i>Mean duration (sec)</i>	<i>66.54±171.73</i>	<i>-0.09</i>
<b>Total number (bouts)</b>	<b>1409.01±3528.61</b>	<b>-0.52</b>
<i>#transitions</i>	<i>34.18±64.02</i>	<i>-0.16</i>
<i>TD (mean)</i>	<i>0.50±10.38</i>	<i>0.06</i>
<i>TD (90<sup>th</sup> percentile)</i>	<i>3.91±25.00</i>	<i>-0.09</i>
<b>LZ complexity</b>	<b>56.47±95.99</b>	<b>-0.56</b>

Load and gait metrics are continued on the following page. None of these metrics provided a high effect size to be considered for latter individual analysis. The toe clearance exhibited a high effect size but in the direction of worsening, and therefore will not be compared to the clinical tests. Potential reasons behind this worsening are detailed in the discussion.

<i>Load and Gait metrics</i>		
<i>Load SI</i>	<i>835.27±</i>	<i>-0.06</i>
<i>SV (mean)</i>	<i>27.30±52.70</i>	<i>-0.34</i>
<i>SV (90<sup>th</sup> percentile)</i>	<i>27.69±44.69</i>	<i>-0.38</i>
<i>SL (mean)</i>	<i>12.95±32.86</i>	<i>-0.22</i>
<i>SL (90<sup>th</sup> percentile)</i>	<i>12.61±25.61</i>	<i>-0.25</i>
<i>Cad (mean)</i>	<i>9.35±14.01</i>	<i>-0.34</i>
<i>Cad (90<sup>th</sup> percentile)</i>	<i>8.89±10.74</i>	<i>-0.34</i>
<i>Icad (mean)</i>	<i>12.32±14.22</i>	<i>-0.41</i>
<i>Icad (90<sup>th</sup> percentile)</i>	<i>-3.03±12.19</i>	<i>0.13</i>
<i>HC, SI (mean)</i>	<i>4.75±44.86</i>	<i>0.03</i>
<i>HC, SI (90<sup>th</sup> percentile)</i>	<i>22.51±51.76</i>	<i>-0.06</i>
<i>TC, SI (mean)</i>	<i>48.38±60.18</i>	<i>-0.50</i>
<i>TC, SI (90<sup>th</sup> percentile)</i>	<i>40.16±49.98</i>	<i>-0.50</i>
<i>%stance, SI (mean)</i>	<i>2.63±40.50</i>	<i>0.06</i>
<i>%stance, SI (90<sup>th</sup> percentile)</i>	<i>2.33±47.54</i>	<i>0.06</i>
<i>Variability (mean)</i>	<i>11.09±32.43</i>	<i>-0.09</i>
<i>Variability (90<sup>th</sup> percentile)</i>	<i>13.21±36.09</i>	<i>-0.19</i>
<i>#Turning/bout</i>	<i>34.61±38.62</i>	<i>-0.16</i>

Parameters that improved with a high effect size are related in Table 7-6 for each subject. It is interesting to note that subjects whose complexity decreased performed less walking bouts and spent more time sitting at follow-up compared to baseline. Some values are extremely high owing to changes in subject 7 who performed only 2 extremely short bouts of walking at baseline.

Table 7-6 - Clinical test scores and relevant objective metrics based on effect size for each individual. Values at baseline (B) and follow-up (F) are shown as well as the %change (highlighted) for each parameter and score

ID		1	2	3	4	5	6	7	8
NIHSS	B	3.00	2.00	6.00	11.00	2.00	1.00	9.00	2.00
	F	3.00	1.00	0.00	11.00	0.00	0.00	0.00	1.00
	%	0.00	-50.00	-100.00	0.00	-100.00	-100.00	-100.00	-50.00
mRS	B	3.00	2.00	3.00	4.00	3.00	1.00	4.00	3.00
	F	2.00	1.00	2.00	3.00	2.00	1.00	2.00	2.00
	%	-33.33	-50.00	-33.33	-25.00	-33.33	0.00	-50.00	-33.33
EBI	B	37.00	59.00	43.00	36.00	54.00	55.00	34.00	40.00
	F	55.00	64.00	63.00	51.00	64.00	64.00	64.00	59.00
	%	48.65	8.47	46.51	41.67	18.52	16.36	88.24	47.50
BBS	B	48.00	56.00	46.00	42.00	54.00	48.00	7.00	33.00
	F	51.00	56.00	50.00	49.00	56.00	52.00	54.00	50.00
	%	6.25	0.00	8.70	16.67	3.70	8.33	671.43	51.52
% sit	B	98.02	86.53	87.29	79.08	83.29	71.33	99.55	72.75
	F	71.38	79.71	74.51	71.27	74.16	92.55	66.96	82.75
	%	-27.18	-7.88	-14.64	-9.88	-10.96	29.75	-32.74	13.75
Total number (bouts)	B	23.00	111.00	149.00	132.00	105.00	244.00	2.00	103.00
	F	254.00	219.00	192.00	206.00	172.00	105.00	204.00	81.00
	%	1004.35	97.30	28.86	56.06	63.81	-56.97	10100.00	-21.36
LZ complexity	B	0.12	0.20	0.22	0.21	0.21	0.29	0.09	0.30
	F	0.32	0.23	0.31	0.29	0.23	0.18	0.31	0.24
	%	165.98	14.36	40.37	40.12	12.73	-38.09	238.55	-22.29

## 4 Discussion

As in Chapter 6, this study aims to show the sensitivity to change of the instrumented shoes to health improvement. The study was designed in order to expect a functional improvement after rehabilitation process and to see in what extend objective outcome measures extracted from instrumented shoes is actually sensitive to this improvement. Outcomes measures divided into four categories (activity, complexity, gait and loading) highlight at different degree their relevance for objective outcome evaluation of rehabilitation in post-stroke population. All dimensions revealed trends in the direction of improvement and a few key trends revealed high effect size comparable to clinical test scores.

## **4.1 Activity profile**

The observed trend in activity profile was in the expected direction, with %sitting time decreasing and %upright (standing and walking) both increasing. For some patients, changes were substantial: patient 7 for example had relatively no walking at baseline (2 short bouts) and increased to more than 4% at follow-up (204 bouts, Table 7-6). None of the trends was statistically significant but the results demonstrate the overall improvement of patients.

