Assessment of Foot Signature Using Wearable Sensors for Clinical Gait Analysis and Real-Time Activity Recognition

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Abstract

Locomotion is one of the most important abilities of humans. Actually, gait locomotion provides mobility, and symbolizes freedom and independence. However, gait can be affected by several pathologies, due to aging, neurodegenerative disease, or trauma. The evaluation and treatment of mobility diseases thus requires clinical gait assessment, which is commonly done by using either qualitative analysis based on subjective observations and questionnaires, or expensive analysis established in complex motion laboratories settings.

This thesis presents a new wearable system and algorithmic methods for gait assessment in natural conditions, addressing the limitations of existing methods. The proposed system provides quantitative assessment of gait performance through simple and precise outcome measures.

The system includes wireless inertial sensors worn on the foot, that record data unobtrusively over long periods of time without interfering with subject's walking. Signal processing algorithms are presented for the automatic calibration and online virtual alignment of sensor signals, the detection of temporal parameters and gait phases, and the estimation of 3D foot kinematics during gait based on fusion methods and biomechanical assumptions. The resulting 3D foot trajectory during one gait cycle is defined as *Foot Signature*, by analogy with hand-written signature.

Spatio-temporal parameters of interest in clinical assessment are derived from foot signature, including commonly parameters, such as stride velocity and gait cycle time, as well as original parameters describing inner-stance phases of gait, foot clearance, and turning. Algorithms based on expert and machine learning methods have been also adapted and implemented in real-time to provide input features to recognize locomotion activities including level walking, stairs, and ramp locomotion.

Technical validation of the presented methods against gold standard systems was carried out using experimental protocols on subjects with normal and abnormal gait. Temporal aspects and quantitative estimation of foot-flat were evaluated against pressure insoles in subjects with ankle treatments during long-term gait. Furthermore, spatial parameters and foot clearance were compared in young and elderly persons to data obtained from an optical motion capture system during forward gait trials at various

speeds. Finally, turning was evaluated in children with cerebral palsy and people with Parkinson's disease against optical motion capture data captured during timed up and go and figure-of-8 tests. Overall, the results demonstrated that the presently proposed system and methods were precise and accurate, and showed agreement with reference systems as well as with clinical evaluations of subjects' mobility disease using classical scores. Currently, no other methods based on wearable sensors have been validated with such precision to measure foot signature and subsequent parameters during unconstrained walking.

Finally, we have used the proposed system in a large-scale clinical application involving more than 1800 subjects from age 7 to 77. This analysis provides reference data of common and original gait parameters, as well as their relationship with walking speed, and allows comparisons between different groups of subjects with normal and abnormal gait.

Since the presented methods can be used with any foot-worn inertial sensors, or even combined with other systems, we believe our work to open the door to objective and quantitative routine gait evaluations in clinical settings for supporting diagnosis. Furthermore, the present studies have high potential for further research related to rehabilitation based on real-time devices, the investigation of new parameters' significance and their association with various mobility diseases, as well as for the evaluation of clinical interventions.

Keywords: Gait analysis, Elderly, Parkinson's disease, Cerebral palsy, Ankle osteoarthritis, Amputee, Spatio-temporal parameters, Foot clearance, Turning, Real-time, Inertial sensors, Wearable system, Validation, Activity classification.

Résumé

La locomotion est une des capacités les plus importantes de l'être humain. En effet, la locomotion, et plus particulièrement la marche, permet la mobilité, synonyme de liberté et d'indépendance. Cependant, un certains nombres de pathologies peuvent affecter la marche, par exemple le vieillissement, les maladies neuro-dégénératives, ou encore un traumatisme. L'examen et le traitement de ces pathologies requièrent de ce fait une évaluation clinique de la marche. Une telle évaluation se fonde habituellement soir sur des analyses qualitatives à base d'observations subjectives et des questionnaires, soit par l'intermédiaire d'outils complexes et coûteux dans des laboratoires dédiés à l'analyse du mouvement.

Cette thèse présente un nouvel outil qui aborde les problèmes des méthodes existantes, en proposant un système portable et des méthodes algorithmiques pour l'évaluation de la marche en condition naturelles. L'outil proposé quantifie la performance de marche grâce à des métriques simples et précises.

Le système comprend des capteurs inertiels sans fils se fixant sur le pied et enregistrant des signaux de longues durées sans gêner la marche du patient. Les algorithmes de traitement du signal présentés permettent une calibration automatique et l'alignement virtuel des capteurs ; la détection des évènements temporels et des phases de marche ; ainsi que l'estimation de la cinématique 3D du pied, et ce à partir de méthodes de fusion et d'hypothèses biomécaniques. La trajectoire 3D que dessine le pied dans l'espace pendant un cycle de marche a été définie comme la *Signature du Pied*, par analogie avec la signature écrite à la main.

Un ensemble important de paramètres spatio-temporels ont ainsi été extraits de la signature du pied. Cela inclu des paramètres classiques utilisés en analyse de marche, comme la vitesse de marche et la durée du cycle, mais aussi des paramètres originaux comme les sous-phases constituant l'appui au sol, l'élévation du pied, et le virage. Les algorithmes ont également été adaptés et implémentés en temps-réel, pour servir d'entrée à des méthodes d'intelligence artificielle capables de reconnaitre les activités telles que la marche à plat, en pente, ou en escaliers.

Les méthodes présentées ont été validées techniquement contre des systèmes de référence à partir de protocoles expérimentaux incluant des sujets avec ou sans pathologies liées à la marche. Les aspects

temporels et la quantification du temps d'appui à plat ont été évalués contre des semelles de pression chez des sujets avec arthrose de cheville pendant des marches longue durées. Les paramètres spatiaux et l'élévation du pied ont été comparés chez des jeunes adultes et des personnes âgées avec un système de capture optique du mouvement. Enfin l'analyse des virages pendant le test de Timed up and Go et la marche en 8 a été validés chez des enfants avec paralysie cérébrale et des personnes atteintes de la maladie de Parkinsons. Globalement, les résultats démontrent une bonne justesse et fidélité, ainsi qu'une bonne concordance avec les systèmes de référence et les évaluations cliniques.

Alors qu'aucune autre méthode basée sur des capteurs portables n'a été jusqu'à présent validée pour mesurer aussi fidèlement la signature du pied et les paramètres qui en découlent, nous avons ici utilisé le système et les méthodes proposées pour une application clinique d'envergure impliquant plus de 1800 personnes âgées de 7 à 77 ans. L'analyse a permis d'obtenir des données de référence pour les paramètres de marche classiques et originaux. Elle a aussi permis de montrer les associations de divers paramètres avec la vitesse de marche, et de les comparer entre différents groupes de sujets avec ou sans pathologies liées à la marche.

Du fait que les méthodes présentées peuvent être utilisées avec n'importe quel système de capteurs inertiels sur le pied voire combinées avec d'autres systèmes, nous pensons que le travail présenté ouvre la porte à l'évaluation quantitative et objective de la marche en routine clinique, en tant qu'outil de support au diagnostic. De plus, l'étude permet d'entrevoir de futures recherches liées aux systèmes de réadaptation temps réels, à l'étude de la signification cliniques des nouveaux paramètres avec les pathologies de la marche, ou encore à l'évaluation des interventions cliniques.

Mots-clefs: Analyse de Marche, Personnes âgées, Maladie de Parkinson, Paralysie cérébrale, arthrose de la cheville, amputés, paramètres spatio-temporels, élévation du pied, virage, temps-réel, capteur inertiels, systèmes portables, validation, classification d'activités.

要旨

運動は人間の能力の中でも重要な能力であり，その中でも特に歩行運動は自身で移動を行うという点で自主独立性の象徴であるとも考えられる．一方で歩行は加齢や神経疾患，外傷などに影響を受けるため，運動疾患の診断やリハビリテーションの処方に対して歩行機能の評価が必要である．現在広く用いられている医師による評価は定性的であり，妥当性の面で限界がある．そのほか，機器を用いた評価が散見されるが，高額な機材や複雑なシステムが必要であることが多い．

本研究ではこれらの問題に対し，装着可能な機器を用いた自然な歩行による評価システムの開発を行う．本システムの開発により，臨床において簡便かつ正確な計測を行うことが可能となり，疾患に対して定量的な評価を行うことが可能となる．

本システムは被検者の歩行動作の妨げにならないような，足部に取り付けられた無線の慣性センサから構成される．センサ信号から検出された歩行運動中の運動パラメータから歩行相, 足部の運動特性等のパラメータをオンライン上で自動的に算出する．その際，歩行周期中の三次元空間上の足部軌跡は，各個人の持つ固有の署名のような“Foot signature”として定義される．加えて，Foot signature から一般的に用いられる歩行速度，歩行周期などと同様に，本研究で独自に定義される，インナースタンス，フットクリアランス，回旋歩行特性等のパラメータを算出する．解析は試行中に実行され，平坦面，階段，斜面における運動を把握する要素として提供される．

正常歩行と非正常歩行の計測において，現在広く用いられている手法と比較することにより，本研究で提案する手法の妥当性の検証を行った．足底接地時の時間相と定量指標を被検者の足底内圧により評価し，加えて異なる速度で行った直線歩行時の運動特性について光学モーションキャプチャシステムを用いて高齢者と若年者間での比較を行った．その後，脳性マヒ児童，パーキンソン病患者において，旋回運動時の特性を評価し，比較した．全実験で，得られた結果は参照システムと比較し十分な正確性があり，臨床評価とも一致することが確認された．

また臨床における実証実験として，本研究で提案するシステムを用いて，異なる疾患を持つ 7 から 77 歳までの 1800 人以上の被検者に対し計測を行い，一般的な運動パラメータと歩行速度等に関連した独自のパラメータを用いた解析によって異なる被検者群の分類を行った.

本研究により提案される慣性センサ，および他の計測システムとの組み合わせによる歩行評価システムによって，様々な運動障害に対し客観的かつ定量的な歩行評価，および診断やリハビリテーションの処方が可能になると期待される.

キーワード : 歩行解析，高齢者，パーキンソン病，脳性麻痺，変形性関節症，切断患者，時空間パラメータ，フットクリアランス，旋回，リアルタイム，慣性センサ，ウェアラブルシステム，妥当性，活動特性

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Glossary

CP = Cerebral palsy

PD = Parkinson's disease

Elderly = elderly persons

OA = Osteo-arthritis

FWS = Foot-worn sensors

IMU = Inertial measurement unit

2D/3D = 2-dimensional/3-dimensional

SAF = Shank-ankle-foot

PC = Principal components

PCA = Principal components analysis

LDA = Linear discriminant analysis

GMM = Gaussian mixture models

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Chapter 1

Introduction

1 Human locomotion

As illustrated artistically by the walking man of Alberto Giacometti (fig. 1), human terrestrial locomotion, referred as gait, is typically achieved by bipedal and biphasic propulsion of the body using alternate movements of the lower limbs. Human gait can also be seen as a step in evolution [1], and although the evolutionary theory of the upright posture and gait in human is still discussed [2], bipedalism is one of the most obvious characteristic that distinguish us from our apes ancestors. Different patterns and strategies are used by humans for achieving locomotion. Locomotion modalities include normal and natural forward walking gait, but also backward, sideward, turning, and running gait. In addition, the terrain can vary between level ground, stairs, inclined ramps and uneven terrain, etc... Finally, although evolution has shaped human body to walk barefoot, most of the people are now commonly using various kinds of footwear, providing an additional artificial interface between the feet and the ground.

Figure 1 - *L'Homme qui marche I*, bronze sculpture by Swiss sculptor Alberto Giacometti in 1961

During normal human life, gait is present in most children by the age of eighteen months, and reach a good level of maturity at the age of three years [3]. Gait locomotion can therefore be considered as one of the most important ability of man, since it guaranties mobility and independence, and therefore social integration and freedom.

2 Mobility diseases

Like any other ability, gait can be affected by different pathologies. The goal of this paragraph is to present a non-exhaustive list of mobility diseases that affect human gait in modern society and which were specially considered in the present thesis as clinical issues. Their main symptoms, etiology and consequences for the patient are briefly presented, as well as some figures on their prevalence, illustrating the global impact on society.

2.1 Risk of falling in elderly persons

Falls are a major cause of morbidity and mortality among the older population and thus a major public health concern in modern societies with ageing populations [4]. Falling can dramatically affect the quality of life and often requires expensive treatments. Consequences can be fracture, or psychological trauma, leading to a self-imposed limitation in mobility, that can precipitate further functional decline. Recent prospective studies undertaken in community setting have found falls incidence rates around 30% in subjects aged 65 years and over [5], fig. 2.

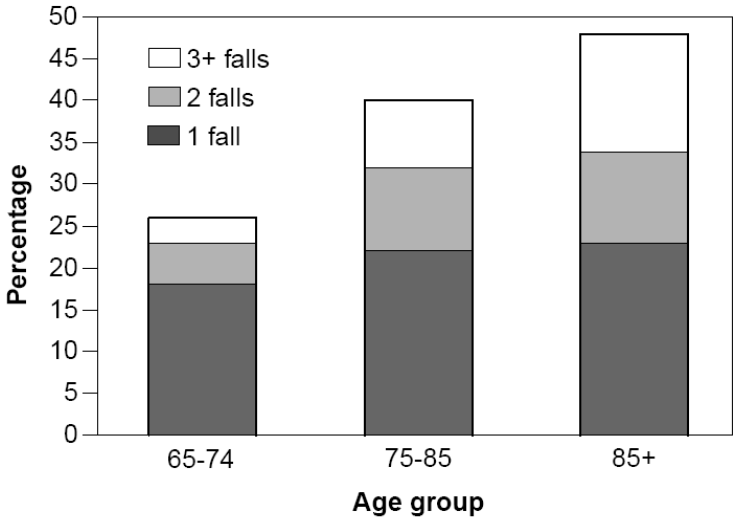

Figure 2 - Incidence of falls in older people : Proportion of older women who took part in the Randwick Falls and Fractures Study who reported falling, once, twice or three or more times in a 12-month period. Diagram adapted from Lord et al. 2007

Multi factorial etiology indicates two types of fall risk factors [6], [7]:

- Intrinsic factors to the individuals. It includes normal or pathologic age related changes. Problems can be of different nature: neurologic, sensory (vestibular and vision), musculo-skeletal, cardio-vascular…

- Extrinsic factors, external to the person, include physical environment, medication, non-adapted assistive device or footwear.

Actual fall is likely to happen after a balance loss when the neuro-muscular system doesn't manage to maintain balance. Efforts have been done to prevent fall and detect intrinsic risks of fall, by understanding and detecting early symptoms that could lead to a fall [8].

2.2 Neurological disorders

Among the various neurological disorders, the present work focuses especially on the study of Parkinson's disease (PD) and Cerebral Palsy (CP).

After Alzheimer's, Parkinson's disease (PD) is the second most common neuro-degenerative disease, with estimated 3 to 4 million people worldwide. PD is a degenerative disorder of the central nervous system. The motor symptoms of PD result from the death of dopamine-generating cells in the substantia nigra, a region of the midbrain; the cause of these cells death is unknown. Early in the course of the disease, the most obvious symptoms are related to movement, namely tremor, rigidity and akinesia (lack of movement). PD is particularly influencing gait, and various combinations of symptoms generate a significant decrease in mobility while the disease progresses [9]. Later, cognitive and behavioural problems may arise, with dementia commonly occurring in the advanced stages of the disease. Other symptoms include sensory, sleep and emotional problems. PD is more common in the elderly, with most cases occurring after the age of 50. Nowadays, this disease concerns about 180 people over 100 000 for Caucasians. Pharmaceutical treatments to Parkinson's disease include L-dopa which is transformed into dopamine in the dopaminergic neurons by L-aromatic amino acid decarboxylase. That treatment is effective at managing the early motor symptoms of the disease, but as the disease progresses, these drugs become ineffective at treating the symptoms and at the same time produce a complication called dyskinesia, marked by involuntary writhing movements. Surgery and deep brain stimulation are used to reduce motor symptoms as a last resort in severe cases where drugs are ineffective. In PD, motor changes are complex and constantly evolving, and movement features have considerable interindividual heterogeneity, making comparison between individual patients difficult.

Cerebral palsy (CP) is an umbrella term encompassing a group of non-progressive, non-contagious motor conditions that cause physical disability in human development, chiefly in the various areas of body movement. Cerebral refers to the cerebrum, which is the affected area of the brain, and palsy refers to disorder of movement. In the industrialized world, the prevalence of CP is about 2 per 1000 live births, with higher incidence in males than in females. CP is caused by damage of the motor control centers in the developing brain and can occur during pregnancy, during childbirth or after birth up to about three

years old. The definition and classification of CP remains a current topic [10]. CP troubles of movement and posture cause activity limitation and are often accompanied by disturbances of sensation, depth perception and other sight-based perceptual problems, communication ability; impairments can also be found in cognition, and epilepsy is observed in about one-third of cases. CP is often accompanied by secondary musculoskeletal problems that arise as a result of the underlying etiology. CP symptomatology is very diverse but characterized by abnormal muscle tone, reflexes, or motor development and coordination. The classical symptoms are spasticity, spasms, other involuntary movements, unsteady gait, and problems with balance. Scissor walking (where the knees come in and cross) and toe walking are common among people with CP who are able to walk.

2.3 Lower limb osteoarthritis

Osteoarthritis (OA) is a pathology that involves the degradation of joints, and particularly the cartilage and bone structure. Symptoms may include joint pain, tenderness, stiffness, locking, and sometimes an effusion. In the particular case of lower limb joints, namely hip, knee and ankle joints, lower limb OA implies a decreased of locomotion ability, from which potential consequences can be the atrophy of muscles and increase of laxity of ligaments, together with the reduction of mobility and subsequent social activities. OA is predominately considered as a "wear and tear" process, where there is gradual degradation of the cartilage that covers the articulating surfaces of the bones in the joint. In most people, the disease is either post-traumatic or hereditary. Treatment generally involves a combination of exercise, lifestyle modification, and analgesics. If pain becomes debilitating, joint replacement surgery is considered, with different operating techniques and replacement structures for each joint. Prevalence of OA varies among countries and is reported in various studies. Typically in the US, using physical examination and radiographic measurement on a cohort of 1424 subjects, knee OA was found to concern 27% of subjects aged 63 to 70 years, and 44% of subjects aged 80 or older [11].

2.4 Lower limb amputation

Amputation refers to the loss of body parts either due to injury (traumatic) or missing from birth (congenital). Statistics about the number of amputees are rare and sometimes old. For example in France, the most reliable estimation of lower limb amputees is 100 000 to 150 000 out of 65.8 million inhabitants. This appraisal depends on the definition of the amputation (lower or upper limb) and on its gravity (major, partial or distal). A finger or toe amputation is completely different from a complete limb amputation which requires the use of prosthesis. A more accurate estimation can be made with the activity reports of the health centers. For instance in France, in 1990, the incidence of major amputees of a lower limb was approximately estimated to 8300 new cases and the total number of lower limb amputees to 90 000. Nowadays, the incidence is appreciably the same: 8203 cases indexed in 2001 and

7525 in 2005. The number of trans-femoral amputations, also referred as “below-knee amputations”, seems to be slightly inferior to the number of trans-tibia amputations. The issue of gait and locomotion for trans-tibia amputees is closely linked to the technology of the prosthesis. From the comparison of ankle biomechanics of healthy subjects and trans-tibia amputees, main issues for amputees are balance, capacity of performing specific activities such as gait in stairs or hills, energy cost of walking, comfort and esthetics (for the integration in society), and the cost of prosthetic devices.

3 Clinical Gait analysis

Since human gait can be affected by mobility diseases such as the ones described in paragraph 2, early has emerged the interest of analyzing in a rigorous and scientific manner the normal and abnormal gait of human beings. A really well-documented history of clinical gait analysis can be found in the book by Kirtley [12], and on his website[1]. Kirtley describes what could have been the first gait analysis report from egyptian in 1800 B.C based on qualitative observation and the work of pioneers in gait analysis such as Etienne-Jules Marey (1830-1904), who had begun investigating the external motion and movement of human gait using ingenious recording devices by 1867. Nowadays, clinical gait analysis still relies on the use of observations, but also on clinical scales established upon questionnaires filled by the subject or therapist, and quantitative measurements of body movements using various kinds of systems. All those tools are more extensively described in chapter 2: State of the art.

First of all, independently of normal or abnormal status, human gait can be described with a general and simplified terminology as follow (fig. 3):

- The gait cycle starts with the contact of one foot and ends with the next contact of the same foot.
- Stance (respectively swing) phase is defined as the period where the foot is in contact with the ground (respectively in the air).
- Double support is defined as the period (if any) when both feet are in contact with the ground, as in the walking man from Giacometti (fig. 1). In running gait, there is no double support.
- Step (respectively stride) is defined from the stance of one foot to the next stance of the other (respectively same) foot. A stride, being the set of right and left steps, is thus equivalent to gait cycle.

[1] http://www.clinicalgaitanalysis.com/

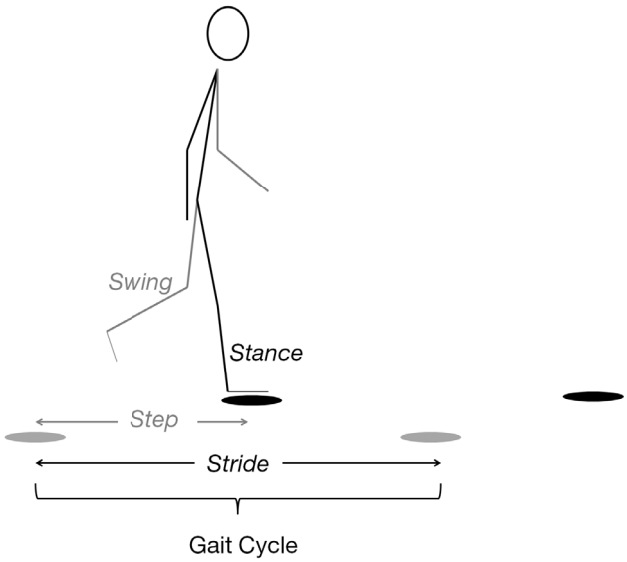

Figure 3 - Simplified diagram for general gait terminology

Second, to describe more in detail the biomechanics of human locomotion, clinical gait analysis relies on the following theoretical approaches:

- **Kinematics**, describing the motion of limbs, with typically time series of joint angles and limb displacements.
- **Kinetics**, describing the relationship between the motion of bodies and its causes, namely forces and torques, which is also referred as dynamics. Kinetics includes the study and modelization of forces and torques within joints.
- **Physiological aspects**, including metabolism and energetic costs, with typically the activity of the brain (using electro-encephalo graphy), muscles (using electro-myography), or cardiac (using electro-cardio graphy).
- **Spatio-temporal parameters**, describing locomotion in a discrete manner by quantifying specific metrics during different phases of each gait cycle. Those metrics relate to kinetics or kinematics, or other measurable quantity. Common spatio-temporal parameters include duration of gait cycle (or its inverse value, referred as cadence), swing and stance phases, double support, as well as step or stride length, and stride velocity (also referred as walking speed), and joint range of motions.

The advantage of spatio-temporal parameters approach is that it synthesizes or compresses the information in a clinically interpretable outcome measure. Furthermore, the study of the fluctuation of parameters from stride to stride can also be interesting in order to assess inter-cycle gait variability.

4 Thesis rational and objectives

The introduction has shown the importance of human locomotion, but also that it can be affected by several mobility diseases with high impact on people and society. Consequently, gait analysis is important for the *assessment* of gait abnormality due to *mobility disease,* the *assessment* of interventions, i.e. *treatment* (fig. 4). Furthermore, gait *assessment* can contribute to interventions, for example by means of real-time devices.

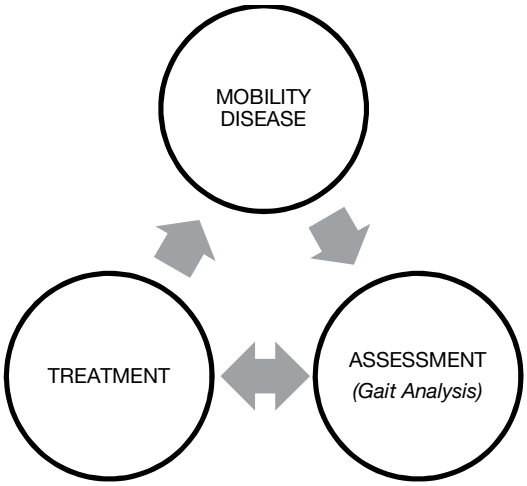

Figure 4 – Gait Analysis: an *assessment* tool of *mobility disease*'s symptoms and *treatment* efficiency

However, common methods for clinical gait analysis suffer from several drawbacks:

- Subjective assessment with questionnaires and clinical scores are prone to error due to self-interpretation of questions or difficulty to recall the truth
- Kinematics and kinetics analysis assessment using dedicated laboratory measurement tools, suffer from being time consuming, high costs, setup complexity, and limited volume of measurement
- Observations and low tech estimation of walking speed or cadence have limited performances to characterize various motor symptoms
- Controlled/imposed conditions such as walking in straight line, does not reflect natural human locomotion and its various modalities in daily-life

The rational of the thesis is therefore to address those issues with new systems and methods for the assessment and treatment of various mobility diseases affecting human gait.

The primary objective can be summarized as the design and validation of a system and dedicated methods that are easy to use in clinical practice, usable in natural and unconstrained walking condition, and still technically and clinically valid. The underlying hypothesis, motivated by pilot results, is that it is possible to provide such a gait assessment tool using foot-worn inertial sensors (FWS), through the estimation of

3D foot kinematics and the extraction of subsequent original spatio-temporal parameters. This thesis focuses on spatio-temporal parameters approach, since it provides interpretable and quantitative outcome measures of gait performance.