All locomotion parameters also improved but did not reach the significant level. An interesting observation was that the maximum locomotion bout duration was not significantly different (which was the case for hip fracture patients in Chapter 6). The number and duration of transitions increased/decreased respectively, but not significantly.

## **4.2 Load evaluation**

The load symmetry index revealed no significant changes even though it slightly decreased, indicating that loading is not a crucial factor of early stroke rehabilitation. However for *LSI*, p-value decreased when only walking was considered. This could be related to the gait spatio-temporal improvements. It seems that the difference between paretic and non-paretic side affects upper limbs more than the load transfer between the feet.

## **4.3 Spatio-temporal gait parameters**

Gait performance improved between baseline and follow-up. Crucially, stride velocity increased up to 1m/s. Stride velocities below 0.8m/s were shown to be too low for some independent tasks (e.g. crossing the road on a traffic light) [350]. Patients were under that threshold at baseline but well over it at follow-up. The stride velocity at follow-up is also similar to what we observed in healthy older adults (Chapter 4). Thus a gain in functional independence can be confirmed by the velocity parameter. Stride length, cadence, and changed in the expected direction as well. The number of turning steps increased, however, when it was expected to decrease (patients would perform less turns to complete pivot tasks). This again could be due to the high increase in mobility of some patients (i.e. patients who walked very little at baseline).

In terms of symmetry, heel clearance improved whereas toe clearance worsened. There is no conclusive explanation for this behavior at the moment, but it could be expected that patients might be overcompensating toe clearance at follow-up to avoid foot-drop or better negotiate obstacles. The percent

stance time did not change much at follow-up but was already at ~60% at baseline, similar to what is observed in healthy persons.

Gait cycle time variability increased non-significantly at follow-up. Both measures were slightly high, indicating rehabilitation has not improved the regularity of walking.

An important result is the *Icad* distribution: a bimodal distribution resembling healthy walking (Chapter 4) was observed for both baseline and follow-up, but the values of cadence mode were low at baseline. This could mean that patients negotiate locomotion bouts in a normal way early after stroke but with reduced cadence.

To summarize, it appears that gait performance is a good first indicator of mobility improvements during rehabilitation of stroke patients, whereas gait symmetry still needs to be investigated. It would be highly relevant to monitor gait performance outside the clinic to see whether this is retained over longer periods of time.

#### **4.4 Complexity**

The *LZ* complexity increased between baseline and follow-up but with a statistically non-significant p-value of 0.065. However, this metric proved to be more sensitive to mobility change than classical posture metrics (i.e. percent time spend in each posture) because of this lower p-value. This result asserts the proposition in Chapter 6 that activity pattern is more important than simply the activity type or frequency, and that the richness of activity barcodes can be a clinical indicator for rehabilitation.

#### **4.5 Comparative analysis**

All clinical tests improved in the expected direction, even though some of them were not statistically significant. Using the effect size metric, it was shown that the *LZ* complexity had similar performances to some clinical metrics, a further argument in favor of using complexity as a global rehabilitation indicator. Beyond statistical significance, Cliff's delta revealed relatively high effect sizes for the percent time spent sitting (and close to high for walking and standing); this could better explain the improvement trend than the p-values of the Wilcoxon Rank sum test with a low number of samples (8 subjects total). The number of walking bouts also had a high effect size.

By observing the barcodes, two subjects (6 and 8) had their complexity scores lower at follow-up than at baseline. Patient 6 for example, had high test scores at baseline (Table 7-6) and this could mean that

their reduction in complexity is not because of deterioration (since they both improved at follow-up based on clinical scores), but rather a chance occurrence due to daily variations in activity. Monitoring time for complexity calculation is still an open question, but it would seem that more than one day would be required in the future to better understand the changes in activity complexity.

Metrics with high effect size were able to show improvements for patients where clinical tests were similar between baseline and follow-up. An example is patient 1 whose clinical scores revealed mild improvements but whose complexity, %sitting, and total number of bouts were amongst the highest improvements across the 8 patients (Table 7-6).

Patient 7 had the lowest scores amongst the group and achieved considerable improvements in both clinical scores and activity metrics, showing that these metrics are highly sensitive to large changes in mobility.

#### **4.6 Study limitations**

The main limitation of this study remains the low number of participants. However, the study is ongoing and up to 30 patients are expected to be enrolled for the final outcome analysis. Another limitation of the patient sample is the heterogeneity of age and stroke severity. Once the full sample is achieved, it would be expected to stratify into groups by either age or severity and perform the analyses for each subgroup. This could inform better on the rehabilitation mechanism, especially since it was observed in this study that patients who had major impairments at baseline benefited highly from the rehabilitation program.

The monitoring duration was limited to one day; and this highlights the results especially in terms of complexity where two well-performing patients at baseline had slightly reduced performance at follow-up. The ongoing debate about the most suitable monitoring time to obtain relevant activity data is crucial, and based on the current results it could be said that one day is probably not enough to measure a full scale improvement especially when patients are already performing well at baseline. However, one day was enough to show improvements for patients whose mobility was quite restricted at the first monitoring day.

The current analysis was limited to the clinic due to the currently available data. This is the first part of an ongoing study where patients will be monitored at home after discharge and 6 months later to quantify whether or not the perceived improvements in the clinic are retained at home. The results of the second part of the study will be highly interesting with regards to the literature since keeping up a good mobility performance at home is related to the rehabilitation program's effectiveness and duration [334].



In this study, functional mobility tests such as 20m gait or 6 minute walking test were not performed. It would have been interesting to have these tests to relate the capacity of patients to their daily performance. The main reason behind omitting these tests is the availability of several clinical scores that take time to obtain, and therefore the physiotherapist was unable to complete more tests with patients. The improvements in gait performance are high enough in this study compared to Chapter 6 though, even without gait capacity measures.

Stroke patients have impairments in the upper limb as well, and this was not studied in this project since it is mainly related to the instrumented shoes. The monitoring also included sensors on both wrists and the sternum to quantify upper body mobility and the data will be analyzed in the future and compared to the outcomes obtained from the instrumented shoes. This will provide a rich and global analysis of functional mobility in stroke patients at the clinic and at home.