More specifically the objectives of the thesis can be summarized as:

- To design FWS-based algorithms for objective and quantitative gait assessment, by estimating 3D foot kinematics, and resulting common spatio-temporal gait parameters, as well as new gait metrics related to foot clearance and turning.
- To assess validity and robustness of the outcomes of proposed algorithms against reference systems during typical tests performed in populations suffering from mobility diseases.
- To evaluate the ability of the proposed outcome parameters for discriminating abnormal gait and effect of treatments on elderly, PD, CP, OA and amputee subjects compared to control subjects.
- To adapt and implement FWS-based algorithm in real-time for the control of active rehabilitation devices and prosthetics, using detected walking phases and extracted gait features.
- To introduce foot signature concept and its subsequent parameters, and evaluate an analysis methodology for its application to the real-time recognition of walking activity and the discrimination of various mobility diseases in a significant cohort of subjects.

5 Thesis outline

The thesis is organized in nine chapters as illustrated in fig. 5.

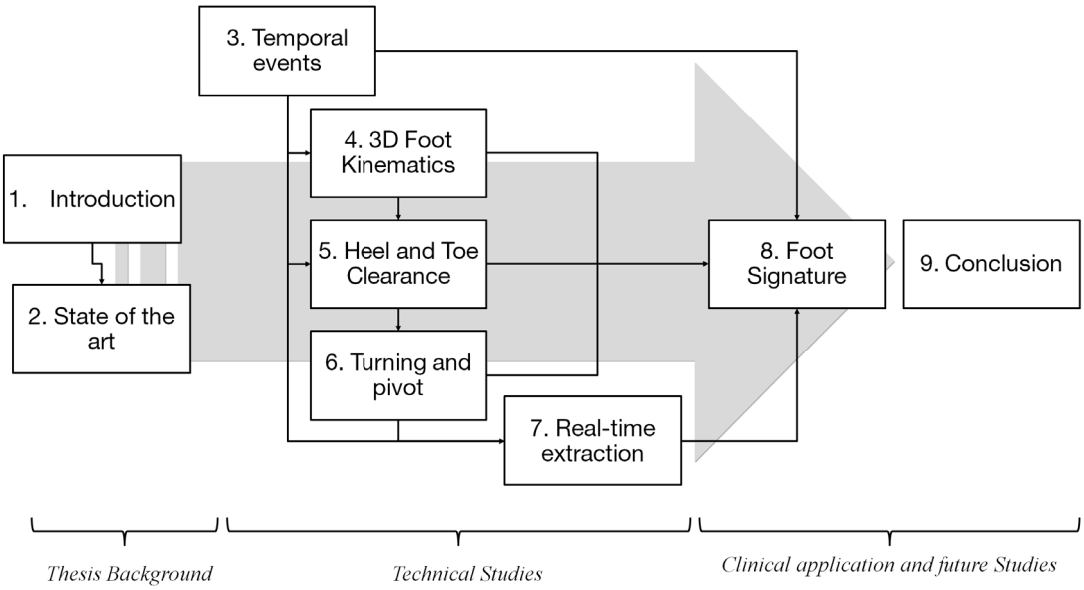

Figure 5 – Gait analysis using foot-worn sensors: outline of the thesis and chapters

Chapter 1 (current chapter) introduces the topic of this thesis, through the presentation of human locomotion and various mobility diseases, as well as the general background theory behind clinical gait analysis. The rational and motivations of the research work are explained together with the objectives and outline of the thesis.

Chapter 2 presents the state of the art in the field of spatio-temporal gait assessment tools, including a short description of reference methods, and a review of methods based on wearable technology for both offline and online analyses.

Chapter 3 proposes new methods for temporal analysis of gait using FWS, through temporal events detection and the quantitative assessment of foot-flat and inner-stance phases. Results of the technical validation of the system and its application to the study of ankle OA treatments are presented.

Chapter 4 proposes new methods for spatial analysis of gait using FWS, through the estimation of 3D foot orientation and displacements and related spatio-temporal gait parameters. Results of the technical validation of the system and its application to the study of young and elderly subjects are presented.

Chapter 5 combines together the finding of temporal and 3D spatial analysis from previous chapters, and proposes an original method for automatic estimation of sensor position on foot and estimation of heel and toe clearance from FWS. Various solving approaches are presented and results of technical validation on healthy subjects are described.

Chapter 6 extents the methods from 3D spatial analysis to PD and CP subjects and further develops the analysis of turning. Original parameters to describe 3D foot trajectory and turning are presented, validated, and compared against age-matched control subjects.

Chapter 7 presents the adaptation implementation of temporal and spatial gait analysis using FWS in real-time. New methods are described for the real-time detection of walking phases and features extraction. Results obtained with instrumented prosthetics in amputees performing various locomotion activities are presented.

Chapter 8 introduces the general concept of “foot signature”, unifying the gait analysis outcomes resulting from all preceding chapters. Its application to recognize walking activity in amputee subjects and to characterize mobility diseases on more than 1800 subjects is presented.

Finally, **Chapter 9** provides a general discussion on the achievements of the thesis and the perspectives for future research.

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Chapter 2

Spatio-temporal gait analysis: State of the Art

1 Overview

Gait analysis tools can be classified in 4 main categories (fig. 1). On one side, clinical scales are well-established reference methods for qualitative assessment of disease symptoms and outcome evaluation of treatments, whereas laboratory systems are reference methods for kinematics, kinetics and spatio-temporal measurements mostly used in research and biomechanical evaluation. With the progress of new technologies based on wearable and embedded systems it is now possible to monitor the patient in more natural conditions, and at the same time to offer a quantitative analysis. However, the measured signals are usually not self-interpretable for a direct outcome evaluation and require further algorithm and analysis methods to reach clinical relevance. Similar to laboratory techniques, wearable systems can be used for kinetics, kinematics and spatio-temporal gait analysis. This chapter focuses more on gait analysis review with wearable and embedded system with a particular emphasis on spatio-temporal gait analysis, while clinical scales and laboratory techniques are briefly introduced.

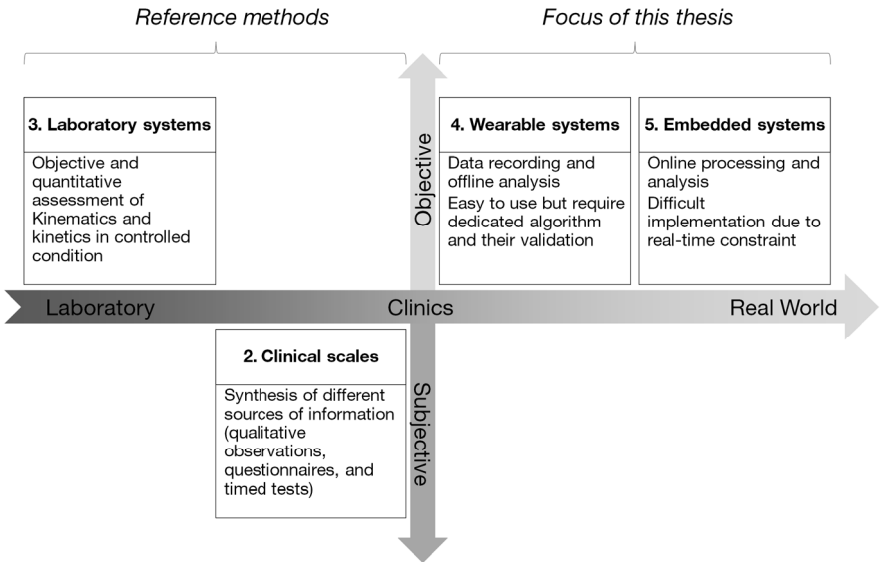

Figure 1 – Summary of the different categories of gait analysis tool versus portability and objectivity

2 Clinical scales

In addition to simple background data, consisting of objective figures such as gender, height, weight and age, there exists a wide range of clinical scores addressing different mobility diseases and clinical status. In this thesis, we used the following scores which are well-known and established in their respective medical fields:

- The American Orthopaedic Foot and Ankle Society (**AOFAS**) scale is the most widely used clinical scale in the foot and ankle literature, and especially in the area of ankle arthritis treatments [1]. The total score ranges from 0 to 100 with higher scores indicating better condition. Points are allocated to grade fain (40 points), function (50 points), and hindfoot alignment (10 points).
- Foot Function Index (**FFI**) is another well designed and tested scale measuring the impact of foot and ankle pathology in terms of pain (9 items), disability (9 items) and activity limitation (5 items), quoted using a visual analog scale [2]. The total score ranges from 0 to 100 with higher scores indicating greater impairment.
- Fall Efficacy Scale (**FES**) is questionnaire asking about subject's confidence (range, 0 [none]–10 [full]) in performing 12 activities of daily living without falling, which was validated and is typically used in elderly persons to measure fear of falling [3].
- The mini–mental state examination (**MMSE**) is a brief 30-point questionnaire test that is used to screen for cognitive impairment, using questions including arithmetic, memory and orientation [4]. It is particularly used in older subjects to screen for dementia.
- Unified Parkinson's disease rating scale (**UPDRS**) is commonly used to follow PD subjects, and is established from interview about mood and self-evaluation of activity of daily-life as well as clinician observations of motor function [5], [6].
- Gross Motor Function Classification System for Cerebral Palsy (**GMFCS**), is a 5 level classification system that describes the gross motor function of children and youth with CP on the basis of their self-initiated movement with particular emphasis on sitting, walking, and wheeled mobility [7]. Distinctions between levels are based on observation of functional abilities, the need for assistive technology, including hand-held mobility devices (walkers, crutches, or canes) or wheeled mobility, and to a much lesser extent, quality of movement.

Further details on how to assess each of those clinical scales can be found in the references. Interestingly, all scales are established on both subjective and objective data, collected from questionnaires and clinical

observations. Observations can be prone to subjectivity, for example the observation of the degree of limping, i.e. asymmetry, during gait.

As part or complementary to those clinical scales, clinician are commonly using functional tests such as 10m gait test [8] or Timed Up and Go Test [9]. The Rehabilitation Measures Database[1] provides a summary of such tests which have shown to be reliable and valid instruments used to assess geriatric patient's outcomes during rehabilitation. The database provides concise descriptions of each instrument's psychometric properties, instructions for administering and scoring each assessment as well as a representative bibliography with citations. Those tests are usually measured with a simple stop watch which allows extracting global information such as average walking speed on a known distance, but are prone to error due to the operator's manual measurement.

Although the set of clinical scales and functional tests achieved useful findings for discriminating pathologic populations, they suffer from the subjectivity of some measure such as pain, and are sensitive to the doctor's observation. Particularly, two main sources of subjectivity can be distinguished:

- On clinical side, the assessment of subject's status might differ from one rater to another, due to rater's personal interpretation of observed symptoms. Indeed, inter-rater reliability in structured visual gait observation has been found to be moderately reliable, even in experienced raters [10].
- On subject's side, its performance in some test might vary from time to time independently of the disease, due to its personal motivation, mood, or fatigue, or if he is used to doing the test. His performing can also be influenced by the rater in both good and bad way.

In addition, the scale or outcome measure of the test might be unable to reflect little changes between normal and abnormal condition, or during a long-term follow-up, and it is therefore a lack of resolution and discriminative power. Finally, although being practical to use, those clinical test scores usually require an operator with expertise and the manual data processing and analysis to obtain the results.

3 Laboratory systems

Laboratory systems, using instruments such as optical motion capture and force plates, are now considered as the gold standard in the field of motion analysis for assessing joint kinematics and kinetics. Measuring body movements in laboratory setting under controlled conditions allow getting precise, accurate and reliable measurements of the walking pattern of the subject, and add quantitative and objective figures to the clinical gait assessment.

[1] http://www.rehabmeasures.org

For kinematics, optical motion capture system consists in tracking the position of markers attached to specific locations on the subject using a set of cameras, and an algorithm that reconstruct the 3D position of those markers in space (fig. 2). Technology is either based on active or passive markers and uses the red and infrared light range.

Figure 2 - Laboratory system: optical motion capture (Vicon, Oxford, UK) with those cameras measuring the capture volume (represented by a black mat) and reflective markers attached to the shoe of a CP child performing walking task.

For kinetics measurements, the reference system used in laboratory setting is force platforms (or force plates). They measure the ground reaction forces generated by a body standing on or moving across them. They can provide also accurate temporal parameters such as foot initial and terminal contact. For longer distance where several steps are involved, instrumented pressure carpet are also used. Such a carpet integrates a matrix of pressure cells, in the form of narrow surface of typically 1*10m, that can measure footprint at each stance and provide spatio-temporal parameters [11].

However, those reference systems have several limitations for clinical gait assessment. First, they require costly equipment and a dedicated laboratory where the volume of measurement is limited to few steps, which can strongly influence the natural behavior of the subject. Second, unless a treadmill is used, one cannot measure long-term gait patterns, and it is particularly challenging to measure inclined walking and stairs climbing situations. For instance during a 15m walking in a restricted space, only few steps could be considered as steady-state walking [12], whereas the first (respectively last) steps are related to gait initiation (respectively termination). Third, those systems are complex and require technical expertise to operate. More importantly, their outcomes, in the form of continuous measurement of kinetics and

kinematics signals, is not self-interpretable by most clinicians and require further processing and analysis by movement science experts or biomechanical engineers. Consequently, the use of those laboratory devices in routine clinical practice is limited and it is mostly used for research purpose.

4 Offline methods with wearable systems

To overcome the limitation of laboratory settings and clinical scores, and using recent advances in the field of Micro-electro-mechanical sensors (MEMS), the last 2 decades have seen the progressive development of gait assessment tools based on miniature body-worn sensors. Being ambulatory, they allow measuring and recording gait in natural condition for the patient. However, contrary to laboratory systems, they do not measure directly orientations or ground reaction forces, but typically accelerations (accelerometers), angular velocities (gyroscopes), magnetic field (magnetometers), or pressure acting on foot. It implies that they require additional and smart signal processing algorithm to provide useful information that can be interpreted in clinical gait analysis. A review of existing system and their application to gait assessment in Elderly, OA, PD and CP subjects is presented in this paragraph.

4.1 Method

In this review we considered articles and publications (excluding conference proceedings), indexed in Scopus[2] with the following criteria:

With a title including at least one of those words, related to **locomotion**:

- *Walking, Gait, locomotion, Turning*

And at least one of those words, related to **assessment**:

- *Parameters, algorithm, features, detection, estimation, analysis, assessment, validation*

And at least one of those words, related to the use of **wearable devices**:

- *Sensors, sensing, inertial measurement unit, IMU, inertial sensors, accelerometer, gyroscope, wearable, ambulatory system, body-worn sensors*

With title, abstract or keywords including at least one of those words, related to **mobility diseases**:

- *Elderly, Parkinson, Cerebral Palsy, Leg, Ankle, Foot*

[2] http://www.scopus.com/home.url

55 Document results were found with the above criteria. After study of the content of each reference, some articles were discarded as they were related to:

- The development of purely hardware sensor systems without dedicated algorithm.
- The detection and classification of daily activities. Those publications are analyzed in the next paragraph focusing on online methods and activity recognition.
- The black box methods based on gait data for direct pathology classification. In fact those methods rather focus on parameters analysis than on their estimation.
- Robotic instrumented devices, which cannot be used for gait assessment in humans.
- The work included in the present thesis.

The 35 remaining articles were considered relevant for spatio-temporal analysis of gait using wearable systems, and were chronologically classified. They provided 4 main types of parameters, namely through *temporal detection*, *spatial estimation*, *angle/orientation estimation* and *other parameters* based on raw signal properties.

The following paragraph presents a short description of each paper. A synthesis table of their main aspects is then given in the discussion.

4.2 Results

Bassey et al. [13] proposed a hip-mounted accelerometer to count the steps and validated it against heel-resistive pad in 8 healthy and 6 elderly subjects.

Aminian et al. [14] detected swing and stance and double support based on thigh mounted accelerometers and local peak detection algorithm. It was validated against pressure measurements on 5 healthy and 12 subjects with hip osteo arthritis.

Jasiewicz et al. [15] detected heel-strike and toe-off from different features of foot and shank inertial sensors' signals (fig. 3), and validated against footswitch in 26 healthy and 14 patients with spinal cord injury.

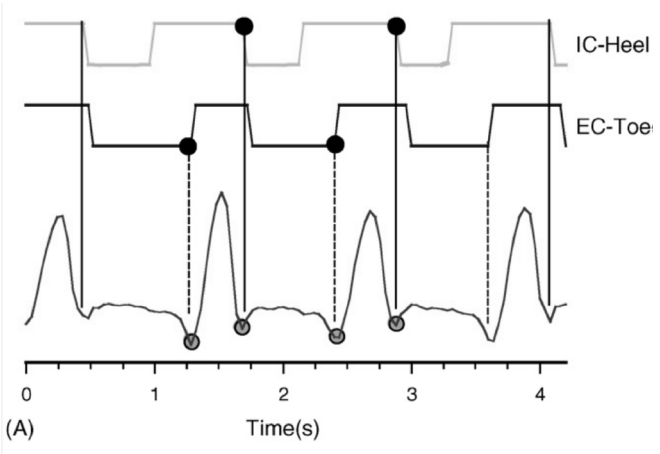

Figure 3 - Representative shank angular velocity traces and the accompanying foot switch signal on heel and toe for normal gait pattern, Toe-off and Heel-strike events are circled, adapted from Jasiewicz et al., 2006

Lemoyne et al. [16] detected gait cycles with accelerometers on shank, without providing clear data on validation protocol.

Liu et al. [17] used IMUs on foot, shank and thigh to compute joint angles and from that detect 8 gait phases within the gait cycle, tested on 10 subjects, but only angles are validated against optical motion capture.

Weng et al. [18] compared swing stance and double support under feet measured from tactile sensors in patients with 87 subjects with various vertigo and vestibulospinal tract disorder against 23 healthy subjects.

Yang et al. [19] estimated cadence and gait cycle detection in 5 PD subjects (and 5 healthy subjects) from waist accelerometer.

Angunsri et al. [20] estimated stance and swing and double support from tactile sensors under both feet in 92 patients with vestibular disorder and 26 controls.

Sant'Anna et al. [21] has introduced an original symbolic approach for detecting temporal events (Heel-strike and toe-off). The system uses accelerometric data from ankle sensors and was tested against Gait Rite on 6 healthy subjects simulating normal and asymmetric gait.

Tong et al. [22] proposed the use of shank and thigh mounted gyroscopes for estimating on segment inclination range, cadence, step counting and stride length and walking speed and validated against Vicon in 1 healthy and 1 spinal cord injured subject.

Aminian et al. [23] estimated stride length and velocity from pendulum model from signal of gyroscopes on shank and thigh in 9 young and 11 elderly subjects against optical motion capture (and temporal against foot switches)

Salarian et al. [24] proposed an algorithm based on double pendulum model from shank and thigh gyroscopes and validated stride velocity, stride length, and stance/double support and gait cycle time against optical motion capture on 10 PD subjects.

Sabatini et al. [25] proposed an algorithm for estimating 2D foot kinematics (fig. 4) and subsequent spatio-temporal parameters from foot mounted IMU (walking speed, stride length) during walking on level ground and incline surfaces. It was validated on a treadmill with 5 healthy subjects.

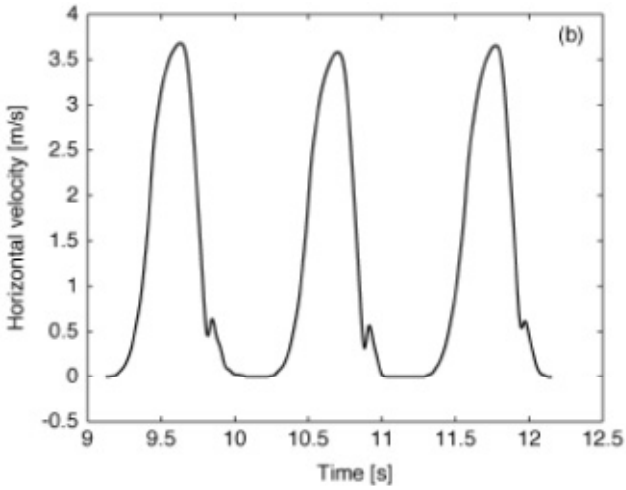

Figure 4 - reconstructed horizontal velocity component from foot inertial sensing, adapted from Sabatini et al., 2005

Moore et al. [26], proposed a system base on ankle-mounted IMU to estimate stride length during long-term daily activity periods (75min) and tested their system on 10 healthy and 7 PD subjects. Stride length was estimated based on a regression model, and its association with ON/OFF medication states were observed.

Bamberg et al. [27] developed an instrumented shoe including inertial sensors, force sensors and bend sensors. With 2D algorithm similar to [25], common spatio-temporal parameters including speed and stride length are estimated and validated in 10 healthy and 5 PD subjects.

Hartmann et al. [28] compared trunk accelerometers to GAITRite (CIR Systems Inc., USA) systems for computing common spatio-temporal gait parameters of walking speed, cadence, step duration and step length on 23 elderly subjects. They found moderate agreement on individual step data.

Schepers et al. [29] estimated stride length and lateral foot placement (i.e. step width) from force and inertial-sensor instrumented sandals with integration algorithm and drift correction by assuming an average walking path. It was validated against optical motion capture with 10 healthy subjects.

Kerr et al. [30] proposed a new optical proximity sensor to assess foot-clearance and validated against optical motion capture on 20 young healthy subjects.

Li et al. [31] proposed a method for estimating walking speed from shank-mouted IMU validated against treadmill on 8 healthy subjects.

Esser et al. [32] estimated stride length in neurological populations (13 healthy controls, 24 PD subjects, 38 other subjects) using a previously described method by *Zjlstra et al.* [33] using trunk acceleration and compared to a force treadmill on 25 healthy subjects.

Dobkin et al. [34] estimated average walking speed in patient after stroke from machine learning algorithm on ankle-mounted tri-axial accelerometers. System was compared to stop-watch measurements on 12 stroke subjects and 6 healthy.

Peruzzi et al. [35] estimated stride length with IMU and zero-velocity update algorithm in 20 healthy subjects with various speed and sensors either located on shank or foot. They conclude that only foot position was acceptable for assuming zero-velocity during stance.

Shin et al. [36], proposed an algorithm based on belt-worn accelerometer for step detection and subsequent step length estimation based on walking frequency regression. Estimates on 6 healthy subjects are compared to total walked distance with reported error of 4.8%.

Goulermas et al. [37] proposed a neural network to estimate hip, knee and ankle joint flexion angles from IMU mounted on foot and shank. They validate against optical motion capture at different speed on 8 healthy subjects.

Takeda et al. [38] described a method for estimating hip, knee and ankle joints from body-worn inertial sensors. This was validated against optical motion capture on 3 healthy subjects.

Cutti et al. and *Ferrari et al.* [39], [40] described gait analysis system based on inertial and magnetic sensors to compute hip, knee and ankle 3D angles. Validated against optical motion capture and tested on healthy subjects.

Saito et al. [41] proposed a method based on kalman-filter on signal of 6D IMU attached on lower limb for estimating 3D joint angle of hip, knee, and ankle, and estimate accuracy of the method on 3 healthy subjects.

Djurić-Jovičić et al. [42] proposed a non-drifted method based on band-pass filtering of leg-mounted accelerometers data for estimating 2D knee and ankle angle and validation against goniometer with few healthy subjects.

Mayagoitia et al. [43] have presented an analytical method for estimation of shank and knee angles at different walking speed based on shank and thigh 2D IMUs (two accelerometers and one gyroscope). System was compared to Optical motion capture during treadmill walking with 10 healthy subjects and yielded RMS error below 7%.

Paquet et al. [44] compared low back side to side acceleration signals between 22 PD subjects and controls. Walking speed was measured by stopwatch.

Karcnik et al. [45] used footswitches and goniometry to assess a stability index during walking and validated against optical motion capture on 5 healthy subjects and one amputee.

Mizuike et al. [46] compared the trunk acceleration pattern from 63 stoke patients and 21 healthy controls. RMS of accelerometers recording was used as an outcome measure to discriminate populations.

Ishigaki et al. [47] analyzed wave shape of acceleration and angular velocity of pelvic mounted sensors on 95 elderly persons to identify stability of posture during walking.

4.3 Discussion

Table I provides a synthesis of the main aspects of the publications included in this State of the art through the wearable sensor configurations, extracted parameters types, and protocols.

TABLE I – STATE OF THE ART IN SPATIO-TEMPORAL GAIT ANALYSIS USING WEARABLE SENSORS. SENSOR TYPE INCLUDES ACCELEROMETERS (ACC), GYROSCOPES (GYRO), OR COMBINATIONS OF ACCELEROMETERS AND GYROSCOPES (IMU). SUBJECT'S TYPE INCLUDE HEALTHY (H), ELDERLY (EL), OSTEO-ARTHRITIS (OA), VESTIBULAR DISORDED (VD), SPINAL CORD INJURY (SCI), PARKINSON'S DISEASE (PD) AND STROKE (ST)

Publication			Wearable Sensors		Parameters				Protocol		
Ref n°	*Authors*	Year	Location	Type	Temporal	Spatial	Angular	Others	subjects type	N	Validation system
13	*Bassey et al.*	1987	Hip	Acc	x				H + EL	8 + 6	Foot-switches
14	*Aminian et al.*	1999	Thigh	Acc	x				H + OA	5 + 12	Foot-switches
15	*Jasiewicz et al.*	2006	Foot + Shank	IMU	x				H + SCI	26 + 14	Foot-switches
16	*Lemoyne et al.*	2009	Shank	Acc	x				?	?	-
17	*Liu et al.*	2009	Lower-limbs	IMU	x		x		H	10	Mocap
18	*Weng et al.*	2009	Foot	Pressure	x				H + VD	23 + 87	-
19	*Yang et al.*	2011	Waist	Acc	x				H + PD	5 + 5	-
20	*Angunsri et al.*	2011	Foot	Pressure	x				H + VD	26 + 92	-
21	*Sant'Anna et al.*	2010	Ankle	Acc	x				H	6	GaitRite
22	*Tong et al.*	1999	Shank + Thigh	Gyro	x	x	x		H + SCI	1 + 1	Mocap
23	*Aminian et al.*	2002	Shank + Thigh	Gyro	x	x	x		H + EL	9 + 11	Mocap + Foot-switches
24	*Salarian et al.*	2004	Shank + thigh	Gyro	x	x	x		PD	10	Mocap
25	*Sabatini et al.*	2005	Foot	IMU	x	x			H	5	Treadmill
26	*Moore et al.*	2007	Shank	IMU		x			H + PD	10 + 7	-
27	*Bamberg et al.*	2008	Foot	IMU + Misc	x	x			H + PD	10 + 5	Mocap
28	*Hartmann et al.*	2009	Trunk	Acc	x	x			H	23	GaitRite
29	*Schepers et al.*	2010	Foot	IMU + Force		x			H	10	Mocap
30	*Kerr et al.*	2010	Foot	Range Sensor		x			H	20	Mocap
31	*Li et al.*	2010	Shank	IMU		x			H	8	Treadmill
32	*Esser et al.*	2011	Trunk	Acc		x			H + PD + Misc	13 + 24 + 38	-
33	*Zijlstra et al.*	2003	Trunk	Acc		x			H	25	Force Treadmill
34	*Dobkin et al.*	2011	Ankle	Acc		x			H + ST	6 + 12	Stopwatch
35	*Peruzzi et al.*	2011	Foot + Shank	IMU		x			H	20	Mocap
36	*Shin et al.*	2011	Back	Acc	x	x			H	6	-
37	*Goulermas et al.*	2008	Foot + Shank	IMU			x		H	8	Mocap
38	*Takeda et al.*	2009	Full-Body	IMU			x		H	3	Mocap
39	*Cutti et al.*	2010	Full-Body	IMU + Mag			x		H	9	Mocap
40	*Ferrari et al.*	2010	Full-Body	IMU + Mag			x		H	4	Mocap
41	*Saito et al.*	2011	Lower-limbs	IMU			x		H	3	Mocap
42	*Djurić-Jovičić et al.*	2011	Shank	Acc			x		H	37	Gonio + Treadmill
43	*Mayagoitia et al.*	2002	Shank + Thigh	IMU			x		H	10	Mocap
44	*Paquet et al.*	2003	Back	Acc				x	H + PD	22	-
45	*Karcnik et al.*	2004	Lower-limbs	Pressure + Gonio				x	H	5	Mocap
46	*Mizuike et al.*	2009	Trunk	Acc				x	H + ST	21 + 63	-
47	*Ishigaki et al.*	2011	Trunk	IMU				x	EL	95	-

In addition, a recent review paper from Kavanagh et al [48] has described the validity and reliability of various accelerometry-based methods for temporal event detection during gait. The evolution of the amount of work in being published in this field in the last years shows a really growing interest.

The bibliographic review of existing wearable systems and offline analysis methods shows that:

- Various body-worn sensor configurations are used with different performances for gait analysis. Some of them use multiple sensor sites or wires, which can be a source of hindrance for the subject. It seems preferable to develop a minimal sensor configuration with wireless sensors.
- Placement of sensors on lower-limb rather than trunk seems preferable for the estimation of spatio-temporal gait parameters. In particular, foot appears to be the only location which verify zero velocity update condition [35].
- Most of the studies do not provide proper validation of their system against references, or uses non gold-standard reference systems such as foot-switches. For those that were validated, reported accuracy and precision can be further improved.
- Most of the systems have been only tested on healthy subjects or in small samples of pathological subjects.
- Finally, most of the system provides only basic and 2D spatio-temporal gait parameters, which is a strong limitation to describe some motor symptoms of the targeted mobility diseases.

5 Online methods with embedded systems

One step further to wearable systems is the use of embedded systems and online methods. It means that sensing, algorithm, and processing power is implemented within a real-time working system worn by the subject. Some applications typically require such hard real-time condition, in order to perform direct feed-back to the user or to control active prosthetic devices. The simple adaptation of assessment methods described in the previous paragraph is not always possible due to the real-time constraint and processing power, and justify an independent approach with dedicated systems and algorithm. A review of the recent state of the art for real-time methods of gait assessment is provided in this paragraph. In addition, some system only based on wearable sensors with offline methods used for classification of walking activities, but with potential adaptation in real-time, are also described in this chapter.

5.1 Method

Articles and publications indexed in Scopus were reviewed by searching with no restriction for the date and the following criteria:

With a title including at least one of those words, related to **locomotion**:

Walking, Gait, locomotion, Stairs, Ramp, Incline

And with at least one of those words, related to **online processing**:

- *Parameters, Real-time, recognition, classification, identification, control, algorithm, features, detection, active*

And at least one of those words, related to **mobility disease**:

- *Prosthetic, Prosthesis, Prostheses, Amputee, Ankle, Foot*

With title, abstract or keywords including at least one of those words, related to **embedded sensors**:

- *sensors, strain gauges, inertial sensors, accelerometers, gyroscopes*

In addition, Google Patent was first used with the same research terms as in scientific publications review, and provided 469 results, which was obviously too much to be analyzed in a systematic way. Then review was therefore restricted to the patent sources that were identified as relevant by collaborators or known from past research.

5.2 Results

37 Document results were found with the above criteria. After study of the content, some articles were discarded, as they were related to the control of purely robotic systems, Motor-Neural interfaces or clinical studies. The 23 remaining documents (17 articles and 6 patents) were classified as *Temporal Detection of gait events* and *Features extraction* and *recognition algorithm*. The following paragraphs provide their main aspects that are relevant for the present thesis, and a synthesis table of their main aspects is given in the discussion.

5.2.1 Publications

Kim et al. [49] has used a FSR-based detection of terminal and initial contact for an active ankle foot orthosis to prevent foot-drop.

Kong et al. [50] measured shank angle from accelerometer to detect gait event in barefoot condition and tested their algorithm in 5 FES subjects.

Lawson et al. [51] described an approach for the real-time detection of stumble, including the real-time detection of walking phases using accelerometers and force sensors in a trans-femoral prosthesis.

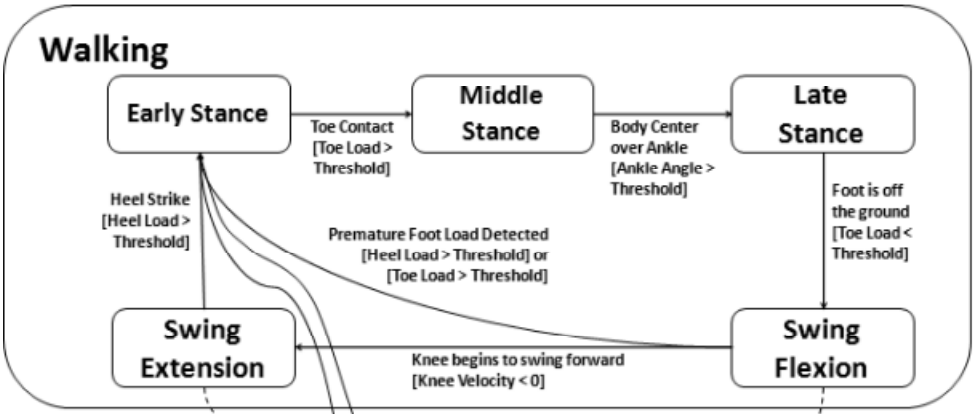

Figure 5 – States machine for gait phases detection with transition conditions, extracted from Lawson et al- 2010

More recently, the same authors described a finite-state model (fig. 5) for standing controller of a prosthetic knee [52].

Kotiadis et al. [53] proposed different algorithm using combinations of shank-mounted accelerometers and gyroscopes to detect gait phases in real-time for control of drop foot stimulator.

Gong et al. [54] used a single potentiometer in an artificial knee joint to predict Swing and stance phase, as well as walking speed. (*Note: publication in Chinese*).

Lee et al. [55] detected swing and stance phase of gait in quasi real-time using shank gyroscopes by adapting methods from *Tong et al.* [23], validated against footswitches on 5 healthy subjects.

Catalfamo et al. [56] proposed a method on shank-mounted gyroscope for swing/stance phase detection on flat and incline surface compared with pressure measurement on 7 healthy subjects.

Hanlon et al. [57] compared footswitches and simple detecting initial contact algorithm determined from the second derivative of foot fore-aft acceleration against forceplate, and tested it on 12 healthy individuals.

Pappas et al. [58] presented a method based on a shoe-mounted gyroscope for detecting gait phases and tested it against foot switches sensors without validation. They use it with two pathologic subjects performing treadmill walking at different inclinations.

Jiménez et al. [59] proposed a ramp detection method based on foot-mounted IMU in order to correct a navigation tracking algorithm. They used the pitch angle (Ψ) of the IMU during stance and the difference in the vertical position between two consecutive steps (δz). Ramp is detected when Ψ·δz is below a threshold of -9 °.cm.

Huang et al. [60] recently proposed a fusion algorithm based on data from EMG and instrumented prosthetic in 5 Trans-Femoral Amputees. Classification algorithm is based on Linear Discriminant Analysis (LDA) and Support-Vector Machine (SVM). The task modes studied in the static state included level-ground walking, stair ascent, stair descent, ramp ascent, and ramp descent. Authors also analyzed the system during transitional periods in terms of prediction time and accuracy.

Sugimoto et al. [61] has proposed a foot pressure sensors and classification algorithm to distinguish between walking, running, standing, sitting, going up and downstairs and cycling. With 50% of training data, discriminant analysis was done and allow to classify walking, upstairs and downstairs with >90% accuracy.

Varo et al. [62] described a real-time classification method taking into acount walking, sitting and standing activities. Authors are vague about which sensor information is used, and report joint angles and angular velocities of the prosthesis joints in addition to measured interaction forces and/or torques between the user and prosthesis, and between the prosthesis and environment, as well as additional (potentially) accelerations and electromyography measurements from the residual limb. It is tested on one subject only. The classification methods include principal components analysis, linear discriminant analysis and gaussian mixture models (fig. 6).

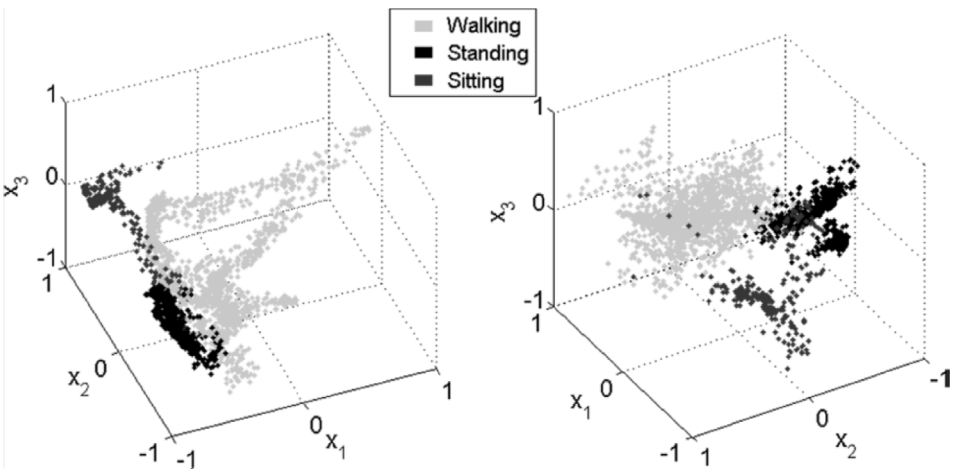

Figure 6 – Statistical classification of walking and other activities, extracted from Varol et al. 2010

Nyan et al. [63] proposed a method for stairs ascent and stairs descent classification with sensitivity and specificity over 97% and 99% respectively. It was tested on 22 subjects against video analysis. The method is based on offline analysis of power of wavelet coefficients extracted on accelerometric signals measured on shoulder.

Coley et al. [64] presented a method based a single gyroscope on shank to recognize stairs ascent. The method is offline and was tested on 10 healthy and 10 patients including elderly persons and subjects with vascular disease. It was validated against visual surveillance.

Lau et al. [65] described an offline SVM classification of walking, stairs and slope activities in stroke patients with foot and shank mounted IMU. Algorithm use only pitch angular velocity and 2D acceleration values at a specific time (initial swing phase). Authors reach an overall accuracy of 82.9 % over the five classes.

5.2.2 Patents

In WO 2010 129716 A1 from Ossur, is claimed a method for recognizing terrain from sensor data without further details.

In US2010 0114329 from iWalk, is presented a powered ankle foot active prosthetic, with foot orientation and displacement estimation for terrain recognition and walking phases detection (fig. 7).

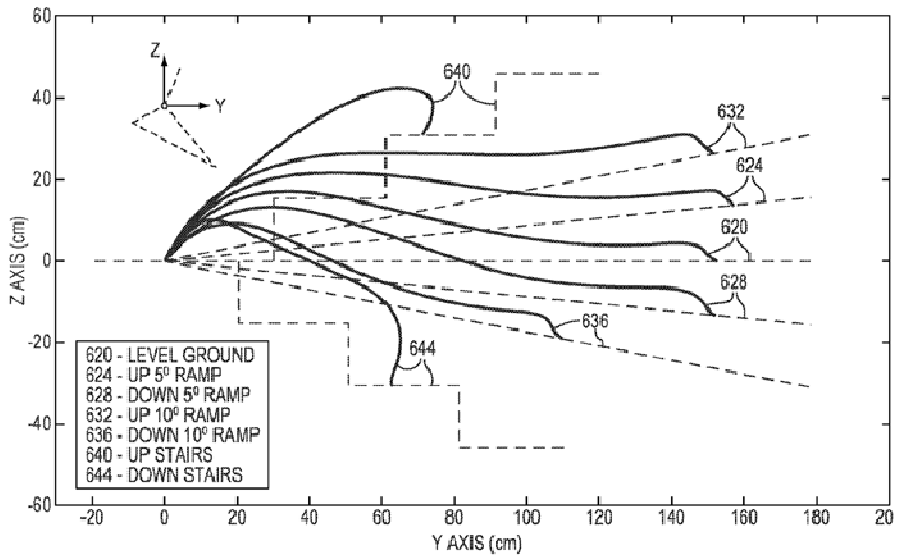

Figure 7 – Foot trajectories during level walking, slope and stairs ascent and descent, extracted from iWALK 2010

The global recognition strategy is also described, showing that the ambulation task type is determined approximately at mid-swing based on ankle position during the last stance phase and ankle trajectory during beginning of swing phase.

In US7,867,284,B2 from Vitchom Human Bionics, a control method is claimed based on phase recognition, trajectory generation and classification by comparison with a look-up table, in order to control a knee prosthetic.

In US 2011 0202144 from Palmer et al., is claimed a method for walking phase detection based on expert rules on a sensorized knee prosthetic. The patent also describes per-subject tuning of the thresholds.

In US6513381 from Dynastream is claimed a method for foot movements estimation based on accelerometers. The method is based on integration of signals.

In US7200517 from Nike, is claimed a method based on foot sensors that detect temporal events (Heel strike and Toe-off), and determine spatio-temporal parameters using a regression model from temporal events (fig. 8).

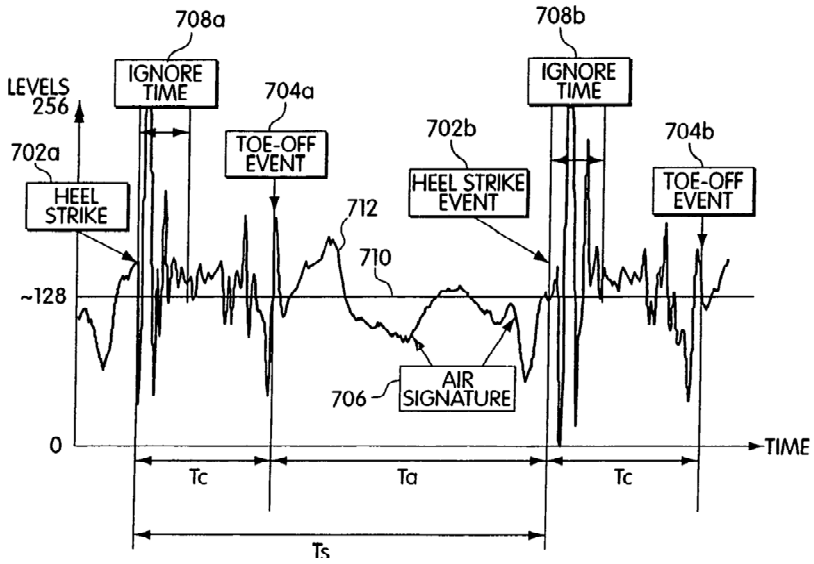

Figure 8 – Running Gait events detection on accelerometric signal, from Nike 2007

5.3 Discussion

The following Table II provides a synthesis of the main aspects of the reviewed publications

TABLE II – STATE OF THE ART IN ONLINE DETECTION AND CLASSIFICATION USING WEARABLE SENSORS. SENSOR TYPE INCLUDES ACCELEROMETERS (ACC), GYROSCOPES (GYRO), COMBINATIONS OF ACCELEROMETERS AND GYROSCOPES (IMU), AND FOOT SENSITIVE RESISTORS (FSR). SUBJECT'S TYPE INCLUDES PATIENT WITH FUNCTIONAL ELECTRICAL STIMULATION (FES).

Publication			Sensors		Method				Protocol		
Ref n°	*Authors*	Year	Location	Type	gait phases	Features extraction	Classification	Online	Subjects	N	walking activity
49	*Kim et al.*	2011	Foot	FSR	x			x	FES	1	Level
50	*Kong et al.*	2007	Shank	Acc	x			x	FES	5	level
51	*Lawson et al.*	2010	Knee Prosthesis	Acc + Force	x			x	Amputee	1?	level
52	*Lawson et al.*	2011	Knee Prosthesis	Acc + Force			x	x	Amputee	1?	level
53	*Kotiadis et al.*	2010	Shank	IMU	x			x	FES	1?	level
54	*Gong et al.*	2010	Knee Prosthesis	Potentiometer	x	x		x	Amputee	1?	level
55	*Lee et al.*	2011	Shank	Gyro	x			x	Healthy	5	level, slope
56	*Catalfamo et al.*	2010	Shank	Gyro	x			~	Healthy	7	level, slope
57	*Hanlon et al.*	2009	Foot	Acc + FSR	x			x	Healthy	12	level
58	*Pappas et al.*	2004	Foot	Gyro + FSR	x			x	FES	2	level, slope
59	*Jiménez et al.*	2011	Foot	IMU		x	x		Healthy	1	level, slope
60	*Huang et al.*	2011	Knee Prosthesis	EMG + IMU	x		x	x	Amputee	5	level, slope, stairs
61	*Sugimoto et al.*	2010	Foot	Pressure			x		Healthy	2	level, stairs, activities of daily-living
62	*Varol et al.*	2010	Knee Prosthesis	IMU, … ?			x	x	Amputee	1	level, activities of daily-living
63	*Nyan et al.*	2006	Shoulder	Acc			x		Healthy	22	level, stairs
64	*Coley et al.*	2005	Shank	Gyro			x		Healthy, Elderly	20	stairs ascent
65	*Lau et al.*	2009	Shank + Foot	IMU	x	x	x		FES	7	level, slope, stairs

In addition, in a recent review paper from 2010, *Rueterbories et al.* [66] described the existing methods for real-time gait event detection that could be applied to FES and concluded that there was still strong limitations for hard real-time implementation of the methods.

The study of existing literature shows interesting existing methodologies based on embedded systems and online processing algorithm for walking phase detection and activity recognition that can be used in active prosthetics or rehabilitation devices. Several conclusions can be made:

- Various sensor configurations are reported, but inertial sensors, including accelerometers and gyroscopes are commonly used in most of the studies, in addition to force and/or moment sensors. Some studies report the use of EMG data in addition.
- Patent describes the overall method of using sensor data fusion for classifying activities, but the recognition algorithms which are the critical aspects of the system are not detailed.
- Temporal detection methods have been mostly tested solely during normal walking on flat surface. No studies reported and validated a method that could be robust to different activities such as walking in stairs and ramp.
- For classification, studies describe different classifications algorithm based on sensor data fusion with promising results, but mostly with offline methods. We can distinguish the use of statistical methods on one side (SVM, GMM), that requires a certain amount of training data, and expert rule based methods on the other side. No studies have compared those two types of methods for the same problematic.
- Most of the studies are focused on trans-femoral amputees or people with drop-foot due to stroke. Interestingly, no studies were found on trans-tibial amputees.
- One limitation of this bibliographic study is that the criteria will not return articles focusing on the design of active prosthetics, which might also include some aspect for recognition of phases and activities.
- Finally, most of the studies, and particularly the one with online methods, have been tested on an extremely small sample size (between 1 to 5 subjects), so there is no evidence of their robustness on a wider sample of subjects with potential different walking patterns.

6 Overall conclusion

In conclusion, this review of the state of the art outlines the established methods (clinical *scores, laboratory measurements*) and latest researches using on wearable sensors carried out for spatio-temporal gait analysis (fig. 1). The focus on spatio-temporal parameters rather than full-body kinematics or kinetics can be justified since they are the most useful outcome measures used to assess the mobility diseases considered in this thesis. Wearable sensors have several advantages to laboratory devices for spatio-temporal gait analysis, since they are less cumbersome for patients and allow long-term assessment of

walking in natural and unconstrained condition. Compared to subjective clinical scores mostly based on qualitative observations, wearable sensors with dedicated algorithm provide quantitative and objective assessment of spatio-temporal gait parameters.

At the present time however, wearable sensors have important limitations to their clinical use in practice. Regarding offline methods, most systems have been poorly validated, either with only healthy subjects, or in small sample size, or without gold standard reference system. More importantly, most of the devices only provide basic spatio-temporal features such as gait cycle time or stride velocity, with limited performances to describe the various motor symptoms of mobility diseases. Regarding online methods capable of providing real-time monitoring of gait phases and activities, although the recent literature described some interesting devices for trans-femoral amputee and FES applications, systems have been mostly tested during level walking and with few subjects. Moreover, most of the recognition methods have not been implemented in real-time, and some of them rely on statistical classification methods using an important set of training data.

Various types of sensors and locations have been described in literature. Nevertheless, it appears that the foot is a particularly interesting location, since it is minimally invasive, allows to include force or pressure measurements, and to verify zero-velocity update for correcting inertial sensors drift. Moreover, most of spatio-temporal parameters of gait, such as stride length, can be derived from foot movements.

In the light of this state of the art, the work presented in the following chapter describes the use of foot-worn inertial sensors and offline methods for the 3D estimation of foot kinematics, and the subsequent extraction of both common and new spatio-temporal parameters allowing characterizing mobility diseases. Algorithms are technically validated against gold standard reference systems and tested on pathologic subjects in clinical condition. In the last chapters of the thesis, the work focus on the design and testing of novel real-time methods for gait phase's detection, features extraction and activity recognition, using force and inertial sensors embedded in the prosthesis of trans-tibia amputee subjects.

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Chapter 3

Quantitative Estimation of Foot-Flat and Stance Phase of Gait Using Foot-Worn Inertial Sensors[*]

Abstract

Time periods composing stance phase of gait can be clinically meaningful parameters to reveal differences between normal and pathological gait. This study aimed, first, to describe a novel method for detecting stance and inner-stance temporal events based on foot-worn inertial sensors; second, to extract and validate relevant metrics from those events; and third, to investigate their suitability as clinical outcome for gait evaluations. 42 Subjects including healthy subjects and patients before and after surgical treatments for ankle osteoarthritis performed 50-m walking trials while wearing foot-worn inertial sensors and pressure insoles as a reference system. Several hypotheses were evaluated to detect heel-strike, toe-strike, heel-off, and toe-off based on kinematic features. Detected events were compared with the reference system on 3193 gait cycles and showed good accuracy and precision. Absolute and relative stance periods, namely loading response, foot-flat, and push-off were then estimated, validated, and compared statistically between populations. Besides significant differences observed in stance duration, the analysis revealed differing tendencies with notably a shorter foot-flat in healthy subjects. The result indicated which features in inertial sensors' signals should be preferred for detecting precisely and accurately temporal events against a reference standard. The system is suitable for clinical evaluations and provides temporal analysis of gait beyond the common swing/stance decomposition, through a quantitative estimation of inner-stance phases such as foot-flat.

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1 Introduction

In clinical gait evaluation, stance phase is defined as the period of time where the foot is in contact with the ground [1]. Stance has been also described as a succession of different sub-phases such as loading response, mid-stance, terminal stance and pre-swing [2]. Gait changes in elderly persons have been characterized by a longer foot-flat [3]. Those previous studies show that quantitative assessment of sub-phases of stance (referred as "inner-stance phases"), such as foot-flat, can bring additional insight into clinical gait assessment.

Stance phase has been detected using stationary devices such as optical motion capture, force-plate [4] and electronic walkways embedding pressure sensors [5]. Ambulatory devices such as Footswitches [6], pressure insoles [7], accelerometers [8,9], gyroscopes [10,11], and combinations of inertial sensors and pressures sensors [12,13] were also used for this purpose. Applications range from the real-time triggering of electrical stimulators to the estimation of temporal parameters that have shown to be relevant for various clinical evaluations such as frailty in the elderly [10,14] or motor symptoms in Parkinson's disease [15].

Using ambulatory measurements for temporal analysis, information can be reliably derived from large datasets collected in natural long-distance gait. Nevertheless, in most previous studies, stance phase was considered as a single block without any subdivision from heel-strike to toe-off [6,9–11,16]. On the other hand, studies that considered inner-stance phase events [8,12,13], didn't assess thoroughly the technical validity of their method in terms of temporal precision and accuracy against a gold standard. A detailed study of the reliability of gait events detection from various inertial sensors was recently proposed [17], but the authors mainly focused on the sensitivity and specificity of detection when using Foot Sensitive Resistors and on a limited population, rather than on temporal precision and accuracy.

The goal of this paper was twofold. First, it aimed to show a novel method based on foot-worn inertial sensors to detect temporal events based on robust features of foot kinematic patterns, and extract inner-stance phases defined between pairs of successive events. As a technical validation, the performance of our method was compared to force reference measurements on a two-segment foot model. Second, we tested the efficacy of inner-stance phase estimates as a potential outcome measure for clinical gait evaluations, by using the system to compare healthy control subjects to age-matched patients suffering from ankle disease during a 50-m gait test.