## **5 Conclusion**

This study demonstrated the clinical validity of instrumented shoes in rehabilitation assessment of stroke patients. Activity, gait and complexity metrics revealed trends in the expected improvement direction as demonstrated by the clinical scores. Gait performance revealed the main improvements at follow-up with positive changes in stride velocity, stride length, and cadence. Even though some differences were not statistically significant, it was shown that complexity analysis in particular has an effect size similar to clinical tests and is therefore suggested to be used as a global metric for rehabilitation. Other metrics with high effect size revealed the possibility to monitor rehabilitation improvements even when clinical scores do not change highly, and were sensitive to change when patients exhibited drastic improvements. A crucial point for future studies will be the number of monitoring days to better assess rehabilitation outcomes as the day-to-day activity variability can have an effect on the results. The potential to provide an objective rehabilitation score from instrumented shoes will be explored at a later stage when the measurements conclude.

# Chapter 8

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## *Conclusion*

### **1 Summary of main contributions**

In this thesis, instrumented shoes consisting of an inertial measurement unit and a force sensing insole were designed for the purpose of accurate activity classification and daily behavior monitoring in healthy and at-risk populations. The system included a relatively large number of sensors (3D accelerometer, 3D gyroscope, 3D magnetometer, barometer, temperature sensor, and 8D force sensing), all placed at a single body location. The prototype in its current state is stable and reliable, providing an autonomy of about 16 hours at a sampling rate of 200Hz, allowing a fine reconstruction of analog signals. The selection of this system as a daily activity monitoring solution was based on several premises related to movement analysis from the lower limb, namely the possibility to measure foot orientation in space and the foot loading during contact with the ground. The instrumented shoes proved to be an all-in-one activity, gait, and complexity analysis tool; an excellent compromise between having a single body sensor location and classifying activity with high accuracy, as well as finely characterizing activity during daily life and measuring outcomes of patient rehabilitation. No system based on single body location has so far provided activity monitoring concurrently with gait analysis, transition characterization, and behavioral complexity in daily life. The clinical application of the instrumented shoes was demonstrated in two longitudinal rehabilitation trials with relevant outcomes.

The signals from the instrumented shoes proved to be appropriate for activity classification. The validation over the semi structured protocol revealed a high accuracy of activity type recognition for basic postures and more detailed locomotion types. The tuning parameters of the algorithm were insensitive to small changes and therefore the algorithm was robust against potential measurement inaccuracies that may appear in the context of long-term daily life monitoring.

The algorithm also performed exceptionally in daily life monitoring, albeit with a slightly lower accuracy. Besides activity classification and daily postural allocation, barcodes were extracted reliably from the instrumented shoes and could be used similarly to the reference system. Gait analysis was performed outside the lab using instrumented shoes for the first time, and reported parameters were similar to what is found in the literature. The system allowed the calculation of parameters such as foot clearance for the first time in real life conditions.

The load measurement from the insoles provided a signal that could be used for transition detection and duration calculation. This was also the first study to perform postural transition characterization from instrumented shoes. Postural transition detection and classification accuracy was excellent, whereas the comparison of transition duration with a reference system was highly acceptable. The load estimation error was low using a simple calibration technique. Transitions in daily life measured with the instrumented shoes compared well to what was found in the literature but differed somewhat from trunk sensor measurements.

Monitoring rehabilitation with instrumented shoes was the highlight clinical application of this novel system. Using all the metrics that could be obtained from the different sensors, improvements could be seen based on the population and analyzed in comparison to clinical tests. Activity, load, gait, and complexity all played their part, revealing interesting recovery outcomes that were also demonstrated by clinical test scores, proving that the instrumented shoe system is a viable objective tool for clinical rehabilitation monitoring.

## **2 Biomechanics-inspired decision tree classification algorithm**

The expert-based decision tree that was designed to classify the different activities in Chapter 3 was implemented with the rationale that typical signal features that are subject independent could inform about the activity type. The selection of these features was based on common movements or states that occur for different activities: lifting the foot to perform locomotion, transferring the load on the feet to transition from sitting to standing and vice-versa, changing the elevation when climbing or descending, and inclining the foot when on a slope. This approach did not require a machine learning step like other common algorithms. In learning approaches, a classifier requires some input data to tune the classifier parameters and output the predicted activity class. This might be difficult to use when the algorithm is validated on a healthy subgroup and applied with patients. For example, hip fracture patients (Chapter 6) exhibited high asymmetry at baseline and therefore features obtained from their affected side are not similar to those obtained from

healthy older adults. The proposed algorithm performed exceptionally well in the semi-structured protocol, demonstrating the effectiveness of the expert-based method. The tuning parameters were changed within plausible ranges and showed that the algorithm is robust to small changes. The achieved accuracy of 97% was similar to what was reported by other studies using instrumented shoes and machine learning algorithms [110]. More importantly, the performance was on a par with multi sensor systems [40], [45] and better than single sensor systems placed at other body locations [48], [271]. The possibility to detect stairs and ramps has meaningful implications on monitoring avoidance behavior, since non-level locomotion requires more energy than level walking and could present obstacles that some persons try not to face (e.g. by taking the elevator).

The application of the algorithm to real life data revealed, once more, an excellent classification accuracy for basic activity types. However, the result decreased slightly from the structured protocol and this was congruent with the literature, even though the classification remained highly accurate at 93%, as described in Chapter 4.

The main conclusion in terms of activity classification is that our designed system and algorithm perform exceptionally well in structured protocols or at home, and are suitable for long term activity monitoring in healthy and at-risk persons. This is further confirmed by other extracted metrics such as the distribution of locomotion periods and cadence, which appeared to be consistent with what was observed in the literature for locomotion outside the confines of the lab [54], [275].

### **3 Gait and complexity in healthy persons**

Gait analysis using inertial measurement at the foot level has been validated in controlled conditions through previous studies [126], [136], [137], [141] from our lab. In this thesis, we extended the use of validated gait analysis algorithms to real life locomotion periods. This was possible because of the high accuracy of the activity classification algorithms, meaning that valid locomotion periods in daily life are analyzed. The analysis was limited to steady-state walking bouts where participants performed more than 20 steps to ensure the measurement of meaningful gait parameters. The extracted parameters were similar to those measured with a large cohort of age-matched older adults performing a 20m gait test [194], [195]. An interesting result was the low correlation between stride velocity, the most commonly measured gait parameter, and foot clearance, a parameter that has not yet been reported in the literature during daily life monitoring (to the best of our knowledge). These two parameters are thus, with a high probability, independent, and should both be measured in daily life. Foot clearance has a crucial effect on fall risk since it determines whether subjects are able to overcome obstacles or not.