2 Method

2.1 Measurement devices and sensor configuration

Ambulatory pressure insoles (Pedar-X, Novel, DE) were used as a reference system to measure the contact time of different regions of the foot with the ground. This pressure sensor technology has shown high linearity, low creep, low hysteresis, and low variability for all performances over the whole sensor matrix [18]. Additionally, it has been reported as accurate and reliable in gait measurements compared to force-plate [7] and repeatable in different foot regions and on different days [19]. Finally, Pedar insoles have been successfully used instead of force-plate for force measurement during gait [20] and clinical evaluation based on temporal and pressure parameters [21]. Therefore, Pedar pressure insoles were considered as a validated reference for this study. Subjects wore the pressure insoles embedded in custom-made shoes (fig. 1). One inertial measurement unit (IMU) consisting of 3D gyroscopes and 3D accelerometers was installed on the forefoot over the bases of first and second metatarsals, such that one gyroscope, referred to as pitch, was aligned to foot's sagittal plane (fig. 1). The IMU was connected to a portable data-logger (Physilog, BioAGM, CH) with an internal low-pass analog filter (17Hz). Both pressure insoles and IMU devices recorded signals synchronously at 200Hz.

Figure 1 - Sensor configuration worn by a subject with inertial measurement unit (IMU) fixed on forefoot and pressure-insoles (reference system) beneath the foot.

2.2 Temporal events detection

Stance phase is the period between initial contact, referred to as Heel-Strike (HS), and terminal contact, referred as Toe-Off (TO). Additionally, stance encapsulates the instant where toes touch the ground and make the foot land flat, referred as Toe-Strike (TS), and the instant where the heel rises from the ground, referred as Heel-Off (HO). {HS, TS, HO, TO} are defined as the temporal events of stance (fig. 2.a).

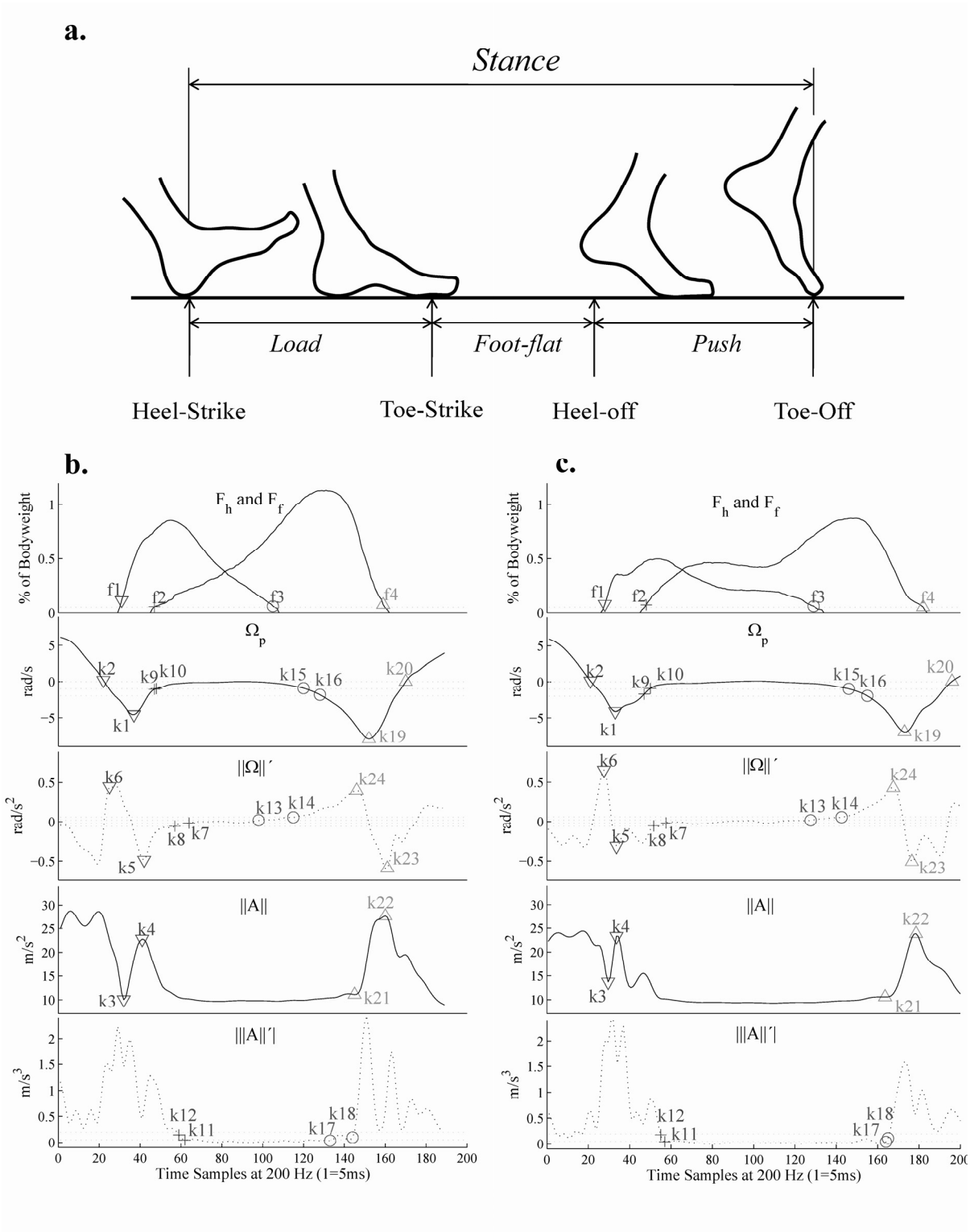

Figure 2 - a) Temporal events during Stance and corresponding inner-stance phases (in italic). b) Kinematic and force signals with the detected features (as listed in table I) at Heel-strike (▽), Toe-Strike (+), Heel-Off (o), and Toe-Off (△), showed for one typical gait cycle of a healthy subject and a c) subject with ankle osteoarthritis.

2.2.1 Kinematic features from inertial sensors signals

During one stride, the two negative peaks of pitch angular velocity of shank are known to be robust approximate estimates of HS and TO on both healthy and patient populations [10,22]. Foot pitch angular velocity (Ω_p) shows similar negative peaks for HS and TO. Consequently, those peaks were detected and used to split gait trials into cycles and define limited time windows for further robust detection of the kinematic features. Candidate features for detecting HS and TO were identified by the minimum (MIN), maximum (MAX) and zero-crossing (ZERO) time sample of the three following signals: Ω_p, the norm of 3D accelerometer signal ($||A||$) and the derivative of 3D gyroscope signal norm ($||\Omega||'$), where $||X||$ is the Euclidian norm of vector X. The phase between TS and HO, so-called foot-flat, is characterized by a lower amount of movement since the ground constrains the foot. So, candidate features for detecting TS and HO were identified by the first and last sample for which signals of $||\Omega||'$, Ω_p, and the absolute value of the derivative of accelerometer signal's norm ($|||A||'|$), were below a specific threshold. Signals norms were preferentially selected in order to be independent of IMU positioning. All these detection rules, and the six subsequent kinematic features extracted for each event are detailed in table I and illustrated in fig. 2.b-c.

2.2.2 Reference Force features from pressure insole signals

A foot frame was defined with its X-axis as the horizontal projection of vector from the great tuberosity of calcaneus to the head of second metatarsal, Y-axis to the left and Z-axis upwards. The foot was divided into two segments: hindfoot and forefoot, and the coordinates of the 99 sensor cells of the insole were determined. Sensors cells with X-coordinate lower than the midpoint between bony landmarks of the navicular and cuboid bones were assigned to hindfoot, while other sensor cells were assigned to forefoot. The vertical force exerted on each segment (F) was calculated based on pressure (P) and sensor cell area (A):

$$F = \sum_{j}^{J} P_j . A_j \tag{1}$$

where j is the sensor cell index and J the set of segment cells. For the vertical force signal on hindfoot (Fh) and forefoot (Ff) segments, a threshold of 5% of bodyweight (BW) was used to detect the time of each segment's contact with the ground. HS (respectively TS) was detected on the rising of Fh, (respectively Ff), whereas HO (respectively TO) was detected on the lowering of Fh (respectively Ff). Those four force features (f1 to f4) constituted the reference values for temporal events (table I).

2.3 Inner-stance phases and foot-flat estimation

Based on detected temporal events, stance and inner-stance phases can be objectively quantified at each gait cycle. Thereby, the duration of stance was computed as:

$$Stance=t(TO)-t(HS) \quad (2)$$

Where t() is the occurrence instant of the event. Subsequently, the duration of the three inner-stance phases composing Stance, namely loading response (Load), Foot-flat and Push-off (Push) were computed as:

$$Load=t(TS)-t(HS) \quad (3)$$

$$Foot\text{-}flat=t(HO)-t(TS) \quad (4)$$

$$Push=t(TO)-t(HO) \quad (5)$$

Absolute values were calculated in milliseconds, and relative values, $Load_R$, $Foot\text{-}flat_R$ and $Push_R$, were expressed as a percentage of Stance.

2.4 Measurement protocol

Both healthy subjects and patients with different degrees of ankle disease were considered to test the proposed method's performance. In total, 42 subjects participated in this study: 10 healthy subjects (HY), 12 patients with ankle osteoarthritis (AO), 11 patients treated by total ankle replacement (TAR) and 9 patients treated by ankle arthrodesis (AA). Both measurement systems were installed on subjects, on the affected foot for patients, and they were asked to walk at self-selected speed in a hospital corridor for two trials of 50 meters. The Foot Function Index (FFI) and the American Orthopedic Foot and Ankle Society scale for ankle-hindfoot (AOFAS) were registered to evaluate the degree of ankle disease and illustrate the outcome of inner-stance phases (table III). The local ethics committee approved the experimental protocol and the subjects gave their informed consent prior to testing.

2.5 Statistical analysis

Temporal parameters validation – To compare the temporal event detection ability of the proposed system against reference, accuracy (Mean) and precision (STD) were calculated on the data sets of time differences between kinematic and force features at each gait cycle. The median absolute deviation (MAD), as a measure of statistical dispersion, and the mean absolute error (MAE), were also computed. The set of best kinematic features obtained using IMU was finally evaluated for reliability by computing Intraclass correlation coefficients ICC(1,1). Furthermore, the mean and standard deviation of the sets of differences

between inner-stance phases' estimates from both the proposed and reference system were computed in each subjects' group.

Comparisons of subject groups – The median and interquartile range (IQR) were estimated for inner-stance phases measured by inertial sensors, clinical scores, and physical characteristics of each population. The results of each patient group (AO, TAR, and AA) were compared to the results of the healthy group (HY) using the Wilcoxon rank-sum test. Rank-sum test, as a robust non-parametric test, was chosen for pair-wise comparisons since population sizes were small and all metrics did not have a normal distribution, and possibly included outliers.

3 Results

3.1 Temporal events detection

After discarding the three first and last gait cycles of each trial from all tested subjects, a total of 3193 gait cycles were recorded and analyzed. Fig. 2 shows typical samples of recorded signals during stance with detected features on kinematic and force signals.

Table I summarizes the differences between kinematic features and reference force features for each event. For HS, k_1, detected at Ω_p minimum peak showed the best precision (8ms), while the best accuracy (-2ms) was obtained with k_3, at the minimum peak of $\|A\|$. For TS, the best results were obtained with k_{10}, detected at low Ω_p, showing an accuracy±precision of -8±39ms; k_{12}, detected at low $\|\|A\|'\|$, showed a better accuracy (2ms) but a bigger MAE than k_{10} (respectively 47ms and 31ms). For HO, the best accuracy (4ms) was obtained with k_{13}, at low $\|\Omega\|'$, while the best precision (46ms) was obtained with k_{15} extracted at low Ω_p. Finally for TO, the best results were obtained for k_{22}, detected at the maximum peak of $\|A\|$, showing an accuracy±precision of -6±12ms.

According to table I, the optimal set of kinematic features for detecting {HS, TS, HO, TO}, was obtained with the set of rules {k_3, k_{10}, k_{13}, k_{22}}. For this set of rules, Coefficients of Intraclass correlation were calculated and show fair-to-good reliability for {HS, TS, HO} with ICC(1,1) of respectively {0.72, 0.51, 0.74}, and excellent reliability for TO with ICC(1,1) of 0.97.

TABLE I - LIST OF FEATURES AND THEIR DIFFERENCES AMONG 3193 RECORDED GAIT CYCLES. TEMPORAL EVENTS ARE DETECTED BASED ON SIGNAL FROM INERTIAL SENSORS (K_1 TO K_{24}) AND PRESSURE INSOLES (F_1 TO F_4). Ω_P AND $||\Omega||'$ CORRESPOND TO THE PITCH ANGULAR VELOCITY OF THE FOOT AND THE DERIVATIVE OF THE NORM OF FOOT ANGULAR VELOCITY. $||A||$ AND $|||A||'|$ CORRESPOND TO THE NORM OF FOOT ACCELERATION AND ITS ABSOLUTE DERIVATIVE. F_H AND F_F ARE THE VERTICAL FORCE SIGNALS ESTIMATED ON THE HINDFOOT AND FOREFOOT SEGMENTS. MINIMUM VALUE OF DIFFERENCES FOR EACH EVENT IS INDICATED IN BOLD ITALIC.

	Kinematic			Force			Difference (ms)			
	signal	rule	feature	signal	rule	feature	Mean	MAE	STD	MAD
Heel-Strike	Ω_p	MIN	k_1	F_h	> 5% of BW	f_1	29	26	***8***	***6***
		0	k_2				-39	43	17	13
	$\|\|A\|\|$	MIN	k_3				***1***	***8***	13	9
		MAX	k_4				37	36	14	8
	$\|\|\Omega\|\|'$	MIN	k_5				36	43	32	18
		MAX	k_6				-6	12	13	10
Toe-Strike	$\|\|\Omega\|\|'$	< -0.02 rad/s²	k_7	F_f	> 5% of BW	f_2	74	73	52	42
		< -0.06 rad/s²	k_8				24	44	52	39
	Ω_p	> -1 rad/s	k_9				-23	41	44	38
		> -2 rad/s	k_{10}				***-4***	***31***	***37***	***31***
	$\|\|\|A\|\|'\|$	< 0.05 m/s³	k_{11}				75	74	49	36
		< 0.2 m/s³	k_{12}				12	47	53	45
Heel-Off	$\|\|\Omega\|\|'$	> -0.02 rad/s²	k_{13}	F_h	< 5% of BW	f_3	***4***	***41***	54	40
		> -0.06 rad/s²	k_{14}				60	73	66	50
	Ω_p	< -1 rad/s	k_{15}				76	81	***51***	***36***
		< -2 rad/s	k_{16}				121	130	63	45
	$\|\|\|A\|\|'\|$	> 0.05 m/s³	k_{17}				113	125	87	61
		> 0.2 m/s³	k_{18}				169	176	71	50
Toe-Off	Ω_p	MIN	k_{19}	F_f	< 5% of BW	f_4	-33	35	14	11
		0	k_{20}				63	65	21	17
	$\|\|A\|\|$	MIN	k_{21}				-81	85	15	11
		MAX	k_{22}				***-3***	***11***	***13***	***9***
	$\|\|\Omega\|\|'$	MIN	k_{23}				5	22	22	21
		MAX	k_{24}				-70	71	18	12

3.2 Inner-stance phases estimation

Using the optimal kinematic features set from temporal events' detection, inner-stance phases were computed. Median values over all gait cycles were then calculated for each subject and compared to the reference system (Table II). Globally, the average (mean±std) error was -3±4ms for Stance, -1±10ms for Load, 19±14ms for Foot-flat and -16±13ms for Push phases. Relative limit of agreement intervals [23], computed as average difference ±1.96 standard deviation in percentage of Stance were -0.6% to 1.8% for Load, 1.3% to 4.7% for Foot-flat and -3.6% to 0% for Push, showing good agreement between IMU and reference system.

TABLE II - MEAN (ACCURACY) AND STD (PRECISION) OF DIFFERENCE BETWEEN INNER-STANCE PHASES OBTAINED FROM INERTIAL SENSORS SYSTEM WITH THE SET OF KINEMATIC FEATURES $\{K_3,K_{10},K_{13},K_{22}\}$ FOR {HS,TS,HO,TO}, AND REFERENCE SYSTEM IN DIFFERENT GROUPS OF SUBJECTS (HY: HEALTHY, AO: WITH ANKLE OSTEOARTHRITIS, TAR: AFTER TOTAL ANKLE REPLACEMENT, AA: AFTER ANKLE ARTHRODESIS).

		AO		AA		HY		TAR		ALL	
Phase	Difference	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Stance	ms	-5	5	-3	3	-2	2	-3	2	-3	4
Load	ms	12	11	-8	4	-3	4	-3	3	1	10
	% of Stance	1.9	1.3	-0.6	0.3	0.0	0.6	0.6	0.1	0.6	1.2
Foot-flat	ms	15	25	16	6	25	3	21	3	19	14
	% of Stance	3.2	3.1	2.5	0.6	3.3	0.4	3.0	0.2	3.0	1.7
Push	ms	-29	18	-7	3	-12	2	-14	2	-16	13
	% of Stance	-3.7	2.4	-0.5	0.3	-1.1	0.1	-1.2	0.2	-1.8	1.8

3.3 Group comparisons

Table III presents Median±IQR of physical characteristics, clinical scores, and inner-stance phases obtained for the four populations. No significant differences were observed for age and height. All three patient groups showed significant difference ($p<0.01$) with the healthy group for both clinical scores. The healthy group showed significantly shorter Stance compared to all patient groups, shorter Load compared to AO and AA, and shorter Foot-flat compared to TAR and AA. This is also qualitatively illustrated in the typical example given in fig. 2 where a patient with ankle osteoarthritis (fig. 2.c) showed a longer foot-flat than a healthy subject (fig. 2.b). Although a tendency for longer $Push_R$ and shorter $Foot\text{-}flat_R$ in healthy subjects was observed, it was not significant.

TABLE III - PHYSICAL CHARACTERISTICS, CLINICAL SCORES (FFI AND AOFAS) AND INNER-STANCE PHASES DURATIONS IN DIFFERENT GROUPS OF SUBJECTS (HY: HEALTHY, AO: WITH ANKLE OSTEOARTHRITIS, TAR: AFTER TOTAL ANKLE REPLACEMENT, AA: AFTER ANKLE ARTHRODESIS) PRESENTED AS MEDIAN (IQR). SIGNIFICANT DIFFERENCES WITH HEALTHY SUBJECTS ARE INDICATED WITH *(P-VALUE<0.05) AND **(P-VALUE<0.01).

		HY	AO	TAR	AA
Physical characteristics	Age (years)	59.0(27.0)	60.5(17.0)	67.0(20.3)	65.0(13.0)
	Height (cm)	166.0(13.0)	169.0(9.0)	170.0(9.0)	177.0(11.3)
	Weight (kg)	66.6(12.6)	79.4(22.4)	82.6(12.5)**	87.7(9.2)**
	Sex	3M,7F	10M,4F	8M,3F	8M,1F
FFI	Total	0(0)	45.8(22.0)**	8.9(18.7)**	6.8(24.7)**
	Pain	0(0)	55.0(26.1)**	10.6(18.2)**	5.4(48.9)**
	Disability	0(0)	51.4(33.3)**	10.1(17.8)**	17.1(19.5)**
	Activity	0(0)	17.6(29.2)**	10.0(18.6)**	5.0(15.7)**
AOFAS	Total	100(0)	46.0(18.8)**	78.0(8.0)**	67.0(26.0)**
	Pain	40(0)	20.0(20.0)**	30.0(0.0)**	30.0(25.0)*
	Function	50(0)	28.0(12.5)**	38(7.8)**	30.0(6.3)**
	Alignment	10(0)	5.0(5.0)**	10.0(0.0)	10.0(0.0)
Stance (s)		0.60(0.06)	0.68(0.05) **	0.69(0.04) **	0.71(0.04) **
Load (s)		0.09(0.01)	0.11(0.03)*	0.09(0.04)	0.12(0.03) **
$Load_R$ (%)		13.45(3.67)	15.55(5.63)	13.28(4.49)	15.20(4.29)
Foot-flat (s)		0.27(0.10)	0.32(0.09)	0.33(0.10)*	0.33(0.04)*
$Foot\text{-}flat_R$ (%)		44.07(9.2)	46.02(10.27)	49.82(14.89)	49.21(5.31)
Push (s)		0.24(0.03)	0.27(0.05)	0.24(0.06)	0.26(0.04)
$Push_R$(%)		39.94(7.03)	38.09(7.45)	36.85(12.59)	36.73(6.76)

4 Discussion

In this study, we showed that main temporal events during stance phase can be detected precisely and accurately using a single IMU attached to the foot. Based on these events, the corresponding inner-stance phases were computed to estimate loading response, foot-flat and push-off durations in normal and pathological gait. These metrics give promising perspective in ambulatory gait analysis, through the analysis of stance phase composition between more active (Load and Push) and passive (Foot-flat) periods. They allow quantitative analysis of the different temporal strategies among healthy subjects and patients with gait disorder.

4.1 Technical validity

The comparison between features obtained from foot-worn inertial sensors and reference systems showed a high accuracy and precision for detecting HS and TO, and slightly lower but acceptable performance for detecting TS and HO. Our study revealed an important limitation of previous methods for HS and TO detection based on negative peaks of Ω_p, which showed a systematic bias leading to an underestimation of stance phase duration. Additionally, the proposed method showed smaller errors than results reported in previous studies using vertical foot velocity (16±15ms for HS and 9±15ms for TO [16]), or shank angular velocity (-8.7±-12.5ms for HS and -2.9±26.8ms for TO [22]). Moreover, we observed that foot angular velocity signals were particularly useful for detecting TS and HO events (i.e., Foot-flat), whereas accelerometers provided better results for detecting HS and TO events (i.e., Stance).

Although the pressure insole was validated for force measurement, errors in location measurement of bony landmarks (the midpoint between navicular and cuboid bones) used to assign sensor cells to foot segments may influence the detected TS and HO moments. However, the dispersions of landmarks' location measurement errors have been shown to be much smaller than sensor cells' length [24]. Advantageously, the detection of TS and HO moment using IMU is not affected by this source of error.

Although threshold values were selected empirically to detect TS and HO, limited movement and low-pass filtering of signal prevented sensitivity to signal artifacts. Proposed thresholds were robust in all healthy subjects and patients with ankle dysfunction. Still, as inertial sensors can present a bias due to extrinsic factors such as temperature and humidity, the threshold values given in table I, except for the detection of minimal and maximal values, might require some tuning. Finally, the use of adaptive thresholds such as those proposed recently [25], could further enhance the detection's robustness.

By using the norm of signals, the detection algorithm is less sensitive to misalignment of the sensors relative to the foot, making it more repeatable without a specific sensor positioning, and generally applicable to any other foot-mounted IMU.

The use of single sensor configurations on the foot is also possible since we have proposed and validated the detection of temporal events using only kinematic features of one gyroscope around pitch ($k_{\{1,2,9,10,15,16,19,20\}}$), or only the use of a single 3D accelerometer ($k_{\{3,4,11,12,17,18,21,22\}}$).

4.2 Clinical applications

Since it was technically validated, the proposed system can then be miniaturized and integrated in the footwear as a fully wearable device and be used in clinical evaluations. This study also investigated the proposed system's clinical suitability.

Inner-stance phases results obtained for healthy subjects were in agreement with reference normative values reported [2], with 16.7% for Loading Response, 33.3% for Mid-stance, and 50 % for the sum of Terminal Stance and Pre-Swing in percentage of Stance, where we found respectively 13±4%, 44±9% and 40±7% for $Load_R$, $Foot\text{-}flat_R$ and $Push_R$. The slight differences are due to the subdivision of stance into three phases rather than four.

Similar performances were obtained for estimating inner-stance phases among the different subject groups, showing that the selected kinematic features were robust to the various healthy and pathological gait patterns recorded. Load, foot-flat, and push durations showed different tendencies in patient groups compared to healthy subjects. However, a dedicated clinical protocol with higher sample size is needed to confirm the clinical significance of these parameters.

Detection algorithms proposed in this paper were based on simple rules that could be further implemented for real-time rehabilitation applications, where precise and accurate triggers of stimulation sequences during walking are needed [13]. Finally, the presented method can be combined with other methods that estimate spatial gait parameters using IMU [26] to provide a simple, wearable, and reliable tool for objective and quantitative evaluation of both spatial and temporal gait parameters. The clinical utility of inner-stance phases should be further confirmed in other populations, and particularly in subjects whose gait is characterized by a longer foot-flat, such as elderly at risk of fall, or people with early phases of Parkinson's disease. Nevertheless, the application to other severe pathological gait patterns, such as those characterized by toe landing at initial contact due to foot-drop after stroke [27] or increased tone (without foot-flat during stance) would require further investigation

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Chapter 4

3D Gait assessment in young and elderly subjects using foot-worn inertial sensors[*]

Abstract

This study describes the validation of a new wearable system for assessment of 3D spatial parameters of gait. The new method is based on the detection of temporal parameters, coupled to optimized fusion and de-drifted integration of inertial signals. Composed of two wirelesses inertial modules attached on feet, the system provides stride length, stride velocity, foot clearance, and turning angle parameters at each gait cycle, based on the computation of 3D foot kinematics. Accuracy and precision of the proposed system were compared to an optical motion capture system as reference. Its repeatability across measurements (test-re-test reliability) was also evaluated. Measurements were performed in 10 young (mean age 26.1±2.8 years) and 10 elderly volunteers (mean age 71.6±4.6 years) who were asked to perform U-shaped and 8-shaped walking trials, and then a 6-minute walking test (6MWT). A total of 974 gait cycles were used to compare gait parameters with the reference system. Mean accuracy±precision was 1.5±6.8cm for stride length, 1.4±5.6cm/s for stride velocity, 1.9±2.0cm for foot clearance, and 1.6±6.1° for turning angle. Difference in gait performance was observed between young and elderly volunteers during the 6MWT particularly in foot clearance. The proposed method allows to analyze various aspects of gait, including turns, gait initiation and termination, or inter-cycle variability. The system is light weight, easy to wear and use, and suitable for clinical application requiring objective evaluation of gait outside of the lab environment.

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1 Introduction

In clinical setting, gait and mobility is commonly evaluated using questionnaire, observation or simple functional performance assessments [1], [2]. These evaluations do not require sophisticated equipments and have the advantage of being easy to perform by trained evaluators. However, they are often subjective and dependant on the experience of evaluator. Furthermore, these measures do not allow evaluating specific spatio-temporal gait parameters that have been associated with frequent geriatric syndromes, such as falls, dementia, or frailty [3–5]. Generally, spatio-temporal gait analysis requires dedicated laboratories with complex systems such as optical motion capture. Recently, ambulatory devices have overcome some of these limitations by using body-worn sensors measuring and analyzing gait kinematics. Unlike standard optical motion capture that requires a dedicated working volume, body worn sensors can be linked to a light data-logger carried by the subject performing his activities outside the lab with minimal hindrance. Nevertheless, recorded data require appropriate algorithms to compute relevant parameters for clinical use [6].

Most common gait parameters, such as stride length or gait cycle time, can be obtained from the analysis of foot kinematics. Systems based on Micro-Electro-Mechanical Systems (MEMS) gyroscopes and accelerometers suffer from measurement errors and integration drifts, which limits position and orientation assessment during long-term measurements. However, by placing sensors on foot, drift can be corrected periodically by assuming null velocity of foot during foot-flat period of stance [7]. Using this hypothesis, [8] proposed a 2D analysis method with periodic linear drift correction at each stance, and [9] used a similar approach with wireless hardware. However, both studies were restricted to analysis in sagittal plane. Subsequently, [10] used a 3D approach using quaternion for foot orientation and position. [11] suggested a method for 3D foot kinematics estimation using ambulatory device for drop-foot stimulator with drift and azimuth resetting at each step. Using additional force sensors, [12] applied similar algorithms, focusing on foot placement in forward and lateral directions. Yet, these previous studies were limited to few subjects and the proposed methodologies were not evaluated against any reference instrumentation or only in "optimal" conditions, i.e. during straight walking. Some other studies have been published to track position wearing additional magnetometers [13] and/or GPS [14], but results remain essentially qualitative and were not validated for use in clinical field.

This study describes a new wearable system based on inertial sensors and dedicated algorithms for precise and accurate assessment of 3D gait spatial parameters. The system is validated in young and elderly subjects during straight walking and turning. The method is based on temporal parameters detection, coupled to an optimized fusion of inertial signals in order to assess 3D gait features outside lab and particularly new parameters such as foot clearance and turning angle.

2 Method

2.1 Foot-worn sensors

A wireless 6 Dimensional-Inertial Measurement Unit (6D-IMU) referred as "S-Sense" has been designed [15]. S-Sense module is a small (57x41x19.5mm³) and low power (18.5mA@3.6V) stand-alone unit integrating microcontroller, radio transmitter, memory, three-axis accelerometer (ADXL, Analog Device, range 3g), three-axis gyroscope (ADXRS, Analog Device, roll, yaw with 300deg/s range, pitch with 800deg/s range), and batteries. In this study two S-Sense modules were fixed on shoes at hind foot position using a compliant foam structure and double sided Velcro straps (fig. 1). Raw sensor data was low-pass filtered at 17Hz, sampled on 12bits at 200Hz, and wirelessly transmitted in real time to a PC using "S-Base" receiver plugged in USB. Signals from two S-Senses were synchronized by considering the absolute real time clock sent by the base station to each module at the start of recording. Raw data were preliminary processed to extrapolate some missing data due to wireless data loss or sensor's output saturation [15]. Data from the two feet were finally converted to physical units (g or °/s) using in-field calibration method [16].

Figure 1 - S-Sense module with compliant foam attached to shoe

2.2 Reference system

An optical motion capture system (Vicon, Oxford Metrics) with sub-millimeter accuracy was used as reference system (fig. 2.a). Motion capture volume was materialized by a black area of 2.5x5.5m (fig. 2.b). A dedicated lightweight and rigid structure was designed to attach 3 reflective markers to each S-Sense module (fig. 2.c) in order to measure 3D position and orientation of the module attached on foot. At each time frame, 3D position of S-Sense module (P_{ref}) was obtained in fixed frame (*XYZ*) by arithmetic mean of the position of each marker (M1, M2, and M3). Velocity (V_{ref}) was obtained by simple time derivative of Pref, high frequency noise obtained with this numerical differentiation was further cancelled since only mean velocity over a single gait cycle was considered. Reference 3D orientation of S-Sense mobile frame in *XYZ* was then expressed as a 3D orientation matrix (R_{ref}) derived from the dimensions of the structure and the vectors defined among markers' positions (fig. 2.d). 3D orientation was also expressed using quaternion representation obtained from matrix representation by classical conversion formulae [17].

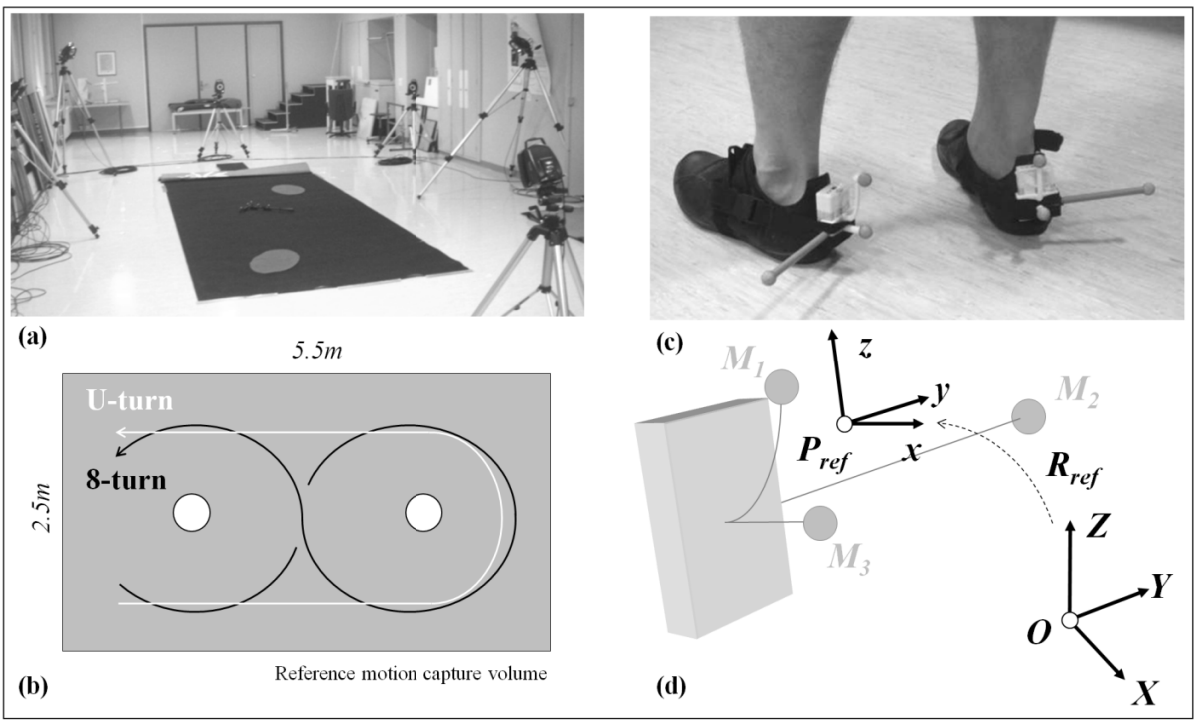

Figure 2 - Experimental Protocol with (a) Optical motion capture reference system, (b) Gait path during U-Turn and 8-Turn tasks, (c) Markers attached to S-Sense, (d) Reference position (Pref) and orientation (Rref) of the S-sense obtained in fixed frame (XYZ)

2.3 3D foot kinematics estimation

During each gait cycle n, 3D orientation (R_n), velocity (V_n), and trajectory (P_n) of foot were estimated from inertial signals. Practically, this involves the temporal detection of cycles, the knowledge of initial conditions of position and orientation, the gravity cancellation of measured acceleration, and the de-drifted integration of g-free acceleration. Moreover, kinematics measured by sensors in *xyz* should be expressed in *XYZ* to be compared with reference. Fig. 3 illustrates the main algorithmic steps, which are described in the following paragraphs.

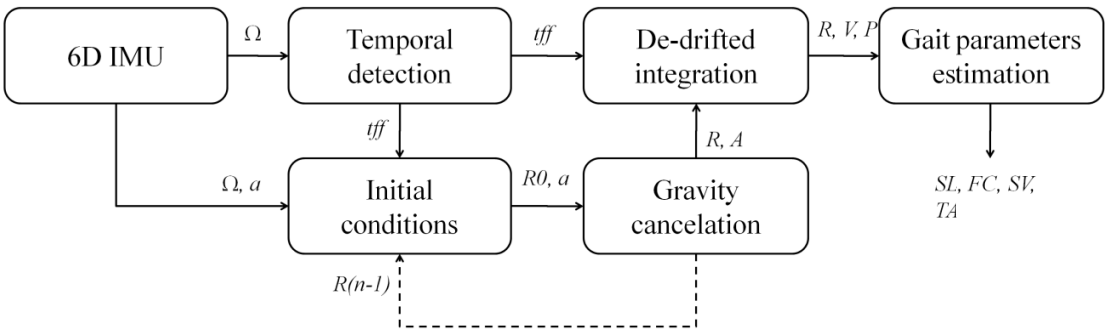

Figure 3 - Block Diagram of 3D Gait Analysis Algorithm

Temporal detection of gait cycles was done using angular velocity of foot (Ω) to identify stance phase, adapted from [18]. For each stance phase, foot-flat was defined as the continuous period where angular velocity norm was bellowing an empirical threshold. The median of foot-flat period (tff_n) was chosen to separate each gait cycle n.

Initial conditions were updated for each cycle n at tff_n, where the foot was considered motion-less. Initial 3D orientation of S-Sense module ($R0_n$) was obtained by using 3D acceleration (a_n) as inclination (i.e. by aligning z axis with Z), and azimuth was set at the value derived from the orientation at last sample (N) of previous step ($R_{n-1}(N)$).

Gravity cancellation was achieved by aligning the accelerometers' axes (xyz) with fixed frame (XYZ) and subtracting gravity vector. From initial orientation $R0_n$, the orientation of the foot relative to fixed frame ($R_n(i)$) was updated at each time frame ($i=1, 2, ..., N$) by a quaternion-based time integration of angular velocity vector Ω_n between two successive foot-flats (tff_{n-1}, tff_n) [10], [19]. At each time frame i of cycle n, using measured accelerations ($a_n(i)$), gravity-free component of acceleration in fixed frame ($A_n(i)$) can be summarized by (1).

$$A_n(i)=a_n(i)*R_n(i)-g, \qquad \text{where} \quad g=(0,0,1) \qquad (1)$$

De-drifted single and double-integration of gravity-free acceleration (A_n) allowed obtaining 3D velocity and position of foot at each gait cycle n. By assuming that foot velocity is null at each tffn [7], estimation of velocity (V_n) was obtained by trapezoidal integration of A_n. However, this operation involves some drift. Instead of a classic linear de-drifting at each gait cycle, the drift was removed by subtracting a sigmoid-like curve modeled based on a p-chip interpolation function [20]. The p-chip interpolation function (PIF), is defined between the value of $A_{n-1}(tff_{n-1})$ and $A_n(tff_n)$, (fig. 4). Position (P_n) was finally deduced by simple trapezoidal integration of velocity (V_n).

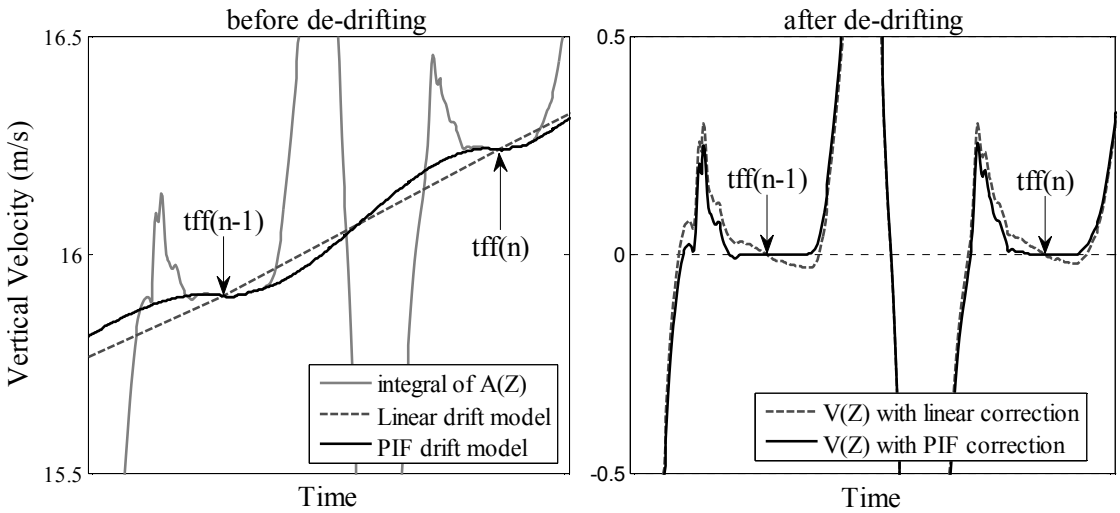

Figure 4 - De-drifted integration of vertical acceleration (*A*) to obtain vertical velocity (*V*) using linear function versus p-chip interpolation function (PIF)

2.4 Validation protocol and gait parameters

Ten young healthy volunteers (age 26.1±2.8 years), referred as "Young" group, and ten fit elderly volunteers (age 71.6±4.6 years), referred as "Elderly" group, took part in the study. Among the 20 subjects, there were 9 males and 11 females with height 170±9cm. Measurements were scheduled over 2 weeks and protocol was approved by the University of Lausanne ethical committee.

Each subject wearing S-Sense modules on shoes performed three different gait tasks. First, participants walked 5 meters straight, turned around a mark, and walked back 5 meters (referred as "U-turn"). Second, participants walked around two marks spaced out by 3 meters, following a 8 pathway [21] (referred as "8-turn"). Finally, a 6-Minute Walk Test (referred as "6MWT") [22] was performed in a 25 meters long corridor. U-turn and 8-turn tasks were performed in optical motion capture volume (fig. 2.b). S-Sense was synchronized with reference by maximizing inter-correlation between both estimated trajectories. Measurements of each task, except 6MWT, were evaluated a second time after removing completely the system and attaching it again to determine test-retest reliability.

From the 3D foot kinematics, the following four gait parameters were extracted at each cycle *n* for both reference system and S-Sense using (2), (3), (4) and (5), where *N* represent the last sample of cycle *n*:

Stride length (SL) was defined as the distance measured between two successive foot-flat positions of the foot. This calculation is valid for curved and turning path as well [23]:

$$SL_n=|P_n(N)-P_n(1)| \qquad (2)$$

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

$$FC_n = max(P_n(1), P_n(2), \ldots, P_n(N)) - P_n(1) \qquad (3)$$

Stride velocity (SV) was considered as the mean value of foot velocity in ground plane (*XY*) during each gait cycle:

$$SV_n = mean(V_{n|XY}(1), V_{n|XY}(2), \ldots, V_{n|XY}(N)) \qquad (4)$$

Turning Angle (TA) was defined as the relative change in azimuth (i.e. the projection of orientation in ground plane (*XY*)) between the beginning and the end of gait cycle.

$$TA_n = \theta_n(N) - \theta_n(1), \text{ where } \theta_n = R_{n|XY} \qquad (5)$$

Extracted 3D Gait parameters are illustrated in fig. 5.

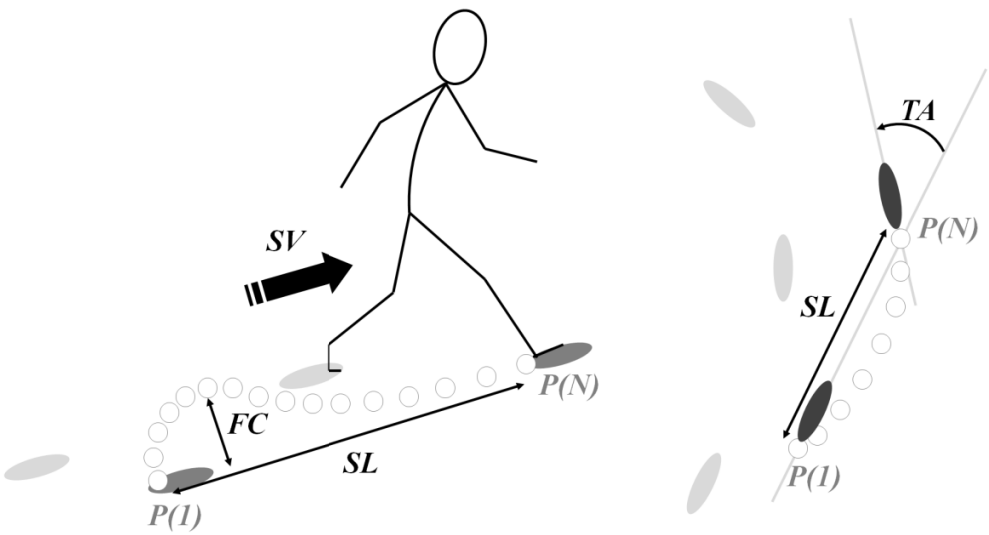

Figure 5 - 3D Gait parameters estimation from 3D foot position (*P*) and azimuth (*θ*): Stride Length (SL), Stride Velocity (SV), Foot clearance (FC) and Turning Angle (TA).

2.5 Statistical analysis

Instrument comparison – Across each cycle n, we estimated the difference (ε) between optical (reference) and wearable (S-Sense) systems for SL, FC, SV and TA. Accuracy (mean of ε) and precision (STD of ε) were reported for each of those estimated gait parameter. Agreement between the two instruments was assessed using graphical way introduced by Bland and Altman [24]. Furthermore, correlation between both

systems was calculated, and Student paired t-test was also performed to evaluate the existence of a systematic error.

Repeatability – The test-retest reliability of S-Sense was evaluated by comparing the results of the first and the second trial of each walking tasks. Coefficient of intraclass correlation ICC(1,1) was calculated [25].

Comparisons of groups – Unpaired two-sample t-tests were used to investigate any significant differences between the mean, STD and CV of gait parameters in Elderly and Young group during 6MWT performed with S-Sense.

Significant differences were considered if the null hypothesis can be rejected at the 5% level ($p<0.05$).

3 Results

3.1 Instrument comparison

1009 gait cycles were obtained with both S-Sense and reference system (corresponding to 20subjects*2tasks*2tests*2feet*6~7gait cycles per task), 35 gait cycles (i.e. 3 %) were discarded because of reflective markers loss. A total of 974 gait cycles were used consequently for comparison. Table I summarizes the differences between the four 3D gait parameters obtained from S-Sense and reference system for the different tasks, tests, groups and foot sides. Fig. 6 shows the comparison between the parameters obtained from both systems in Elderly and Young group.

TABLE I - CORRELATIONS AND ABSOLUTE AND RELATIVE DIFFERENCES BETWEEN S-SENSE AND REFERENCE SYSTEM FOR STRIDE LENGTH (SL), FOOT CLEARANCE (FC), STRIDE VELOCITY (SV), AND TURNING ANGLE (TA)

Task	Test	Group	Side	number of Cycles	ε (SL)					ε (FC)					ε (SV)					ε (TA)		
						mean		std			mean		std			mean		std			mean	std
					R	cm	%	cm	%	R	cm	%	cm	%	R	cm/s	%	cm/s	%	R	°	°
U-turn				493	95.8	0.9	0.7	6.9	6.4	91.5	2.0	8.1	2.0	8.6	97.0	0.9	0.9	5.7	5.7	99.2	1.6	6.1
8-turn				481	96.2	2.1	1.9	6.6	6.5	91.7	1.7	6.9	1.9	8.1	97.3	2.0	2.1	5.4	5.8	99.4	1.5	6.0
	test			452	95.8	1.9	1.7	6.7	6.4	92.1	1.8	7.1	2.0	8.2	96.8	1.7	1.9	5.5	5.8	99.1	0.8	6.0
	retest			522	96.3	1.1	0.9	6.8	6.5	91.1	2.0	7.9	2.0	8.5	97.5	1.2	1.2	5.6	5.7	99.5	2.4	6.1
		Elderly		492	96.0	0.7	0.4	6.1	6.1	92.7	1.2	5.2	1.7	8.1	96.9	0.6	0.7	5.0	5.4	99.5	1.9	4.7
		Young		482	96.0	2.4	2.1	7.5	6.8	90.5	2.6	9.8	2.3	8.6	97.3	2.2	2.4	6.2	6.1	99.1	1.3	7.4
			Right	483	95.2	-0.4	-0.5	6.9	6.8	91.0	1.0	3.7	1.9	7.6	96.9	0.0	0.0	5.7	6.0	99.4	-2.2	6.1
			Left	491	96.8	3.4	3.0	6.6	6.2	92.2	2.8	11.3	2.1	9.1	97.3	2.9	3.0	5.4	5.5	99.2	5.4	6.1
			Overall	**974**	**96.0**	**1.5**	**1.3**	**6.8**	**6.5**	**91.6**	**1.9**	**7.5**	**2.0**	**8.4**	**97.1**	**1.4**	**1.5**	**5.6**	**5.8**	**99.3**	**1.6**	**6.1**

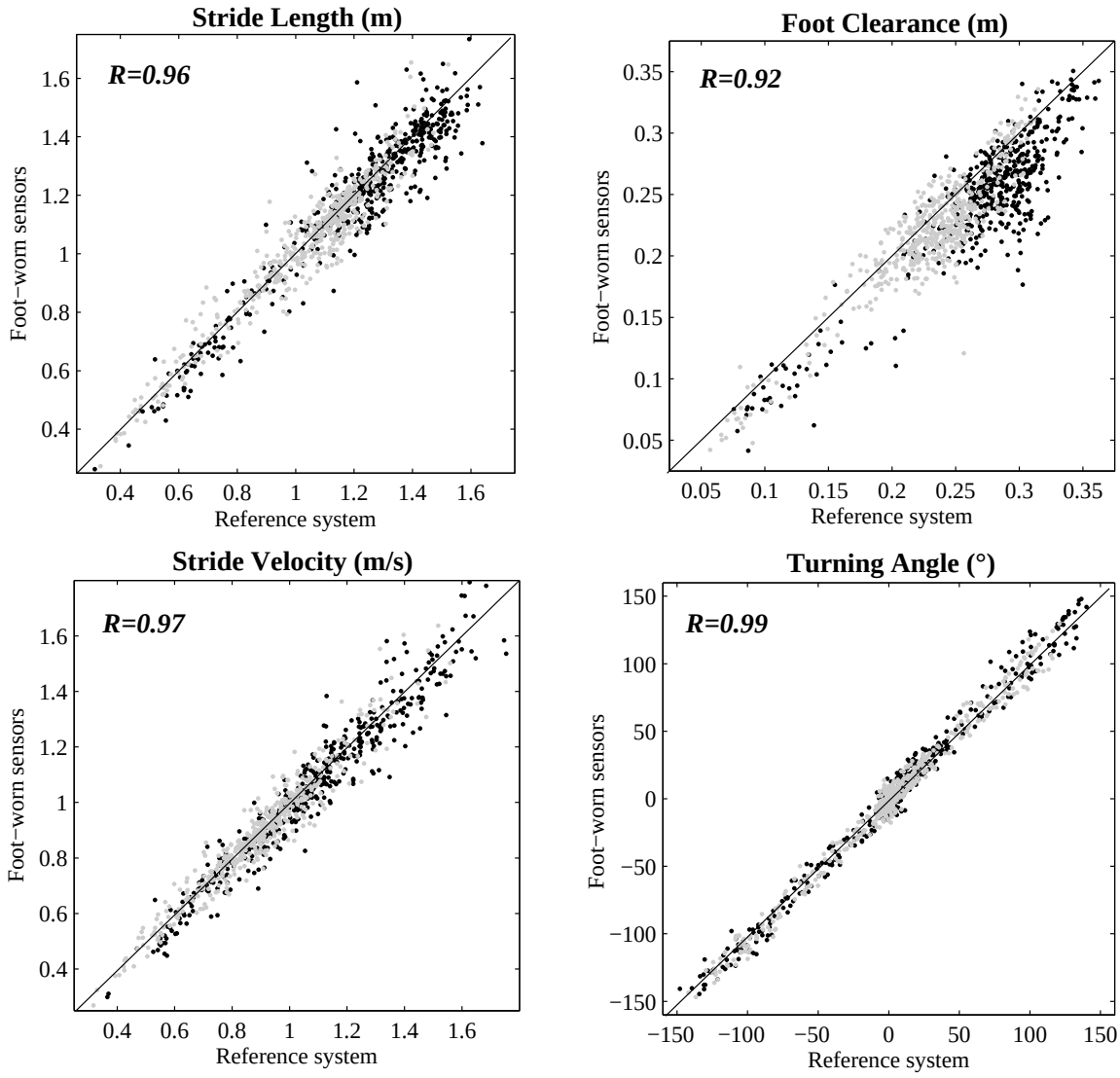

Figure 6 - Comparison of Stride Length (SL), Foot clearance (FC), Stride Velocity (SV), and Turning Angle (TA), estimated by Foot-worn sensors (S-sense) against reference system for 974 gait cycles in Young (•) and Elderly (•) subjects

Agreement between proposed system and reference was shown in fig. 7. We found a significant difference ($p<0.05$) between the two systems, confirming the existence of a small bias (accuracy) in estimating the given gait parameters. We obtained an accuracy±precision of 1.3±6.5% for SL, 1.5±5.8% for SV, 7.5±8.4% for FC and 1.6±6.1° for TA. Note that TA estimation error was not evaluated as percentage since its value is sometime null. Similar differences (ε) were found during U-turn and 8-turn, showing the robustness of the system to turning condition.