The barcodes defined in Chapter 4 using instrumented shoes activity output were used to calculate a complexity metric that correlated significantly with the reference system but demonstrated no correlations with gait parameters except for the maximum locomotion bout duration. This result corroborates the use of activity complexity as a global metric complementary to gait parameters.

## **4 Classification and characterization of postural transitions and load under the feet**

In Chapter 5, the detection of sitting and standing postures that was proposed for the activity classification algorithm was improved by a transition detection method. This method was initially developed to analyze pulse and transition signals. After wavelet filtering, the total force signal resembled a bi-level signal that could be similarly analyzed. The method revealed sensitivity and precision exceeding 90% in detecting transitions and their types, a result that matches and even outperforms other single sensor location systems [244], [285]. From a clinical point of view, postural transitions are extremely relevant since they convey crucial information about mobility and independence. The number of transitions during a day can be an indicator of poor mobility, owing to the fact that transitions are necessary to start ambulation but have a high energetic impact in terms of performance. The transition duration is an equally important parameter, since it can be an indicator of lower limb strength [351] as well as frailty and fall risk [285], [352]. This duration was obtained through instrumented insoles and was validated in Chapter 5 using a force plate as reference system. The results were enhanced by applying a wavelet transform to the total force data, allowing a reliable detection of start and end events of postural transitions. Only a handful of start/end event combinations yielded low errors in laboratory conditions and were retained for real-life assessment. It was interesting to have a comparative result with the trunk inertial sensor as well, with a relatively similar performance in the lab but not entirely congruent in real-life. This could be explained by the differences in transition characteristics between lower body (load transfer) and upper body (trunk tilt), as well as the additional presence of the sit-to-walk and walk-to-sit transitions. Nevertheless, the transition characterization is a major achievement since this was never reported for instrumented shoes before. Moreover, the instrumented insoles that were used were not particularly designed for this type of analysis but rather for detecting load changes during locomotion activities. Hence the detection and characterization algorithm is all the more powerful, showing a completely innovative aspect of the instrumented shoes.

The load estimation based on a simple calibration rule, i.e. that the weight measured during static standing corresponds to 100% body weight, returned low errors compared to force plate reference and showed the potential of our system in accurate load monitoring.

## **5 Application to rehabilitation**

Having shown the technical validity of the instrumented shoes to quantify activity, locomotion, transitions, gait, and complexity, the next step was to use the large number of parameters for outcome evaluation in rehabilitation programs. In order to have information on mobility improvement in homogeneous groups, two separate studies were conducted, one with post hip fracture patients and the other with stroke survivors. The results revealed excellent sensitivity to improvements when compared to clinical scores, and advocated the use of complexity as a global assessment metric, complementary to gait and load measurement.

Hip fracture patients improved globally in terms of postural allocation, locomotion, and transition parameters. Incidentally, a major significant improvement was the maximum locomotion bout duration. Daily gait parameters also improved substantially, but gait capacity during the 20m clinical test revealed that patients could walk faster compared to daily life. Loading symmetry ameliorated significantly in this study, indicating a gain of function in the affected side post operatively. Changes in stride velocity at follow-up were congruent with the literature [353] but were not sufficient for total functional recovery [354]. This could be explained by the use of walking aids and the presence in the clinical environment, reducing the need to walk faster. Instantaneous cadence showed interesting improvements as demonstrated by its distribution change from unimodal at baseline to bimodal at follow-up. The increase in activity complexity was significant, indicating that this global metric could characterize improvement better than metrics of activity and locomotion considered separately.

Activity profiles improved well in stroke patients, whereas the loading symmetry changed only slightly. However, based on clinical scores, their upper limb test scores ameliorated at follow-up. This could indicate that upper limb symmetry is more crucial at this stage of rehabilitation than foot loading. Patients performed more walking bouts and longer durations at follow-up but differences were not statistically significant. More importantly, they were able to achieve stride velocities of more than 1m/s indicating functional recovery of normal velocities after rehabilitation. An interesting result was the decrease in symmetry for toe clearance that could be due to overcompensation by the affected limb at follow-up in order to better lift the foot from the ground and avoid foot-drop. Complexity showed to be sensitive to change once again even though its improvement was not significant.

Finally, objective metrics complemented clinical test scores by showing improvements for patients whose scores did not change substantially between baseline and follow-up. This is an important outcome since patients who already perform well at baseline could still benefit from mobility improvements notwithstanding their good clinical scores. For patients who improved drastically over the course of

rehabilitation as seen from their clinical scores, the objective metrics revealed similar trends and therefore were highly sensitive to mobility improvements.

The significance of statistical tests is limited by the low sample size in both studies (8 patients each). Definitive conclusions will be drawn when the studies are completed with appropriate number of patients. A comparison of effect size for clinical scores and objective metrics was undertaken and showed that several parameters had a large effect size, therefore have little overlap between their distributions at baseline and follow-up: a good indicator of recovery. Once the measurements are completed, the correlation between objective metrics and clinical scores will be analyzed to identify associations between these measures. For the stroke population it would be possible to analyze upper limb movement as well, since inertial data from sensors attached to the wrists and sternum are available. This, of course, will be clear once the final sample size is reached and the full dataset analyzed.

These findings are unique since monitoring patients for an entire day using instrumented shoes was not previously reported in the literature. The instrumented shoes, designed and validated in the current thesis, provide new possibilities for monitoring patients in their daily environment and offer new perspectives in wearable devices for clinical studies as described in the following section. The different recovery strategies (i.e. activity, complexity, load, or gait) can be detected with the instrumented shoes, and with appropriate monitoring timeline the succession of their improvement could also be revealed, e.g. improvement in gait at the clinic followed by increased activity levels at home.

## **6 Future perspectives**

Research in wearable activity monitoring is at its peak today, especially in terms of activity classification and characterization. There are many potential areas of development, and in the case of instrumented shoes, several technical and clinical improvements can be foreseen.

### **6.1 Technical developments**

#### **6.1.1 System miniaturization and robustness improvement**

Examples of early designs of the instrumented shoes system are shown in Figure 8-1. These versions were not robust enough to withstand the forces applied on the insoles. The wires connecting the sensors would break after relatively few days of use. Therefore an alternative solution where sensors were connected in a flexible manner was important. This was demonstrated by the force insoles from IEE, LU.