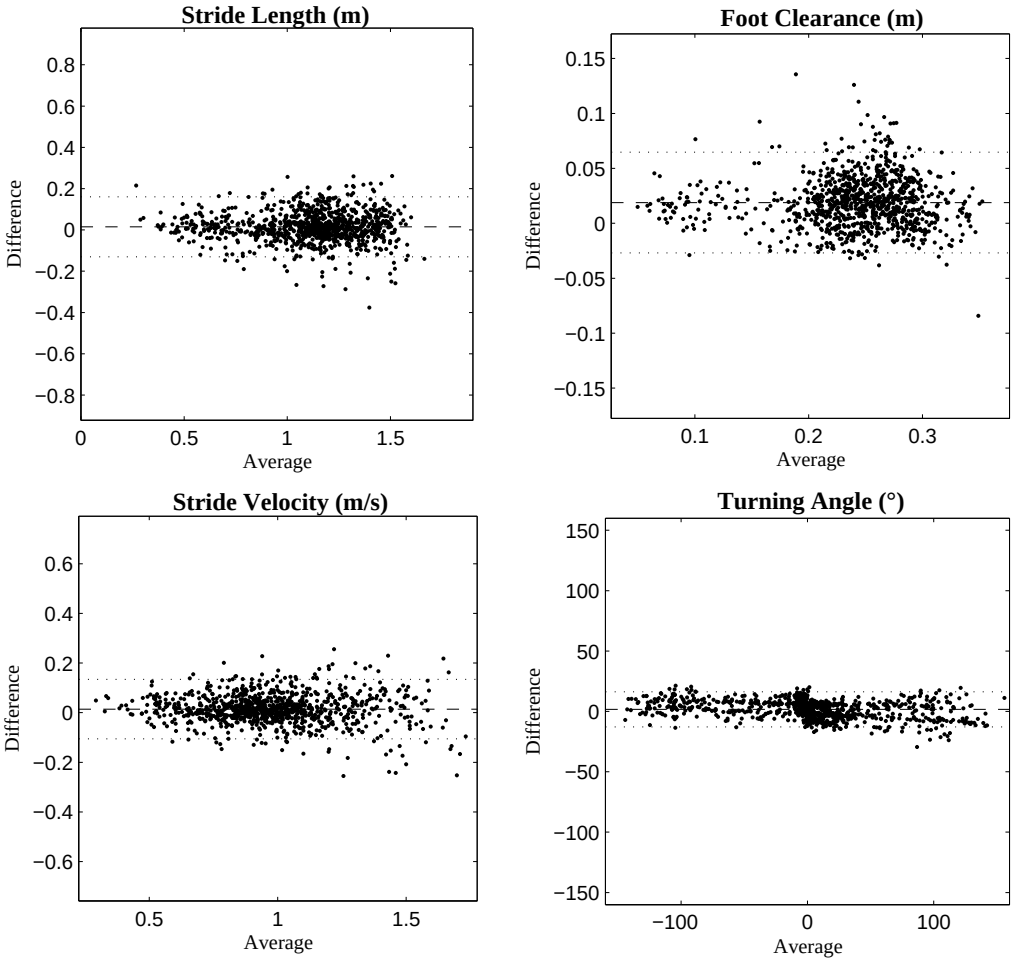

Figure 7 - Bland-Altman plot with mean (x-axis) and difference between (y-axis) between the two values estimated by the wearable system (S-Sense) and reference system across 974 gait cycles in young and elderly subjects. Limits of agreement are specified as average difference (dashed line) ± 1.96 standard deviation of the difference (dotted line).

3.2 Repeatability

From the mean gait parameters of each subject, (20 "test" and 20 "re-test" samples), ICC(1,1) with 95% confidence intervals were computed for each of the given gait parameters. Results reported in table II show excellent repeatability of mean values (ICC values above 0.9), according to benchmarks suggested by [26].

TABLE II - TEST-RETEST RELIABILITY OF STRIDE LENGTH (SL), FOOT CLEARANCE (FC) AND STRIDE VELOCITY (SV) DURING U-TURN AND 8-TURN TASKS

	SL	FC	SV
ICC (1,1)	0.91	0.96	0.93
CI of ICC	[0.79-0.96]	[0.91-0.99]	[0.83-0.97]

3.3 Comparison of elderly and young subjects

Gait performances of elderly and young subjects were compared during 6MWT. A total of 10,515 gait cycles were recorded among 20 subjects. Turning Angle was used to separate turning periods (every 25 meters) and straight walking for analysis. The three other gait parameters were averaged and reported in fig. 8. Whereas relatively small, non significant-differences ($p>0.05$), between mean value of SL and SV were observed, FC appeared to significantly discriminate performance between the two groups ($p=0.02$ for straight walking, $p=0.003$ during turns). Moreover, during turns, SL, SV, and FC were significantly reduced in all subjects compared to period straight walking ($p<0.015$ for all mean, STD, and CV of those parameters). Interestingly, differences in mean gait parameters between Young and Elderly groups were larger during turns. We also observed that elderly subjects walked slightly faster than young subjects in straight walking whereas an opposite trend was observed during turning. In addition, mean and STD values obtained during straight walking were consistent with values reported in literature for this population [27].

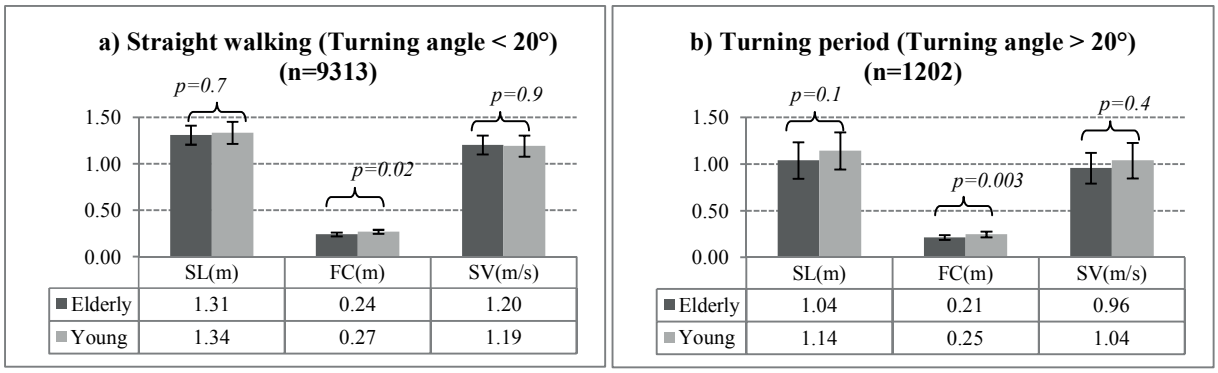

Figure 8 - Comparison of mean Stride Length (SL), Stride Velocity (SV), and Foot clearance (FC) for Elderly and Young subjects during 6-Minute Walk Test. Significant differences ($p<0.015$) are observed between straight walking (a) and turning (b) for all parameters.

4 Discussion

In this paper we propose a new wearable system with dedicated algorithm for 3D gait assessment and describe validation of its performance against a reference optical motion capture system. A set of original gait parameters is provided that can be measured when performing normal activity, straight and curved trajectory or during outdoor condition. These parameters show promising preliminary discriminative performance, as they make it possible to distinguish young and elderly subjects.

Hind-foot position of the module was chosen for practical reason, but the proposed algorithm does not require an exact positioning on foot, as illustrated by the high test-retest reliability reported in table II.

Consecutively, the proposed method could also be applied with sensor worn on other foot positions such as the forefoot. Regarding wireless functionality, frame loss was assessed to 2% during validation protocol, which didn't seem to have any influence on the results. However, if consecutive frames were lost, error would become important, so we believe recording of signal on the modules should be better for practical use. We also observed few cases of sensor's saturation with accelerations above 3g at heel-strikes during active walking, especially in the young group. This observation could explain the smaller error observed among elderly subjects (Table I).

Azimuth (or Heading) is tracked from initial position with no correction, thus it is subject to drift. Nevertheless, it has negligible influence on the gait parameters computed at each gait cycle separately, as only overall long-term trajectory is affected. In practice, the proposed system could be used to study 3D foot trajectory during object avoidance, but it would require additional hypothesis or sensors such as magnetometer or GPS for long-term navigation. Even though these sensors might improve orientation estimation [28], they are sensitive to nearby mass of iron in the floor for magnetometer, and to satellites occlusion for GPS. Moreover we found that main source of error seems to be mostly in acceleration measure, which may be physically explained by the influence of centrifugal acceleration generated by rotation [29].

By considering subjects with various performance and including gait initiation and termination cycles we obtained a wide range of parameters with SL from 30cm to 160cm, turning angle from -150° to 150° etc…(fig. 6). This provided a robust evaluation of method's performance in a wide range of possibilities, and the assessment of various aspects of gait ability such as turning. Compared to other inertial-based gait analysis system [8], [12], [18], [30], similar or slightly better accuracy and precision was obtained for SL and SV. The method also provides stride-to-stride variability of gait, and previous systems with similar precision were shown to be sensitive enough to identify significant associations between gait variability and various syndromes associated with aging, such as frailty [5], and fear of falling [31]. However, variability estimations, as well as influence of age or gender, should be further investigated in larger population.

The method allows analyzing curved trajectories, it requires fewer sensors' sites and provides new parameters such as TA and FC. Actually, TA is an important outcome to evaluate gait in Parkinson disease [32] and FC, which was the most discriminative parameters between our young and elderly subjects, could also be an important new gait parameter to estimate risk of fall in elderly [33], [34]. Finally, the system is lightweight and it can be worn directly on user's casual shoes, thus minimizing intrusiveness and interference with normal gait conditions. As a result, volunteers gave a good qualitative

feedback on the system, telling they forgot about it while walking. We therefore believe that such a fully wearable device is especially adapted and practical for objective study of gait impairment and daily use in research or rehabilitation centers.

5 Conclusion

The proposed foot-worn system and its outcome parameters were evaluated on a wide range of gait cycles obtained in young and fit elderly subjects, and showed good suitability for clinical gait evaluation. Additional studies are needed to further investigate the applicability of this system when studying frailer elderly subjects with gait impairment. Nevertheless, the current study makes an important contribution to this field of research because this new system provides original gait parameters, such as turning angle and foot clearance, while still maintaining good accuracy and precision for other, commonly used gait parameters (i.e. stride length and stride velocity). The system can be used as an objective tool in many applications requiring gait evaluation in real conditions. It might prove particular relevance to study gait abnormalities during long-term measurements or to investigate the significance of irregularity during turns for outcome evaluation of medical and rehabilitation interventions.

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Chapter 5

Heel and Toe Clearance Estimation for Gait Analysis Using Wireless Inertial Sensors[*]

Abstract

Tripping is considered a major cause of fall in older people. Therefore foot clearance (i.e. height of the foot above ground during swing phase) could be a key factor to better understand the complex relationship between gait and falls. This paper presents a new method to estimate clearance using a foot-worn and wireless inertial sensor system. The method relies on the computation of foot orientation and trajectory from sensors' signal data fusion, combined with temporal detection of toe-off and heel-strike events. Based on a kinematic model that automatically estimates sensor position relative to the foot, heel and toe trajectories are estimated. 2D and 3D models are presented with different solving approaches, and validated against an optical motion capture system on 12 healthy adults performing short walking trials at self-selected, slow, and fast speed. Parameters corresponding to local minimum and maximum of heel and toe clearance were extracted and showed accuracy±precision of 4.1±2.3cm for maximal heel clearance and 1.3±0.9cm for minimal toe clearance compared to the reference. The system is lightweight, wireless, easy to wear and to use, and provide a new and useful tool for routine clinical assessment of gait outside a dedicated laboratory.

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1 Introduction

Among community-dwelling people older than 65 years, one third falls each year. Falls have many adverse consequences in older people, including major injuries, functional decline, activity restriction and reduced quality of life. Foot clearance, defined as the foot's height during the swing phase, seems an important gait parameter related to the risk of falling. Contrary to other gait parameters, there is an unambiguous mechanism that links impaired foot clearance to falls. During walking, insufficiency or fluctuations in foot clearance could lead directly to tripping, a major cause of fall in older people. In previous studies investigating circumstances of falls in community-dwelling older people, tripping was the most frequent condition causing falls [1], [2]. In these studies, tripping accounted for up to 50% of all falls.

Surprisingly, despite this intuitive relationship, only few studies investigated so far the characteristics of foot clearance pattern, and only in small selected population. Therefore, several major gaps remain in our knowledge about the clinical significance of foot clearance in older persons. Some studies have evaluated specific features of foot clearance during level walking, mostly Minimum Toe Clearance (MinTC), also referred as Minimal Foot Clearance (MFC) which can be defined as the minimal vertical distance between the shoe sole and ground during the swing phase [3], [4]. A recent systematic review on the association between falls history and MinTC concluded that greater MinTC variability was observed in older fallers compared to older non-fallers [5]. A recent study showed increased MinTC variability in 10 older people reporting a fall in previous year compared with older people without fall history [6]. Theoretical models based on MinTC variability to predict the risk of falling have also been proposed recently [4], [6].

These promising preliminary clinical results have several limitations, mostly due to technical issues. First, foot clearance was evaluated only in very small samples of young and elderly subjects due to the complexity of the measurement protocol in gait laboratory, using camera based motion system and treadmills. Systems using these technologies provided information for a limited number of gait cycles and could be used only in a closed environment. In addition, analyses then had to assume that observed performance corresponds to usual performance, even though walking requires several steps to reach a steady state [7], and aspects such as variability of gait requires extended periods of time to be assessed [8]. Finally, results can be strongly influenced by reflective markers' placement on the foot by the operator.

In the past years, technical progress made possible the development of wearable sensors featuring combinations of accelerometers, gyroscopes and force sensors fixed to lower-limbs to measure gait characteristics [9–13]. Due to very low energy consumption, these sensors can be battery powered and thus have a potential application for extended ambulatory monitoring. They allow mobile as well as outdoor motion capture and can provide information over extended periods of time. In addition, since there is no localization marker, signals can be continuously recorded without any trajectory loss due to marker hiding. Lately, a new generation of miniature wireless sensors fixed directly on foot was developed and was able to estimate sagittal [11] and global 3D foot kinematics [14]. Those methods rely on periodical corrections of sensors drift based on biomechanical assumptions such as motionless during stance.

So far, only few attempts have been made to apply this inertial sensors technology to estimate a limited set of foot clearance parameters, such as minimal toe clearance [15], [16] or maximal foot clearance [14].

This study aims at addressing those technical limitations in order to investigate various aspects of foot clearance in clinical studies. The paper presents a method based on a portable and wireless foot worn inertial sensor system, and dedicated biomechanical model to estimate both heel and toe clearance patterns during gait in real world conditions. To this end, two independent models relying on 2D and 3D movement hypothesis, and 3 solving approaches are presented and compared, and validated against a gold standard system composed of optical motion capture. Several parameters are then introduced to characterize foot clearance and their changes according to different walking speeds are analyzed and discussed.

2 Method

2.1 Inertia-based measurement system

A stand-alone Physilog® unit integrating microcontroller, memory, three-axis accelerometer (MMA7341LT, Freescale, range ±3 g), three-axis gyroscopes (ADXRS, Analog Device, range ±600 deg/s), and battery (3.7 V, 595 mAh) was designed. Physilog module is small (50 mm × 40 mm × 16 mm) and low power (71 mA in recording, 51 mA in standby mode), lightweight (36 g) and was conveniently fixed in few seconds on the front foot of subjects using elastic strap (fig. 1) with shape memory foam beneath the system to guaranty a stable position together with easy manipulations. The kinematics data (3D acceleration and 3D angular velocity) was low-pass filtered at 17Hz [13], [14], sampled on 16 bits at a frequency f_s of 200 Hz, converted to physical units (g or °/s) and recorded on micro SD cards before transferring to the PC. Signals from two modules were synchronized wirelessly. Preliminary, by assuming that during walking, pitch

angular velocity was maximal in sagittal plane; each sensor was aligned with the principal axis of the measured angular velocity. In addition, in the absence of foot movement (e.g. standing posture), the vertical gravity axis was determined from accelerometer. Subsequently, sensor inclination was corrected so that the pitch angle (θ_Y) was null at rest. The components of angular velocity (pitch: Ω_p, yaw: Ω_y and roll: Ω_r) and acceleration (forward: a_f, vertical: a_v and lateral: a_l) were aligned accordingly. This way, measurement was not influenced by the sensor location on foot.

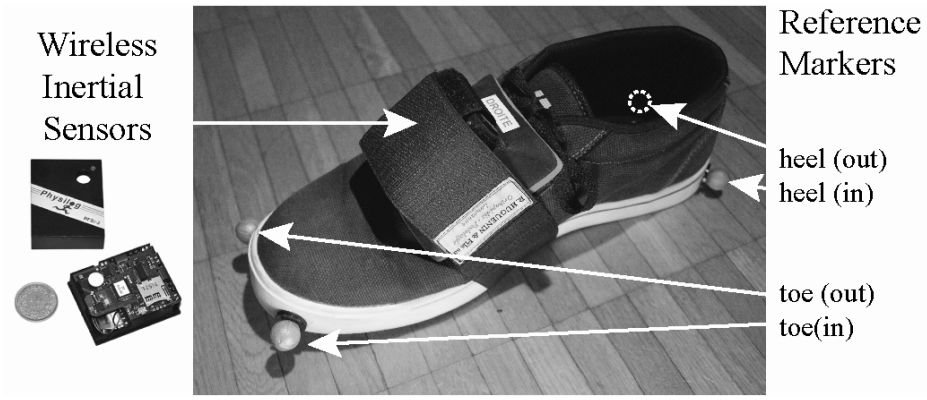

Figure 1 - Physilog wireless unit with embedded inertial sensor attached on foot. Internal (in) and external (out) markers fixed on heel and toe for reference optical motion capture.

2.2 Foot kinematics estimation

Foot kinematics was estimated from sensor data fusion using method inspired from previous work in 2D [11] and in 3D [14]. Principal steps and equations of the process are presented in this paragraph. At first, for each cycle n temporal events were detected on pitch angular velocity (Ω_p), namely time of foot-flat (tff_n), heel-strike (ths_n) and toe-off (tto_n). Foot-flat was detected as the minimum of absolute value of Ω_p, whereas heel-strike (respectively toe-off) was detected as the negative peak of Ω_p, before (respectively after) foot-flat. Gait cycle was defined as the interval between two consecutive foot-flat [tff_n:tff_{n+1}].

In 2D, for each cycle n, the pitch angle or inclination in sagittal plane (θ_Y), as illustrated in fig. 2, was obtained from periodic integration Ω_p between two successive foot-flat events (tff_n and tff_{n+1}) :

$$\forall n, \forall t \in [tff_n : tff_{n+1}], \theta_Y(t) = \frac{\sum_{i=tff_n}^{t} \Omega_p(i)}{f_s} \qquad (1)$$

Estimated pitch angle $\hat{\theta}_Y$ was linearly de-drifted assuming a flat orientation of foot at foot-flat.

$$\hat{\theta}_Y(t) = \theta_Y(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * \theta_Y(tff_{n+1}) \right) \qquad (2)$$

Accelerations were then aligned in fixed frame and the gravity component was cancelled on Z axis:

$$a_Z(t) = -\sin(\hat{\theta}_Y(t)) * a_f(t) + \cos(\hat{\theta}_Y(t)) * a_v(t) - 1 \qquad (3)$$

By considering gravity (g), vertical velocity in fixed frame was estimated by integration and linear de-drifting of acceleration:

$$v_Z(t) = g * \frac{\sum_{i=tff_n}^{t} a_z(i)}{f_s}, \quad \hat{v}_z(t) = v_Z(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * v_z(tff_{n+1}) \right) \qquad (4)$$

Finally vertical trajectory was obtained by integration and linear de-drifting, assuming locomotion on flat ground.

$$Z^{2D}(t) = \frac{\sum_{i=tff_n}^{t} \hat{v}_z(i)}{f_s}, \quad \hat{Z}^{2D}(t) = Z^{2D}(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * Z^{2D}(tff_{n+1}) \right) \qquad (5)$$

In 3D, the orientation of the sensors was represented by a 3D rotation matrix (*M(t)*) relative to the fixed frame (XYZ) [14], and was updated at each time frame by a quaternion-based time integration of angular velocity between two consecutive foot-flat [tff_n:tff_{n+1}]. Then *M(t)* was used to express the accelerations in XYZ from (a_f, a_v a_l). Double time integration using a p-chip interpolation function was performed to find the 3D position of the foot sensor, and its projection on Z axis $\hat{Z}^{3D}$ [14].

2.3 Heel and Toe trajectory estimation

From previous paragraph, sensor trajectory has been estimated in 2D and 3D. Considering the sensor location relative to heel and toe (coordinates *{a, b, c}* in fig. 2), the vertical trajectory of Sensor, Heel and Toe can be computed as follow in 2D:

$$\begin{aligned} Z^{2D}_{Sensor}(t) &= \hat{Z}^{2D}(t) + b \\ Z^{2D}_{Heel}(t) &= Z^{2D}_{Sensor}(t) - b * \cos(\hat{\theta}_Y(t)) - a * \sin(\hat{\theta}_Y(t)) \\ Z^{2D}_{Toe}(t) &= Z^{2D}_{Sensor}(t) - b * \cos(\hat{\theta}_Y(t)) + c * \sin(\hat{\theta}_Y(t)) \end{aligned} \qquad (6)$$

And in 3D:

$$
\begin{aligned}
&Z^{3D}_{Sensor}(t) = \hat{Z}^{3D}(t) + b \\
&U(t) = M(t)|_X = M(t)^T * (1,0,0) \\
&W(t) = M(t)|_Z = M(t)^T * (0,0,1) \\
&Z^{3D}_{Heel}(t) = Z^{3D}_{Sensor}(t) - b * W(t) - a * U(t) \\
&Z^{3D}_{Toe}(t) = Z^{3D}_{Sensor}(t) - b * W(t) + c * U(t)
\end{aligned} \tag{7}
$$

Nevertheless, in (6-7), the values of a, b and c are unknown. That could have been manually measured after the sensor placement on foot, but that would be practically cumbersome and could lead to important errors due to an imprecise manual operation. Thus an automatic method independent of sensor placement was proposed to estimate those three unknown variables at cycle n $\{a_n, b_n, c_n\}$ by the following three hypotheses:

- At Heel-strike, vertical coordinate of estimated heel trajectory should be equal to 0:

$$Z^{3D}_{Heel}(ths_n) = Z^{2D}_{Heel}(ths_n) = 0 \tag{8}$$

- At Toe-off, vertical coordinate of estimated toe trajectory should be equal to 0:

$$Z^{3D}_{Toe}(tto_n) = Z^{2D}_{Toe}(tto_n) = 0 \tag{9}$$

- Heel to toe distance is equal to shoe size which can be measured by shoe size (*Ssize*):

$$a_n + c_n = Ssize \tag{10}$$

For each cycle *n*, we obtain a system of 3 equations {(7), (8), (9)} with three unknown variables $\{a_n, b_n, c_n\}$. Three different ways to solve those equations systems were considered. The first solving approach was to analytically find the solution at each cycle *n*, this is referred as the *per-cycle (PC) approach*. In a second time, by assuming that the sensor position remains fixed on the foot during one gait trial, it implies that $\{a_n, b_n, c_n\} = \{a, b, c\}$. Considering all cycles of a gait trial, $\{a,b,c\}$ was estimated by the median of the set of solutions $\{a_n, b_n, c_n\}$, this is referred as the *median (ME) approach*. Finally by using all cycles, it was also possible to consider having multiple equations with three unknowns, and that overestimated system was solved using least square criteria, this is referred as the *least-square (LS) approach*.

- During $[tff_n:tto_n]$, it was assumed that the toe is in contact with the ground and therefore:

$$\forall t \in [tff_n : tto_n], Z^{2D}_{Toe}(t) = Z^{3D}_{Toe}(t) = 0 \tag{11}$$

- During $[ths_n:tff_{n+1}]$, it was assumed that the heel is in contact with the ground and therefore:

$$\forall t \in [ths_n : tff_{n+1}], Z_{Heel}^{2D}(t) = Z_{Heel}^{3D}(t) = 0 \qquad (12)$$

Those corrections do not bring discontinuities to the clearance signals since the equations were solved with null values at tto_n and ths_n.

2.4 Foot Clearance Parameters

Heel and toe clearance were defined as the vertical coordinates of heel (Z_{Heel}^{2D}, Z_{Heel}^{3D}) and toe trajectories (Z_{Toe}^{2D}, Z_{Toe}^{3D}). Although the full time-trajectory patterns were obtained, several basic statistical features were extracted to characterize foot clearance patterns through simple and interpretable parameters. These foot clearance parameters were based on the local maximum and minimum of heel and toe clearance and were computed for each cycle measured by the system (fig. 2).

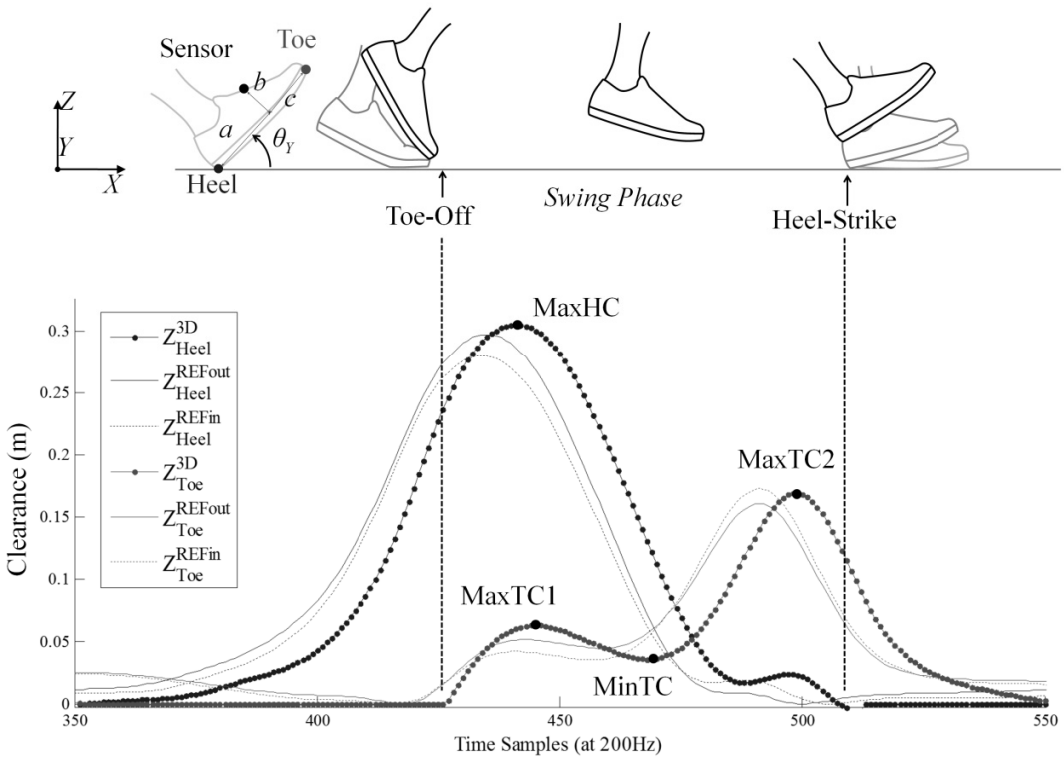

Figure 2 - Sensor location relative to heel and toe {*a, b, c*}. Schematic of foot kinematics, temporal events and clearance parameters during one gait cycle. Heel (light grey) and toe (dark grey) clearance are dashed for 3D model (Z^{3D}), and plain lines for internal and external reference markers (Z^{REF}).