The current prototype of the instrumented shoes described in Chapter 3 requires two connectors: one from the insole to the electronics box and another from the box to the inertial measurement unit. A system miniaturization would be beneficial since it would provide more comfort, ease of use, less hazards (e.g. wires getting disconnected), and no sensors protruding from the shoes. This implies that all sensors, electronics, logging, and power unit be inserted in an insole. This is not a simple task, with many ergonomic and mechanical stability requirements. In fact, a recently concluded European project was dedicated to the design of such a fully integrated insole<sup>1</sup>. The insole should be thin enough to remain comfortable, and the circuit design should allow some flexibility to prevent connection breaks. One option would be to use the surface under the medial arch of the foot, which is not fully in contact with the ground during walking, to place bulky components (e.g. battery, memory card). In order to provide better mechanical robustness and avoid broken connections under the foot, a future possibility would be to use stretchable electronics, an area that is expanding rapidly with good overall results [355]. In our current configuration, the insole sensors are almost sealed shut between two layers of neoprene (to avoid drastic changes in humidity and temperature), meaning that the access to individual sensors is practically impossible. This is an additional consideration when building a miniaturized prototype: how to protect the sensors from humidity and temperature changes while keeping the sensors and electronics accessible. Another perceivable development is to improve power autonomy in order to extend the duration of monitoring time and avoid interaction with the users (i.e. necessity to charge the system overnight). Currently, this is limited by the available battery technology and size, and also by the sampling frequency required to perform accurate gait analysis. Testing should be done at lower frequencies to validate the effects of down-sampling on parameter accuracy. There have been prototypes of self-powering insoles [356]; this could well be an alternative power source but it does require loading triboelectric nanogenerators during walking and could be inefficient with at-risk populations (or any population that does not walk enough). Another interesting future perspective in foot-worn sensing would be tailoring sensor insoles to the individual by 3D printing techniques, an idea already proposed by [357].

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<sup>1</sup> <http://www.wiisel.eu/> (accessed 26.05.2016)



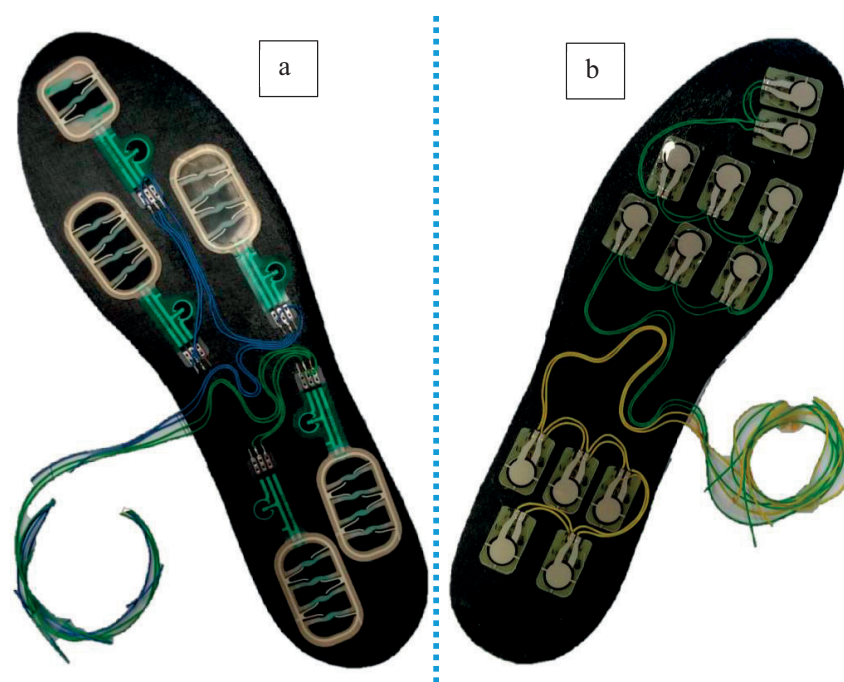


Figure 8-1 - Initial insole prototypes; a) Insole with standalone sensors from IEE, LU, b) Insole with standalone FSRs from Tekscan, USA.

We are already testing a first miniaturized prototype where the inertial unit and the electronics are deported to a single box that is clipped on the lateral side of the shoe, therefore eliminating the need for external connecting wires, Figure 8-2.



Figure 8-2 - Miniaturized instrumented shoe prototype with insole inserted in the shoe and inertial measurement unit clipped on the lateral side of the shoe. This system is also equipped with a Bluetooth data transmission chip

The durability of such insoles and their wear over time could be the topic of a future study. Due to repetitive high loading during dynamic activities it would be crucial to know the long-term repeatability and stability of the sensors.

### **6.1.2 Force sensor characterization**

Throughout this thesis, a simple calibration method was used to obtain the total force under the feet, by assuming that the load measured during static standing corresponds to body weight. However, this assumption does not allow accurate load measurement of each sensor. Hence, a calibration procedure would be required to obtain individual forces. This could be done using a dedicated device such as Trublu® (Novel, DE)<sup>2</sup>, providing uniform, user-controlled pressure on the insole sensors. It would be worth investigating if such static calibrations retain their performance during dynamic activities such as locomotion.

### **6.1.3 Real time activity monitoring and feedback**

An extremely powerful development in this area of research is to provide tailored feedback to individuals based on their mobility levels. For healthy older adults, this would benefit their longevity and increase their independence, whereas for populations at risk, fall prevention and balance/strength feedback could be crucial. One version of the instrumented shoes has already been equipped with Bluetooth transmission and real-time data from the system was used to create a stepping exergame that aims at increasing balance in older adults. The game uses the Kinect simultaneously to provide 3D foot position. The user is prompted to move one foot in a single direction and shift their weight, then go back to the initial position to start a second trial. The game recognizes stepping movements forward, backward, lateral, and oblique directions and gives direct feedback to the user on their correct/incorrect stepping patterns. Recognizing steps from non-step confounding movements was achieved with an accuracy exceeding 98% and the step direction classification accuracy was more than 99%. An illustration of the exergame is presented in Figure 8-3.

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<sup>2</sup> [http://www.novelusa.com/assets/pdf/pedar/pedar\\_mobile-pedography\\_web.pdf](http://www.novelusa.com/assets/pdf/pedar/pedar_mobile-pedography_web.pdf) (accessed 26.05.2016)

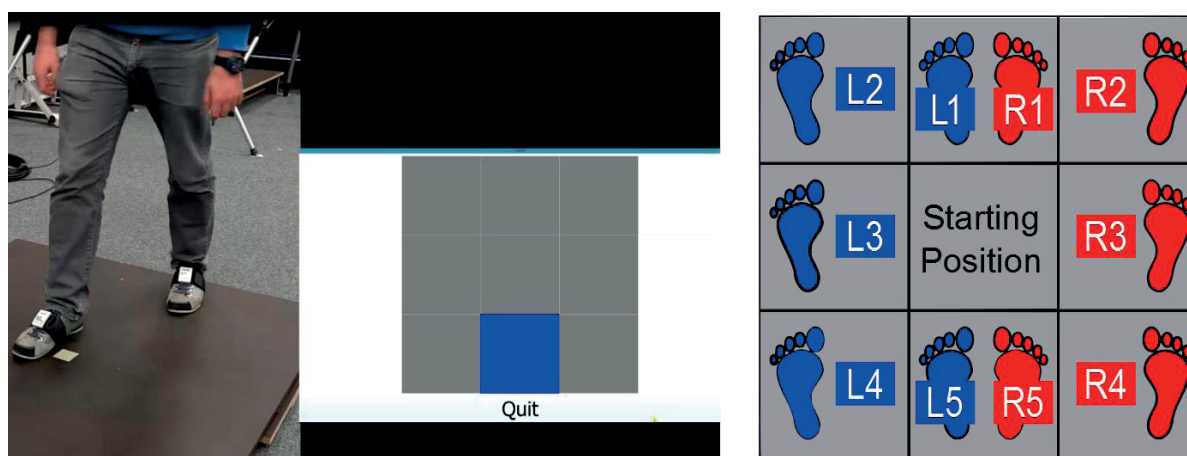


Figure 8-3 - Exergame with instrumented shoes. Left: user equipped with sensor system, middle: game visual interface, right: possible steps for each foot (blue for left, red for right).

The integration of our activity classification algorithm into a real (or quasi-real) time framework has a great prospect in delivering a two way feedback: from the sensors to clinicians and from clinicians to patients, e.g. via a smartphone. For example, the time spent in sedentary posture (sitting or lying) would be logged and sent to the clinician. In turn, the clinician could send a suggestion to the patient or user to have a short walk. This example is interesting because it has been shown that breaks in sedentary time are beneficial for an individual's health [309], [358], [359]. A possible system architecture illustrated in Figure 8-4 was presented as a finalist of the student contest at the Singapore Challenge<sup>3</sup>, and a developed version won the first prize at the Nursing Informatics conference in June 2016 (also part of a student design contest)<sup>4</sup>. The proposed system relies on the data transmission of the current instrumented shoes' sensors and a real-time algorithm that would be implemented on the smartphone. This algorithm should be capable of profiling the activity and analyzing gait as well as postural transitions. These parameters can then be provided to clinicians as described earlier. The smartphone will be used as the feedback interface to the user through motivational messages.

<sup>3</sup><http://www.nrf.gov.sg/gyss-one-north/gyss@one-north-2015/singapore-challenge/singapore-challenge-2015-finalists/christopher-moufawad-el-achkar> (accessed 26.05.2016)

<sup>4</sup>[http://www.ni2016.org/newsletters/en/newsletter\\_160711.html](http://www.ni2016.org/newsletters/en/newsletter_160711.html) (accessed 10.08.2016)

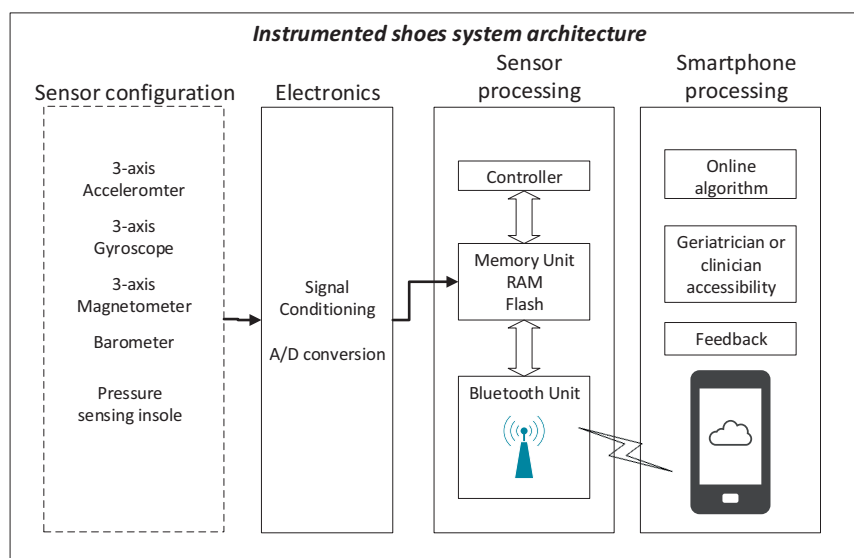


Figure 8-4 - Proposed system architecture for real-time activity monitoring and feedback through instrumented shoes and smartphone interface.

The current algorithm relies on several decision tree rules some of which might be impossible to implement for real-time monitoring. For example, the elevation change is not a single event in time, but rather a continuous increase or decrease throughout the activity. For that reason, it would be valuable to have algorithms that could detect the type of each step and not only a bout with elevation change. This work was investigated in the framework of this thesis with dynamic time warping technique to classify different step types, achieving an accuracy exceeding 90% with only a subset of all the sensors. Since dynamic time warping is not ideal for online implementation (the calculation of cost matrices is rather time consuming), other techniques would have to be explored. The center of pressure under the foot could be an additional parameter used for improving movement classification and balance characterization. The accuracy that could be achieved with 8 sensors is questionable, but preliminary results showed that it could be possible to estimate the center of pressure with less than 10% error compared to force plate. These results should be fully validated before drawing any final conclusions.

#### 6.1.4 Fusing instrumented shoes with other sensors

The instrumented shoes provide highly accurate activity, gait, and postural transition parameters. However, they do not evaluate upper body movement, for example. For more specific clinical applications they could thus be fused with sensors placed at the trunk or wrists, and measurements are already underway in the stroke study with one IMU on the sternum and one on each wrist. It is expected to profile upper body

behavior as well as activity and gait to provide a full picture of the recovery of stroke patients. The results will be available once the measurements are completed.