2.5 Experimental Validation

In this study, 12 healthy adults (9 Males, 3 Females, mean age 32±7 years, mean height 176±8 cm, mean weight 71±15 kg) were asked to walk 5 times at slow, self-selected (also referred as normal) and fast

speed a 15m corridor while wearing the two Physilog units on their feet. The middle 5-meters of the corridor, where gait could be considered as steady-state, were tracked by a reference optical motion capture system (Mocap) with sub-millimeter accuracy [13], including 7 cameras (Vicon, UK). The Mocap tracked the position of four reflective markers placed manually on internal and external side of the shoe at the toe and heel extremities of subject's shoe according to fig. 1. Shoe's heel and toe trajectories and related foor clearance parameters estimated from Mocap were considered as reference data (REF) and used for the validation of the Physilog based system. The protocol was approved by local ethical comity.

2.6 Data Analysis

Shoe size (*Ssize*) was obtained directly from the measure of the distance between heel and toe markers and used for heel and toe trajectory estimation based on Physilog system. To compare the extracted parameters at each recorded gait cycle within the frame limited by Mocap volume, the clearance pattern given by Mocap was temporally delayed to match clearance pattern estimated with Physilog, using the maximum of cross-correlation between the two clearance patterns. That provided juxtaposed clearance curves, as in fig. 2. The same dely was applied to toe clearance pattern. Accuracy and precision were then computed as the mean and STD value for the difference between foot clearance parameters extracted with Mocap reference system (REF) and each of the algorithms (3D and 2D), and for each approach of solving sensor's position (PC, ME, LS). Accuracy and precision were reported in millimeters (absolute value), and in percentage of average parameter values (relative value). The reference itself was assessed through the difference between parameters extracted on internal and external side of the shoe. Bland and Altman plots were investigated to estimate the limit of agreement between proposed system and reference.

Finally, walking velocity was estimated using the same inertial sensors configuration [14] to check significant changes between low, normal and fast speed. Two-sample t-tests were performed on speed and foot-clearance parameters to investigate the significance of foot clearance changes with speed, and observe the influence of walking speed on the error in foot clearance estimation.

3 Results

3.1 Comparison with reference system

Fig. 2 shows a good correspondence between Z_{Heel}^{3D} and Z_{Heel}^{REF} (respectively Z_{Toe}^{3D} and Z_{Heel}^{REF}) patterns during a typical recorded gait cycle. Four parameters were extracted from these patterns. Heel pattern reached its maximal value (MaxHC), right after toe-off. Before heel-strike, a local minimum and maximum of heel clearance were sometimes observed (fig. 2), but it was not consistent in all subjects, so

it was not considered in the analysis. Regarding toe-clearance, right after toe-off, a first local maximum was reached (MaxTC1). It corresponded to the highest position of the foot during swing phase. Then toe clearance reached a minimum (MinTC) around mid-swing time, and then a second maximum (MaxTC2) prior to heel-strike.

Table I provides a quantitative one-by-one comparison of foot clearance parameters obtained with 2D and 3D models and different equations solving approaches (PC, ME and LS) and the reference system (REF). Due to the limited capture volume of the reference system and the variation of heel and toe clearance patterns among subjects, the sample size for the different parameters was not always the same but ranged between 154 and 378 cycles. MaxHC was obtained with an error of 40.6±22.5 mm for 3D and LS approach and 42±22.6 mm for 2D and LS approach. Best absolute accuracy and precision (expressed as mean±STD of the set of difference with the reference system) were observed for MinTC, with 0.4±12.6 mm and -12.7±9.1 mm respectively for 2D and 3D models solved with LS criteria. Other toe clearance parameters, namely MaxTC1 and MaxTC2, showed absolute accuracy between 13.7 mm and 19.6 mm depending on the different models and approaches. However, when looking at relative error, we observed that MaxHC and MaxTC2 showed the best performances with minimal random error below 10%, whereas this random error was between 30% and 40% for MaxTC1 and MinTC, due to the small quantity being measured. The intrinsic variations of the heel and toe clearance reference estimation were evaluated by the difference obtained between the markers placed on the internal and external side of the shoe (REF, ext/in in Table I). Those intrinsic variations were 4.0±5.4 mm for MinTC and 10.5±10.6 mm for MaxHC.

Results were comparable among the different solving approaches (table I). Regarding precision in particular, which can be interpreted as the random error, slightly better results were obtained with LS criteria for MaxHC, MinTC and MaxTC1 on 3D model. Only MaxTC1 showed better precision with PC approach (14.1 mm) compare to LS (14.5 mm). Results obtained with 2D model showed lower performances in terms of precision than 3D model, except for MaxTC2. Therefore, in the following, only the 3D model with LS approach (3D_LS) was used for further analysis.

TABLE I

ACCURACY (MEAN) AND PRECISION (STD) OF FOOT CLEARANCE PARAMETERS WITH 3D AND 2D MODEL AND AUTOMATIC ESTIMATION OF SENSOR LOCATION USING PER-CYCLE (PC), MEDIAN (ME) AND LEAST-SQUARE (LS) APPROACHES, COMPARED TO MOTION CAPTURE (REF)

Values are expressed in mm and % of average parameters. REF ext/In corresponds to the intrinsic error of reference system obtained by the difference between external and internal side of the shoe.

			Accuracy (mean)		Precision (STD)		
			mm	%	mm	%	Samples
MaxHC	REF	ext/in	10.5	3.9	10.6	4.0	378
	3D	PC	43.4	16.2	23.9	8.9	
		ME	47.6	17.7	25.6	9.6	
		LS	40.6	15.1	22.5	8.4	
	2D	PC	45.9	17.1	25.1	9.4	
		ME	48.1	17.9	24.0	8.9	
		LS	42.0	15.7	22.6	8.4	
MaxTC1	REF	ext/in	4.0	10.7	5.4	14.4	169
	3D	PC	21.0	56.0	14.1	37.6	
		ME	25.6	68.3	17.7	47.0	
		LS	20.5	54.5	14.5	38.6	
	2D	PC	27.8	74.0	15.3	40.7	
		ME	30.4	81.1	16.2	43.2	
		LS	27.3	72.6	15.1	40.1	
MinTC	REF	ext/in	4.0	15.5	4.4	16.7	154
	3D	PC	-14.3	-54.8	9.5	36.4	
		ME	-12.7	-48.7	9.0	34.5	
		LS	-12.7	-48.8	9.1	35.0	
	2D	PC	-0.9	-3.6	13.5	51.7	
		ME	0.2	0.6	12.7	48.5	
		LS	0.4	1.7	12.6	48.1	
MaxTC2	REF	ext/in	-7.5	-5.1	6.1	4.2	182
	3D	PC	-20.2	-13.8	19.6	13.4	
		ME	-22.0	-15.1	18.0	12.3	
		LS	-23.6	-16.2	17.8	12.2	
	2D	PC	-9.6	-6.6	13.7	9.4	
		ME	-10.4	-7.1	14.1	9.7	
		LS	-13.9	-9.5	13.7	9.4	

Fig. 3 shows Bland & Altman plot for all parameters obtained with 3D_LS against reference and the limit of the 95% confidence interval (±1.96 SD) around perfect agreement. We can observe systematic biases in accordance with accuracy measure of Table I. Moreover, fig. 3 shows that the differences between reference and proposed system increases as the average of MaxTC1 increases, whereas opposite tendency is observed for MaxTC2.

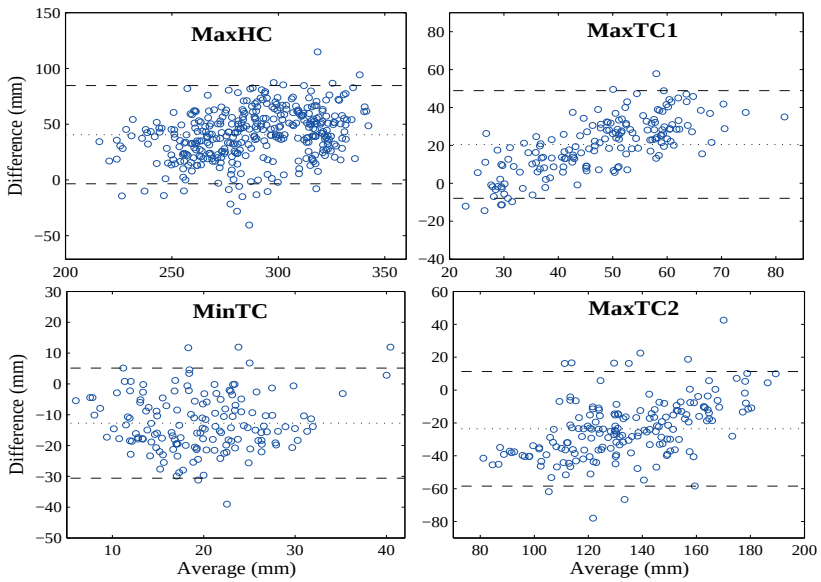

Figure 3 - Bland and Altman plots of the mean (dotted line) ± 1.96 STD limit of agreement (dashed line) of the difference between the 3D model with Least-square approach and reference for Foot clearance parameters.

3.2 Influence of walking speed on foot clearance parameters

Table II provides the values of speed and foot clearance parameters for instructed walking speed. The walking speed of subjects was significantly different ($p<0.01$) between slow (0.83±0.14 m/s), fast (1.46±0.35 m/s) and normal (i.e. self selected) speed (1.18±0.26 m/s). The variation of foot clearance parameters with speed was investigated through mean and STD value of each parameter (Table II).

TABLE II
FOOT CLEARANCE PARAMETERS AT DIFFERENT WALKING SPEEDS

		Slow			Normal		Fast		
		mean	STD	p	mean	STD	mean	STD	p
Speed (m/s)		0.82	0.10	0.00	1.19	0.20	1.62	0.15	0.00
MaxHC (cm)	REF	25.3	2.3	0.00	27.6	2.1	28.7	2.2	0.00
	3D_LS	30.2	3.1	0.00	31.5	3.3	31.2	3.4	0.52
	Error	5.0	1.7	0.00	3.9	2.1	2.5	2.5	0.00
MaxTC1 (cm)	REF	3.5	0.9	0.00	4.1	0.7	3.8	0.7	0.10
	3D_LS	5.6	1.9	0.00	6.5	1.5	5.3	1.7	0.00
	Error	2.1	1.4	0.08	2.5	1.2	1.5	1.6	0.00
MinTC (cm)	REF	2.5	0.7	0.06	2.7	0.7	2.7	0.8	0.88
	3D_LS	1.1	0.7	0.05	1.4	0.7	1.7	1.1	0.11
	Error	-1.3	1.0	0.94	-1.3	0.8	-1.0	1.0	0.15
MaxTC2 (cm)	REF	13.5	1.8	0.00	15.0	1.6	16.4	1.5	0.00
	3D_LS	10.7	2.4	0.00	12.9	2.4	14.5	2.6	0.00
	Error	-2.8	1.7	0.01	-2.1	1.8	-1.9	1.8	0.64

Significant change of parameters compared to Normal (i.e self-selected) speed is shown with the p value.

The influence of speed on the error for estimating foot clearance parameters was found to be significantly higher at slow speed for MaxHC and MaxTC2, whereas it was significantly lower at fast speed for MaxHC and MaxTC1. Estimation of MinTC however, was not affected by changes in walking speed ($p>0.05$). Overall, the mean error was found to be smaller for all parameters at fastest walking speeds, while STD error was smaller at self-selected speed for MaxTC1 and MinTC, and at slow speed for MaxHC and MaxTC2 (Table II). Those changes can be interpreted by a higher signal-to-noise ratio compensated by a lower accuracy of temporal detection at higher speeds.

In fig. 4, significant changes in clearance parameters were observed for MaxTC2, which was increasing with speed. MaxTC1 was higher at normal speed, and MaxHC was smaller at slow speed. Although a tendency for increased MinTC with speed was observed, this was not statistically significant. We observed MinTC ranging from 1.1 cm at slow speed to 1.4 cm at self-selected and 1.7 cm at fast speed.

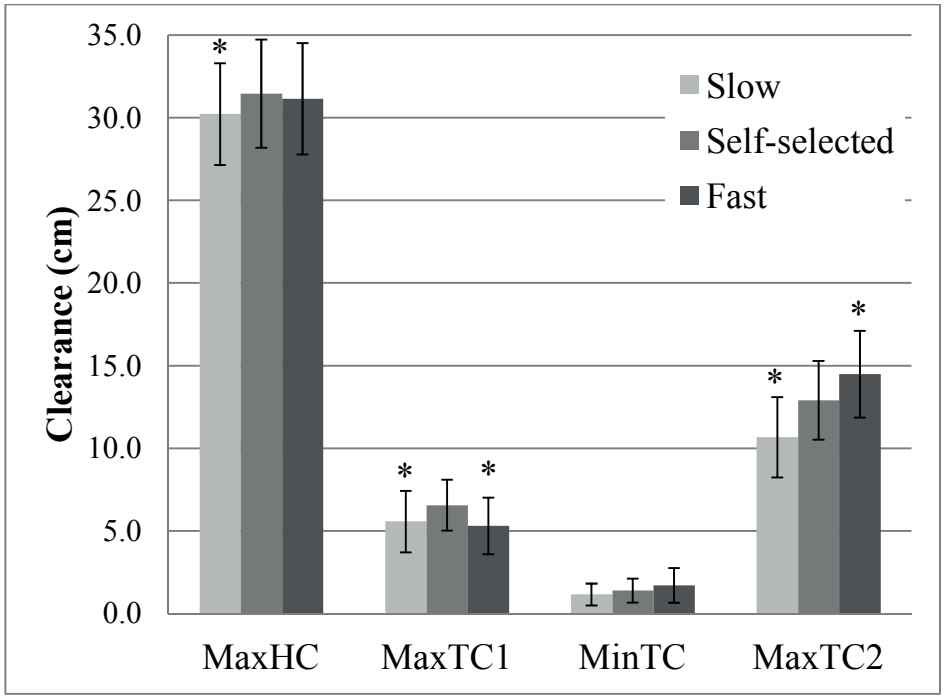

Figure 4 - Foot clearance parameters at slow, self-selected and fast walking speed. *Significant differences with self-selected speed ($p<0.01$).

4 Discussion

Primary aim of the study was to propose a wearable and wireless system with a model to obtain relevant parameters characterizing foot clearance. To our knowledge, this is the first study that used wireless inertial sensors and shows technical validity against a reference system for estimating foot clearance

parameters. The methods consider both temporal detection and kinematic estimation with models based on biomechanics of foot movements.

Overall results show a good agreement between both 3D and 2D based model and reference, and allow observing different foot clearance patterns changes with velocity in a group of healthy subjects. Those tendencies were similar to the ones observed with reference system, showing face validity. In addition, our method for foot clearance parameters estimation showed better accuracy and precision than previous studies using inertial-based systems [14], [16]. Previous studies on foot clearance have shown that MinTC values in older people were similar to those found in younger people and ranges between 1.1 and 1.5 cm [4], which is congruent with the results we obtained. However, intra-individual or inter-cycle variability in MinTC was shown to be significantly increased in older people compared to younger [4–6]. Results for MinTC showed a random error of 9 mm (34.5 %) compared to the reference Mocap, which showed itself a difference of ±5.4 mm (16.7 %) between internal and external marker. So, our system seems to be acceptable to observe change of minimal toe clearance. Nevertheless that requires further confirmation in clinical setting. No other bibliographic data was found for the other foot clearance parameters obtained in this study, but interestingly they show better precision below 10 % (Table I).

This study establishes a proof of concept that the proposed methods can quantitatively assess heel and toe clearance characteristics during gait, with no relevant difference of performance. Nevertheless, we could expect that 3D model would perform better than 2D model in case of turning, which should be further evaluated with an adequate protocol. Since the full trajectory of heel and toe was obtained with the proposed method, other foot clearance-related parameters could have been investigated such as the time duration were toe clearance is below a certain threshold or the foot velocity at minimal toe clearance as an important factor in tripping and fall risk. Using longer gait trials, and since the system assess foot clearance at each gait cycle, it could also be used to assess the inter-cycle variability of foot clearance parameters. All together, we believe that the presented method has a very promising potential for further investigations of foot clearance.

Proposed algorithm assumes a heel-strike at initial contact and a toe-off at terminal contact, as in normal gait and even in many type of abnormal gait [17], [18]. However, in specific diseases where this assumption is not valid, the algorithm needs adaptation. Moreover, important factors and potential sources of errors have to be carefully considered for the successful implementation of the proposed method. First, the error of sensors calibration can be improved by using more efficient sensors. Second, the double integration of gravity-free acceleration signals produces some drift which was minimized in this study by periodical updates of the signal at motion-less period (foot-flat), which validity has been recently

evaluated [19]. Third, an additional source of error using our model was the time detection of heel-strike and toe-off event. While [20] proposed a validated inertial sensors-based time detection algorithm, other sensors such as pressure insoles could be used to increase the accuracy [21], [22], with the drawback of having more sensors. Fourth, the location of the sensor was prone to error since it was automatically estimated during gait. In per-cycle (PC) approach, this location estimation does not require multiple gait cycles. Nevertheless, we still observed a better robustness with solving approaches using the information of all cycles together (ME and LS). Finally, other sources of error comes from the manual placement of markers on the shoe, and our rigid single segment model of the foot, whereas its shape is modified during stance due to shoe and soft tissue deformation and the rotation of metatarsal joint.

One of the main advantages of the proposed system is the possibility to perform gait analysis out of the laboratory and in natural conditions. The system being lightweight and wireless, it is easy to use and attach on feet. Gait parameters are automatically computed in few seconds by the proposed algorithm after data transfer to PC. All participants reported wireless system was convenient to wear and did not disturb their walking. Our method offers new applications for clinical assessment of mobility associated with different pathologies or conditions, such as frailty in elderly persons [9], or neuro-rehabilitation studies focused on foot clearance alteration with obstacle avoidance [23], without requiring complex system such as optical motion capture. The proposed system has been consequently used for gait evaluation on a cohort of more than 1800 elderly persons, and results will be further analyzed.

5 Conclusion

New methods have been proposed and described for estimating heel and toe clearance using foot-worn wireless inertial sensors. The position of the sensor on foot was automatically estimated and foot clearance parameters were extracted and validated against a reference motion capture system. This study provides new insight into foot clearance signature at different walking speed in a healthy population. The results prove that small distances can be estimated with inertial sensors with adequate models and hypothesis on the movement. The proposed system adds new relevant features for spatio-temporal gait analysis and offers a promising tool for routine clinical assessment of walking outside laboratory.

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Chapter 6

On-shoe wearable sensors for gait and turning assessment of patients with Parkinson's disease[*]

Abstract

Assessment of locomotion through simple tests such as Timed Up and Go (TUG) or walking trials can provide valuable information for the evaluation of treatment and the early diagnosis of people with Parkinson's disease (PD). Common methods used in clinics are either based on complex motion laboratory settings or simple timing outcomes using stop watches. The goal of this paper is to present an innovative technology based on wearable sensors on shoe and processing algorithm, which provides outcome measures characterizing PD motor symptoms during TUG and gait tests. Our results on 10 PD patients and 10 age-matched elderly subjects indicate an accuracy±precision of 2.8±2.4cm/s and 1.3±3.0cm for stride velocity and stride length estimation compared to optical motion capture, with the advantage of being practical to use in home or clinics without any discomfort for the subject. In addition, the use of novel spatio-temporal parameters, including turning, swing width, path length, and their inter-cycle variability, was also validated and showed interesting tendencies for discriminating patients in ON and OFF states and control subjects.

Note: the validation and application of the same methods for gait and turning assessment of children with Cerebral Palsy is given in appendix.

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1 Introduction

Parkinson's disease (PD) is a neurodegenerative disorder that can cause multiple impairments, notably in motor function due to different symptoms: Tremor, Rigidity, Bradykinesia/Akinesia, Postural instability. Nowadays, this disease concerns about 180 people over 100 000 for Caucasians. Pharmacological treatments for Parkinson's disease include L-dopa which is transformed into dopamine in the dopaminergic neurons by L-aromatic amino acid decarboxylase. During the ON state, the medication is active and motor performance is improved while in OFF state the effects of the medication wear off. Outcome evaluation and ON-OFF monitoring in PD is mainly based on clinical score such as Unified Parkinson's Disease Rating Scale (UPDRS) [1] and common techniques including posturography [2], gait analysis [3] and Timed Up and Go test (TUG) [4].

Gait analysis and TUG have shown to be powerful tools to assess motor symptoms in PD. However, gait analysis is usually performed in laboratory, which does not replicate natural conditions for the subject. In addition, long-term variability of gait parameters, which has shown to be a particularly relevant outcome in PD [5], cannot be assessed unless a treadmill is used. TUG is a simple and practical test, but its outcome is limited to time measured by stop-watch.

Recently, using motion sensors, effort has been done toward the instrumentation of TUG [6], [7] and gait [8], [9]. For instance, trunk sensor allowed to characterize different phases of TUG, and showed that the turning phase was particularly relevant in PD analysis [7]. Regarding gait analysis, wearable sensor technology has been so far limited to the 2D assessment of walking with limited outcome measures [9], whereas 3D aspects have shown to be important in PD analysis [10].

The goal of this paper is to present and validate the use of on-shoe wearable sensors and dedicated algorithm, which can assess both TUG and long-distance walking in PD patients. The method provides outcome measures which quantify objectively 3D gait spatio-temporal parameters and allow detecting gait initiation, steady-state, turning and termination. The potential of the method is illustrated by comparing PD patients in ON and OFF states and control subjects.

2 Method

2.1 Wearable measurement system

A stand-alone Physilog® module integrating micro-controller, memory, three-axis accelerometer (MMA7341LT, Freescale, range ±3 g), three-axis gyroscopes (ADXRS, Analog Device, range ±600 deg/s), and battery (3.7V, 595 mAh) was designed. Physilog module is small (50 mm x 40 mm x 16 mm),

lightweight (36 g) and low power (71 mA in recording, 51 mA in standby mode). One module was conveniently fixed on each upper shoe using elastic strap (fig. 1) with shape memory foam beneath the system to guaranty a stable position together with easy manipulations. Signals were low-pass filtered at 17Hz, sampled at 200 Hz on 16 bits, converted to physical units (g or °/s), and recorded on micro SD cards before transferring to the PC. Signals from two modules were synchronized wirelessly during measurements.

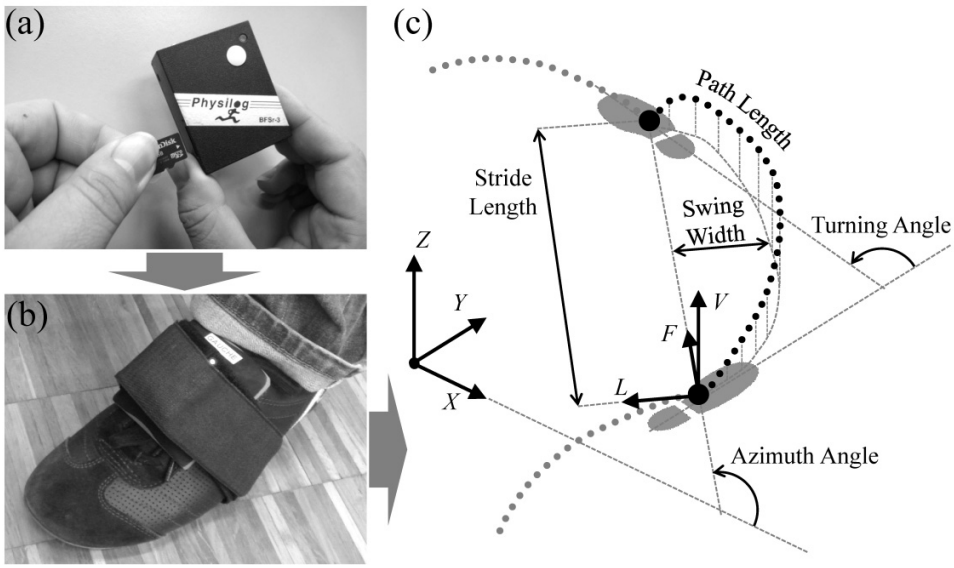

Figure 1 - (a) Physilog inertial sensing module, (b) on-shoe fixation, (c) Spatio-temporal parameters extracted from foot trajectory with fixed (XYZ) and walking frame (FLV)

2.2 Spatio-temporal analysis of gait

Based on angular velocity signal around pitch axis of foot, midswings were first detected as positive peaks above a threshold. Initial (respectively terminal) contact was then detected by the first zero-crossing after (respectively before) midswing. This way of detecting gait cycles from initial and terminal contact (i.e. stance) using zero-crossing rather than negative peaks of angular velocity was robust to PD gait pattern. A method for assessing 3D foot kinematics with periodic drift correction at each foot-flat (*ff*), was previously validated on elderly subjects [11], and was used for obtaining at each time frame *t:* 3D orientation *M(t),* 3D velocity *V(t)*, and 3D position *P(t)*, expressed in fixed frame *XYZ* (fig. 1).