### **6.1.5 Postural transition characterization**

The proposed system was able to correctly classify transitions with high accuracy and measure their duration with low error, a substantial improvement compared to other single sensor based systems. However, only the duration was proposed to characterize the movement itself. Several studies reported for that the smoothness of trunk movement during sit-stand-sit transition is a clinically relevant parameter to quantify movement impairment in frail older adults. A perspective of the instrumented shoes system could be to estimate a “projection” of upper body dynamics evaluated by the trajectory of the center of pressure measured with the insole force sensors.

## **6.2 Clinical applications**

### **6.2.1 Home monitoring of patients after discharge**

The results of Chapters 6 and 7 demonstrated the possibility to use instrumented shoes for rehabilitation assessment in hip fracture and stroke inpatients. The presented results were limited to a small number of patients (data available during the timeframe of this thesis) but the two studies are ongoing, with more patients expected to be enrolled in the next months. It would have been interesting to compare the rehabilitation outcomes before and shortly after discharge, as well as a few months later, to understand if patients retain their improvements once intensive rehabilitation stops. This will be available for the stroke group since it was included in study design. The number of monitoring days was shown to be critical in relating reliable metrics, especially in terms of pattern complexity, and it would be desirable in future studies to include more than one day. This goes hand in hand with further technical developments allowing longer monitoring without having to change or recharge systems.

In future studies, it would be interesting to investigate the relationship between functional tests (e.g. 20m walk test, 6 minute walk test, 30s chair rise, 5 times sit to stand, timed up and go) that reflect the *capacity* of patients, and their daily *performance*. As observed in Chapter 6, post-surgery hip fracture patients improved their gait during a 20m test, but not during daily life. This indicated that patients were able to walk at higher speeds and with higher stride lengths, but did not reproduce this in their daily life behavior, possibly because their presence at the clinic did not require walking faster. Rehabilitation could be improved by tailoring it to each patient based not only on their clinical scores, but also on their maximal

capacity that would be reflected in their daily performance by appropriate means. Another interesting perspective would be to analyze the effect of using walking aids on activity and gait in daily life.

### **6.2.2 Real time feedback on activity performance**

Feedback to patients on their mobility levels proposed in the previous section remains a major future development goal of the smart shoes. It was suggested that appropriate motivational feedback could increase the subject's adherence and improve the quality of life of older adults [360], [361]. The delivery of feedback has many variables that should be accounted for, such as when to send feedback, how often, what type, how to involve the users/patients, etc... In the framework of instrumented shoes, it would be plausible to think of a smartphone or smart and connected watch (potentially using cloud storage) as the medium of information exchange. The data sent from the instrumented shoes could be processed on the phone itself, then the activity profile or gait performance would be sent to a clinician who will act accordingly. On a finer level, real-time feedback could be given to patients after surgery during gait rehabilitation, when they exceed a maximum allowed load threshold on their affected side. This could be given by an auditory or vibratory cue, and conveniently so if a vibrating motor were to be placed in the insole under the foot. Gait retraining would also become possible within a real-time framework by striving to correct asymmetries like those observed in Chapters 6 and 7.

### **6.2.3 Application to sports and other environments**

The studied populations in this thesis consisted of able-bodied older adults for technical, and at-risk populations for clinical validation. Other applications could be relevant for the instrumented shoes. Several sports could benefit from such a system to measure variables like contact time, speed, load, and relate these to fatigue, performance, and injury prevention. The system is currently being tested on running performance analysis in the framework of a research grant in collaboration with industry, and could be extended to sports like football, rugby, basketball, golf, and many others. Sports that include frequent jumping movement such as volleyball or basketball could also benefit from the instrumented shoes: the time of flight or time spent in the air could be estimated from non-contact time of the insoles and used to calculate the height (through equations of projectile motion considering zero initial velocity). Another likely application is for occupational health in industrial environments, especially where workers are concerned with lifting loads regularly or walking on uneven surfaces. Workers could be trained with instrumented shoes to avoid excessive load and prevent injury.

#### **6.2.4 Fall detection and risk estimation**

A paramount concern in today's activity monitoring is fall detection [119] and risk estimation [362], due to the high socio-economic impact of fall events on the elderly community and geriatric bodies. It is unknown at the moment if falls could be detected using instrumented shoes. This would require the detection of events such as slipping or high shocks, requiring dedicated studies to build accurate fall detection algorithms. However, activity programs to decrease fall risk could be monitored and the interventions evaluated with the vast number of parameters the smart shoes could offer, several of which have already been linked to fall risk (e.g. stride velocity, foot clearance).

#### **6.2.5 Application in diabetes**

People suffering from diabetes are at high risk of foot ulceration leading in many cases to foot amputation. Appropriate loading of ulcer-prone regions under the foot could decrease the risk, and this is traditionally enhanced by selecting appropriate insoles and shoes [363]. Measuring accurate loading with the instrumented shoes after individual sensor calibration as described previously could be crucial in decreasing ulceration risk through direct feedback to patients. The patient could be continuously guided during walking to avoid excessive load in risky zones of the foot and prevent deterioration of lesions. On the other hand, tailored insoles and shoes could be improved by measuring gait parameters from the instrumented shoe system.

#### **6.2.6 Gait freezing**

It is common in persons with Parkinson's disease that movement initiation becomes difficult; this is often referred to as gait freezing [364]. It is also a precursor of fall risk, but its detection in real life remains challenging. The instrumented shoes could be used for this type of detection as well as vibratory feedback to prevent the occurrence of freezing in Parkinsonian patients. Vibratory feedback has already shown promise in this field of gait monitoring [229]. A research grant has been submitted to pursue this application.

#### **6.2.7 Evaluation of ankle or knee arthrosis patients**

Unlike hip fracture, patients with ankle or knee arthrosis do not start walking immediately after surgery but spend some time on crutches or in a cast, without total loading of their affected side. It would be relevant to measure the improvement of such patients when they start walking and a few months later to see the effect of both the choice of surgery and the rehabilitation program on their daily mobility. To that

effect, we have already submitted an application to perform measurements with ankle arthrosis patient post operatively in collaboration with the university hospital (CHUV).

*In conclusion, the instrumented shoes present a myriad possible applications and have the potential to play a crucial role in activity monitoring in the coming years.*



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# Curriculum Vitae

## Education

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PhD	2012-2016
Laboratory of Movement Analysis and Measurement (LMAM) Ecole Polytechnique Fédérale de Lausanne Supervisor: Professor Kamiar Aminian Thesis topic: Instrumented shoes for daily activity monitoring in healthy and at risk populations	
Master of Science in Biomedical Engineering	2010-2011
University of Oxford, Pembroke College Master project: "Preparation of thermal and pH-responsive Hydrogel Nanoparticles (Nanogels) for Ultrasound-induced localized Drug Delivery"	
Bachelor of Engineering, Mechanical Engineering	2006-2010
American University of Beirut (AUB) Bachelor project: "Setting up a hydraulic test bench for position and pressure control applications and generate precise simulation models by measurement"	

## Research Experience

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Research assistant	2012-2016
Laboratory of Movement Analysis and Measurement (LMAM) Ecole Polytechnique Fédérale de Lausanne Supervision of 8 master semester projects, 1 full time bachelor and 2 full time master theses Assistant for the course "Sensors in Medical Instrumentation"	
Research internship	2009
Ecole Polytechnique de Montréal Project: "Dielectrophoretic force for lab-on-chip applications". Supervisor: Prof. Mohamad Sawan.	

Research assistant 2007  
American University of Beirut (AUB)  
Project: “Analysis of air contamination data in reconstruction regions of Beirut”

### ***Other relevant experience***

*Vice president of the Oxford Biomedical Engineering Society (OBMES),* 2011  
*Secretary of the Oxford Engineering World Health (EWH) chapter,* 2011  
*Member of the Pembroke College MCR committee (cultural representative),* 2011

## ***Journal Publications***

Moufawad el Achkar C.; Lenoble-Hoskovec C.; Paraschiv-Ionescu A.; Major K.; Büla C.; Aminian K., “Instrumented shoes for activity classification in the elderly”, *Gait & Posture*, Volume 44, February 2016, Pages 12-17, ISSN 0966-6362, <http://dx.doi.org/10.1016/j.gaitpost.2015.10.016>.

Aminian K. and Moufawad el Achkar C., “La chaussure instrumentée pour l’analyse de la marche et de l’activité quotidienne”, *Fachzeitschrift Rheuma Schweiz* Nr. 3 | 2016

Moufawad el Achkar C., Lenoble-Hoskovec C., Paraschiv-Ionescu A., Major K., Büla C., Aminian K., “Physical behavior in older persons during daily life: Insights from instrumented shoes”, *Sensors (Basel)* 2016, 16, 1225

Moufawad el Achkar C., Lenoble-Hoskovec C., Paraschiv-Ionescu A., Major K., Büla C., Aminian K., “Classification and characterization of postural transitions using instrumented shoes”, to be submitted to *IEEE transactions on Biomedical Engineering*

## Conferences

Miled, M.A.; El-Achkar, C.M.; Sawan, M., "Low-voltage dielectrophoretic platform for Lab-on-chip biosensing applications," *NEWCAS Conference (NEWCAS), 2010 8th IEEE International*, pp.389,392, 20-23 June 2010 doi: 10.1109/NEWCAS.2010.5603998

El Achkar, C.M.; Masse, F.; Arami, A.; Aminian, K., "Physical activity recognition via minimal in-shoes force sensor configuration," *7th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, pp.256,259, 5-8 May 2013

Moufawad el Achkar C., Paraschiv-Ionescu A., Bourke A.K., Aminian K., "Stair descent detection using foot-worn inertial sensors", 13th International Symposium on 3D Analysis of Human Movement, 2014

Bourke A.K., Barré A., Mariani B., Moufawad El Achkar C., Paraschiv-Ionescu A., Aminian K., Vereijken B., Skjaeret N., Helbostad J., "Design and Development of an Inertial Sensor Based Exergame for Recovery-Step Training" Wearable and Implantable Body Sensor Networks Workshops (BSN Workshops) 2014, 11th International Conference on, pp 27-32

A. Paraschiv-Ionescu, C. Büla, K. Major, H. Krief, C. Moufawad el Achkar, K. Aminian, "Mobility and movement complexity change with ageing and risk of falling", Engineering in Medicine and Biology Society, 37th Annual International Conference of the IEEE, August 2015

Major K., Moufawad el Achkar C., Lenoble-Hoskovec C., Paraschiv-Ionescu A., Büla C., Aminian K., "Instrumented shoes for activity monitoring in the elderly: Measurement System and in lab Validation", Healthy Medicine - SGIM Jahresversammlung 2015

Moufawad el Achkar C., Maier, J., Eskofier B., and Aminian K., "Smart shoes for daily activity monitoring and exergaming in older adults" Congrès annuel de la Société Suisse de Gériatrie 2016

A. Paraschiv-Ionescu, K. Major, C. Lenoble-Hoskovec, H. Krief, C. Moufawad El Achkar, C. Büla, K.Aminian, "How functional capacity assessed in clinical setting is related to daily-life physical activity behavior" Congrès annuel de la Société Suisse de Gériatrie 2016

Major K., Ionescu A., Krief H., Moufawad Ch., Aminian K., Büla Ch. “Relationship between daily physical activity complexity pattern and frailty, falls, and fear of falling”, Congrès annuel de la Société Suisse de Gériatrie 2016\*

Moufawad el Achkar C., Lenoble-Hoskovec C., Paraschiv-Ionescu A., Major K., Büla C., Aminian K., “Instrumented shoes for real-time activity monitoring applications”, Nursing Informatics Conference, Geneva, 2016

Moufawad el Achkar C., Lenoble-Hoskovec C., Paraschiv-Ionescu A., Major K., Büla C., Aminian K., “Outcome evaluation in older patients admitted to rehabilitation after a hip fracture”, accepted in ESMAC 2016 International Congress

## Other dissemination

Global Young Scientists Summit, GYSS@one-north 2015

*Finalist of the Singapore challenge “Ageing-In-Place”. 9 proposals accepted out of 55 submissions.  
Proposal title: “Smart Shoes to Promote Active Ageing.”\**

Nursing Informatics 2016

*Winner of the NI2016 Student contest, abstract title: Instrumented shoes for real-time activity monitoring applications.†*

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\*Winner of the best poster award

\*<http://www.nrf.gov.sg/gyss-one-north/gyss@one-north-2015/singapore-challenge/singapore-challenge-2015-finalists> (accessed 26.05.2016)

† [http://www.ni2016.org/newsletters/en/newsletter\\_160711.html](http://www.ni2016.org/newsletters/en/newsletter_160711.html) (accessed 10.08.2016)