Finally, spatio-temporal parameters were extracted at each cycle *n* between successive foot-flats (ff_n, ff_{n+1}). Stride Velocity was obtained by the average of *V(t)* projection in *XY* plane:

$$Stride\,Velocity_n = \sqrt{\sum_{t=ff_n}^{ff_{n+1}} V_X^2(t) + V_Y^2(t)} \qquad (1)$$

Since subject's locomotion was unconstrained in *XY* plane, walking direction was expressed at each cycle *n* by azimuth angle (AA_n), the projection of linear displacement on *X* axis:

$$AA_n = [1,0,0] \bullet \frac{(P_{XYZ}(ff_{n+1}) - P_{XYZ}(ff_n))}{\|(P_{XYZ}(ff_{n+1}) - P_{XYZ}(ff_n))\|} \qquad (2)$$

Position in Frontal-Lateral-Vertical (*FLV*) frame of walking can then be expressed by the rotation of position in *XYZ* frame around *Z* axis with a value of AA_n:

$$\forall t \in \{ff_n : ff_{n+1}\}, \quad P_{FLV}(t) = P_{XYZ}(t).\begin{bmatrix} \cos(AA_n) & -\sin(AA_n) & 0 \\ \sin(AA_n) & \cos(AA_n) & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad (3)$$

Stride Length was thus defined as the relative linear distance between two successive foot-flat positions in frontal axis:

$$StrideLength_n = \sqrt{(P_F(ff_{n+1}) - P_F(ff_n))^2} \qquad (4)$$

In order to assess the amount of circumduction of lower limb, Swing Width was defined as the maximum of lateral deviation of foot trajectory during swing:

$$Swing\,Width_n = \max_{t \in \{ff_n : ff_{n+1}\}}(P_L(t)) \qquad (5)$$

The rectification of the 3D curve *P(t),* was normalized to Stride Length, and defined as Normalized Path Length :

$$Path\ Length_n = \frac{\sqrt{\sum_{t=ff_n}^{ff_{n+1}} P_F^2(t) + P_L^2(t) + P_V^2(t)}}{Stride\,Length_n} \qquad (6)$$

Finally to assess Turning Angle, the change of azimuth between two successive foot-flat orientations was computed by the Euler axis/angle:

$$Turning\ Angle_n = \arccos((tr(R_n) - 1)/2) \qquad (7)$$

$tr(R_n)$ being the trace of the rotation matrix between $M(ff_n)$ and $M(ff_{n+1})$.

Parameters extracted using (1) to (7) are illustrated in fig. 1.

2.3 Gait initiation, termination, turning and steady phases

Gait cycles were automatically classified into Transition, Steady, and Turning phases, by using specific spatio-temporal parameters. Transition cycles were defined by analogy to system response time as the gait

cycles with a Stride Length below 63% of steady state value, estimated by the median over all cycles. The first and the last Transition cycles were classified as Gait Initiation and Termination. Turning cycles were defined by Turning Angle over a threshold of 20° [11]. Finally, after discarding Turning, Initiation and Termination, the remaining cycles were classified as Steady gait. For each phase, the number of cycles were detected and total duration was computed by the sum of gait cycles time.

2.4 Experimental set up and validation

This study included 10 PD patients with mild to moderate disease (UPDRS=15.7±7.6, mean age 64±7 years) and 10 age-matched control subjects (UPDRS= 1.2±1.3, mean age 66±7 years) who were asked to perform a standard 3m TUG and gait tests with Physilog® inertial units attached on both feet (fig. 1). Gait was performed at self-selected speed in hospital through a long and wide corridor on moderate (2x20m) and long (4x50m) distance, including 180° turns between straight walking periods. The protocol was approved by local ethical comity. All the patients were evaluated in ON state, under their current medication, and four of them also consented to perform the same trials in practically OFF condition (at least 8 hours off medication).

During TUG tests, four reflective markers were attached to the shoe and tracked by the reference optical motion capture system (Mocap) including 7 cameras (Vicon, UK). Spatio-temporal parameters were also estimated from Mocap trajectories using (1) to (7), and constituted reference data for the validation of the on-shoe system. TUG tests were realized two times, first on self-selected turning side and second by asking the subject to turn on the opposite side. That was repeated twice by removing and fixing again the shoe sensors to assess test-retest repeatability of the system and methods.

3 Results

3.1 Comparison with reference system and validation

Accuracy and precision of extracted spatio-temporal parameters were estimated by the mean and standard deviation (STD) of the set of difference between proposed and reference systems, among 1243 recorded cycles from both control subjects and PD patients. Compared to reference system, Stride Velocity and Stride Length showed an accuracy±precision of 2.8±2.4cm/s and 1.3±3.0cm. For Normalized Path length, Swing Width and Turning Angle, accuracy±precision was 4.5±3.6%, 0.15±2.13cm and 0.12±3.59°. Test/retest repeatability of spatio-temporal parameters obtained by the wearable system during each TUG phase was evaluated using intraclass correlation coefficients ICC(1,1) and interpreted using standard benchmarks [12]. Overall PD patients and control subjects, TUG total duration, step count, mean Stride

Velocity and Stride Length during Steady gait, and number of steps during Turning phase, obtained excellent repeatability (ICC(1,1)>0.75). The other parameters during Steady gait and Turning phases all showed fair to good repeatability (ICC(1,1)>0.4), whereas parameters during Transition phases were least repeatable (ICC(1,1)<0.4).

3.2 Analysis of Timed Up and Go test

Using Wilcoxon rank-sum test as a robust non-parametric statistical test for pair wise comparison, significant differences ($p<0.05$) were found between most of parameters obtained on self-selected and opposite turning side in both PD patients and control subjects. Nevertheless, Stride Length was not significantly affected by turning side in control group ($p=0.091$) contrary to PD group ($p=0.016$), showing a lower ability of PD patients to change turning side. Normalized Path Length was not significantly influenced by turning side in both PD ($p=0.08$) and control group ($p=0.55$).

TUG phases were detected in the three groups of subjects (fig. 2). All TUG phases duration were increased in ON and OFF PD patients compared to control subjects. Turning (including the 180° pivot and the final sit-to-stand transition) was the longer phase during TUG in control and ON group, but not in OFF group. Finally, total TUG durations obtained were comparable to the one reported in literature for PD subjects [13].

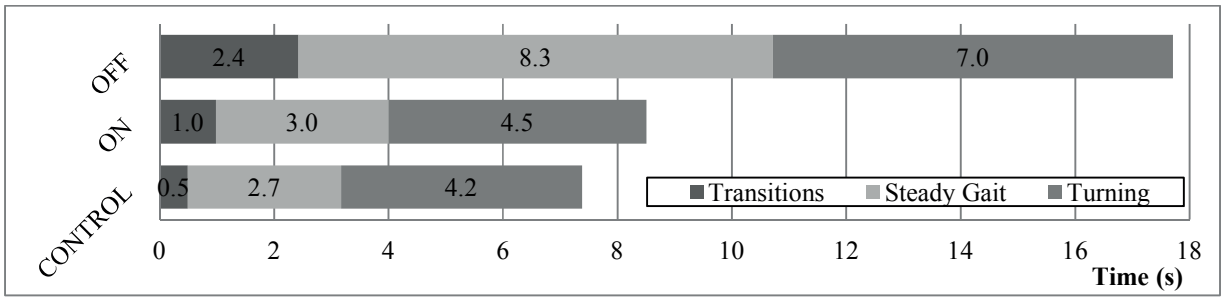

Figure 2 - TUG phase's duration estimated from on-shoe wearable sensors

3.3 Short, moderate, and long-distance gait analysis

Turning and Transition cycles were discarded during TUG, 2x20m and 4x50m gait tests, to obtain parameters representing short, moderate and long distance gait respectively. Mean and variability of those parameters were computed for the different groups of subjects (fig. 3). Inter-stride gait variability was estimated by the coefficient of variation (CV=Mean/STD in %) except for Swing Width, which variability was reported using STD, due to small mean.

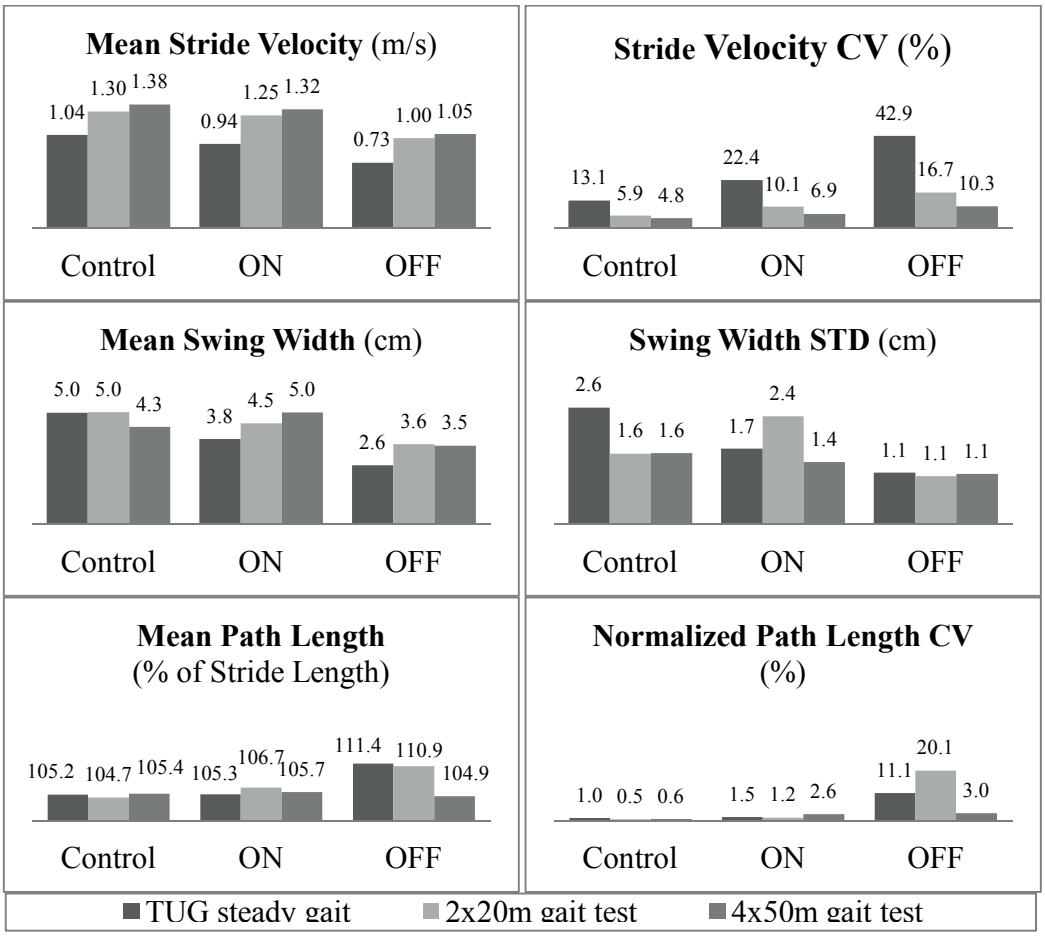

Figure 3 - Mean and variability of spatio-temporal gait parameters obtained from shoe-sensors versus walking distance and subjects groups.

In all groups, mean Stride Velocity was increased with walking distance, while its variability was decreased. Mean Stride Velocity was similar between control and ON groups for all tests but lower in OFF group. Stride Velocity variability was increased in ON and OFF groups compared to control group. Same tendencies were observed for Stride Length (not reported in fig. 3). Both mean and variability of Swing Width tended to be smaller in OFF group compared to control and ON groups, independently of walking distance. On short and moderate walking distance, Normalized Path length showed both higher mean and variability in OFF group compare to control and ON groups, though such changes were not observed during long-distance gait.

4 Discussion

In this study, on-shoe wearable sensors were used to instrument two commonly used motor function tests for PD, namely TUG and Gait tests. TUG and Gait were assessed through standard spatio-temporal

parameters such as Stride Velocity and Stride Length beside new parameters, i.e. Turning Angle, Path Length and Swing Width. These parameters were validated during TUG against a gold standard Mocap system and results indicate their technical validity in terms of accuracy and precision. Particularly, for Stride Velocity and Stride Length, our results showed better accuracy (2.8cm/s and 1.3cm) and precision (2.4cm/s and 3.0cm) than previously reported system based on inertial sensors, which reported an accuracy (precision) of 3cm/s (7.6cm/s) for Stride Velocity and 3.5cm (8.5cm) for Stride Length [9]. The system is simple to attach on shoe, and allows automatic calibration and estimation of parameters. It offers therefore a practical tool to assess objectively TUG and Gait in people with movement disorder such as PD at home or clinics.

The proposed method confirmed the pertinence of the turning analysis and novel parameters quantifying 3D foot trajectory during swing phase (Swing Width and Path Length) for discriminating PD and control subjects. Interestingly, whereas Stride Length changes were strongly associated with Stride Velocity changes in the different subjects groups, it was not the case for Swing Width and Path Length. In particular, the lower Swing Width obtained in OFF group could be interpreted as a consequence of axial rigidity. We believe those novel parameters bring a new insight into PD motor signs quantification during gait. This study offers new perspectives with regard to the feasibility of home monitoring of patient with movement disorder, by the implementation of those tests in home and field setting using wearable devices [14]. Nevertheless further clinical research is needed to confirm the tendencies observed in the novel gait parameters.

5 Appendix: application to gait and turning assessment in children with cerebral palsy*

5.1 Introduction

Generally, spatio-temporal gait analysis requires dedicated laboratories with complex systems such as optical motion capture. It is likely that a child's natural gait pattern may be affected by a short distance walkway and the laboratory setting. Recently, ambulatory devices have overcome some of these limitations by using body-worn sensors measuring and analyzing gait kinematics. The aim of this study was to explore the use of foot-worn inertial sensors and dedicated method described in this chapter, as a

* Abstract submitted to 21th congress of the European Society of Movement Analysis for Adults and Children, *2012*.
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3D gait measurement tool during turning gait tasks and a 200-meter walking test in independently walking children with cerebral palsy (CP).

5.2 Patients/materials and methods

We performed a case-control study. We analysed 14 children with CP, aged 6 to 15 years old, who were followed in the tertiary outpatient child neurorehabilitation Unit of CHUV and 15 controls. There were no significant differences in age (CP 11.4±3.6 years, controls 10.6±2.6 years) or gender between cases and controls. In the CP group 9 children were graded GMFCS I, 5 were graded GMFCS II, 12 children had unilateral and 2 had bilateral CP. Two U-shaped and two 8-shaped (i.e. turning) trial walks per subject were performed during which the accuracy and precision of the foot-worn device was measured using an optical motion capture system (Vicon,Oxford Metrics) as the reference system (fig. 4). All subjects then performed a continuous 200-meter (4x50m) walk test at their self-selected pace wearing the foot-worn inertial sensors (Physilog III, LMAM-EPFL, Switzerland), in a long and wide corridor. 180° turns between straight walking periods were discarded from the analysis using a threshold of 20° on turning angle [11]. Limb-related spatio-temporal parameters were compared between paretic and control limbs while bilateral gait characteristics were compared between CP and control subjects, using nonparametric analyses.

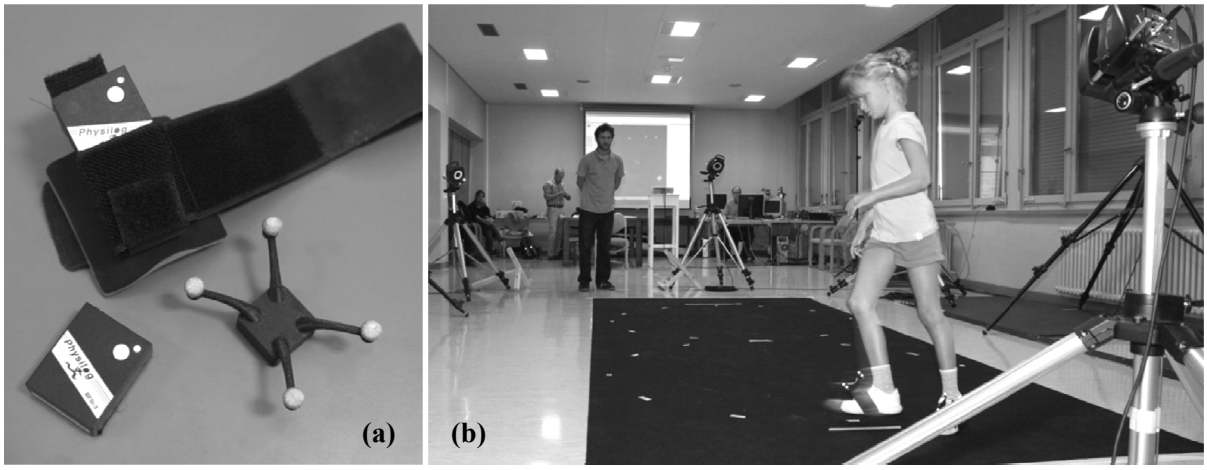

Figure 4 – (a) Foot-worn inertial sensors, attachement strap, and structure with 4 reflective markers. (b) Validation protocol with CP child performing figure of 8 walking task measured by both foot-worn inertial sensors and reference optical motion capture systems

5.3 Results

Mean accuracy±precision for both groups was 3.4±4.6 cm for stride length, 4.3±4.2 cm/s for stride velocity and 0.5±2.9° for initial contact foot pitch angle. For temporal parameters paretic limbs showed longer stance (61.9±2.5% vs 60±0.9%, P=0.006) and shorter swing (38.1±2.5% vs 39.9±0.9%, P=0.006)

phases, with an increase in double support in children with CP (24.8±4.7% vs 20.3±1.7%, P=0.001). For spatial parameters stride length (1.07±0.18 m vs 1.32±0.14, P<0.001), speed (1.13±0.23 m/s vs 1.39±0.11 m/s, P<0.001) and peak angular velocity during swing (385±74°/s vs 450±41°/s, P<0.001) were decreased in paretic limbs, with significant differences in foot pitch at both heel-strike and toe-off (P<0.001). Both maximal heel clearance (22.7±3.1 cm vs 25.6±3.5 cm, P=0.004) and maximal toe clearance (7.6±2.9cm vs 13.4±1,6cm, P<0.001) were lower in paretic limbs.

5.4 Discussion & conclusions

Foot-worn inertial sensors allowed us to analyze gait kinematics outside a laboratory environment with a good accuracy and precision. The case control comparison yielded results which were congruent with what is known of gait variations in children with cerebral palsy who walk independently. Participants found the system light weight and easy to wear and use. While not substituting for complete 3D gait analysis, portable sensors provide precise information about gait in conditions that are closer to the child's habitual environment and motor behaviour, and could therefore prove to be a useful complement.

6 References

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Chapter 7

Real-time analysis of amputee daily-locomotion using instrumented shank-ankle-foot prosthesis[*]

1 Introduction

1.1 Gait in trans-tibia amputees

The issue of gait and locomotion for trans-tibia amputees (also referred as "below-knee amputees") is closely related to the design of shank-ankle-foot (SAF) prosthesis which replaces the missing joint and limb. In fact, during normal gait, the dorsiflexion and the plantiflexion of the ankle should be adapted to the type of walking activity, such as incline or stairs locomotion. For instance, while walking on level ground, non-amputee subjects usually hit the floor with the heel first (the so-called "heel-strike" event), whereas during stair climbing it is generally the toes that hit the ground first (referred as "toe-strike" event). Daily locomotion can be subdivided in 5 main walking "activities": *Level walking, slope ascent, slope descent, stairs ascent, stairs descent.* Main changes and issues for trans-tibia amputees in those activities are presented here according to literature.

Level walking consists in walking in forward direction on flat or quasi-flat ground surface. It may include turns as well as gait initiation and termination. Early in the past, studies have compared the differences between amputee and healthy gait [1], demonstrating notably compensatory motor patterns from the residual muscles at the hip and knee.

*Slope ascent (respectively Slope descent)***,** consists in walking up (respectively down) any ramp or slope. Past studies have focused on different ramp inclination from 3° to 10° and the comparison to reference pattern observed in level walking [2–4]. During ramp ascent, the ankle angle at the beginning of stance is increased compare to level ground, whereas it is increased at the beginning of swing phase in ramp descent. Those studies are consistent together and show important changes of ankle biomechanics during

[*] Patent pending, PROTEOR, *2012*

ramp locomotion which could be particularly challenging for trans-tibia amputee since they cannot adapt the ankle angle to the terrain.

Stairs ascent (respectively Stairs descent), consists in walking up (respectively down) any type of stairs. Stairs are construction designed to bridge a large vertical distance by dividing it into smaller vertical distances, called steps. Although stairs offer a flat surface at each step, the biomechanics is strongly influenced by the need to deal with change of potential energy while going up or down. Ankle biomechanics of healthy subjects has been shown to be completely different than during level ground during ramp ascent and descent, with notably a different pattern of dorsi/plantar flexion angle within the gait cycle [5–7]. So, it represents one of the most challenging activities for amputees. In addition, in studies about stair ambulation using prosthetic feet, it has been observed that trans-tibia amputees have a slower velocity and asymmetrical gait pattern compared to non-amputees [8]. This asymmetry between limbs was shown to be more significant in stair ambulation than level walking. Other studies has shown that the limitation in the prosthetic ankle motion required compensatory functions at hip and knee [9].

So, the question arises as to how an amputee subject can manage the various locomotion activities, depending on the prosthesis he is using? Whereas some amputees are able to perform almost all locomotion activities with adapted strategies and changes in biomechanics, some other subjects prefer to restrain their activities due to a weakness in musculo-skeletal system or to avoid risky situations.

1.2 State of the art in SAF prosthesis

Some general elements are common in all types of ankle-foot prostheses. First of all, the interface between amputee's body and the prosthesis is made with silicon or rubber materials and handcrafted by a specialist for each particular subject, since the result of surgical operation or malformation that leads to amputation is always different. In addition, amputees generally use plastic envelopes, referred as "cosmetics", so that their artificial limb looks like a real limb in terms of size and shape. Regarding the functionalities offered by the devices, the state of the art in SAF prosthesis can be subdivided in two different categories: "*passive*" prostheses, which only feature a specific mechanical structure with various materials and designs, and "*active*" prostheses, which include various kinds of sensors, electronics, mechatronics, and which have been developed recently by research laboratories and companies.

1.2.1 Passive SAF prostheses

"Passive" lower-extremity prosthetic devices have been around for centuries, if not millennia. However, until very recently, there were few attempts at applying new technologies to improve mechanism function [10]. External devices were first made from crude materials such as wood and leather, making them heavy, non-adaptive and difficult to use. In the 1970s some researches lead to advance the prosthetic knee

joint from a passive, non-adaptive mechanism to device with variable damping capabilities. Today's SAF typically use elastomeric bumper springs or carbon composite leaf springs that store and release energy throughout each walking or running step. Compared to noncompliant or dissipative (damping only) ankle-foot devices, these contemporary elastic mechanisms offer considerable heel, toe, and vertical compliance to the below-knee amputee, increasing the amputee's perceived comfort and walking speed, but only during level ground walking.

1.2.2 Active SAF prostheses

At the time of this thesis work, there is only one commercially available SAF active prosthesis from Ossür company[1], in contrast with the different knee active prosthetic products. The so-called "Proprio foot" is shown in fig. 1.

Figure 1 - Propriofoot form Ossür with external battery module

According to Ossur, the sensing part of the prosthesis relies on an accelerometer sampled at a rate of 1600 Hz. A black-box module called Terrain Logic™ acts as a decision maker and provides the most appropriate response for the next step. As toe-off is detected, for example, it directs a toe lift in order to clear the ground. Having "sensed" an inclined surface, which takes up to few gait cycles, it directs ankle flexion proportional to the slope. From the actuators point of view, the prosthesis provide dorsiflexion (toe lift) in swing phase; ankle angle adjustment on varying terrain, in chair exit mode and relaxed mode; and heel height adjustment when changing shoes, using a manual procedure. User feedbacks show that this technology already reached a good level of efficiency to enhance the gait of the amputees, notably in slopes and stairs locomotion, but yet several flaws could be further improved, especially on the number of steps which is necessary for activity recognition and its robustness to unexpected events.

[1] http://www.ossur.com/?PageID=12704

In research, past studies have tried to address the limitation of passive designs by introducing "active" prosthetic designs able to change the ankle angle and/or dynamic properties by means of actuators [11–13]. Yet, those studies focused their attention on particular activities, such as level walking and stairs descent [11] or slopes [12]. Those prostheses prototypes are controlled by means of different sensing configurations. *Li et al.* used only one potentiometer to control the ankle angle [13], whereas *Svenson et al.* used a system based on inertial sensors and the real-time computation of kinematics features such as the ground inclination or foot elevation [12]. *Svenson et al.* also used strain sensors in order to determine stance and swing phases [12]. *Au et al.* has introduced a system based on myoelectric measure of the subject's residual limb [11], with the advantage of giving the control to the subject himself instead of having a robotic artificial intelligence. Nevertheless, to our knowledge, none of those control algorithms and systems were fully validated against references in terms of classification performance nor tested in real daily locomotion.

1.3 Rational and objectives

From the comparison of ankle biomechanics of healthy subjects and trans-tibia amputee, and with the limitation of existing prosthetic designs, the main issues for amputees during locomotion can be summarized as balance, capacity of performing specific activities such as gait in stairs or hills, energy cost of walking, comfort and esthetic (for the integration in society), and cost.

In this context, the ambulatory gait analysis methods (chapter 2) and the use of foot-worn inertial sensors can provide strong insight into foot motion, by quantifying spatio-temporal parameters of gait such as foot-clearance or walking speed during level walking in various kind of subjects (chapter 3 to 6). Our hypothesis is therefore that it is possible to adapt and extend those methods to the real-time analysis of daily-locomotion of amputee subjects, and that it could further provide an input for the control of active prostheses. In order to verify our hypothesis, the objectives of this chapter can then be summarized as follow:

- Design an instrumented SAF prosthesis prototype featuring embedded inertial and force sensors
- Design real-time algorithm for temporal detection and kinematics estimation
- Evaluate the performances of the system during a measurement protocol involving daily-locomotion activities performed by amputee subjects with instrumented SAF prosthesis

That leads to the design of a classifier able to recognize the type of locomotion from the real-time analysis, which is addressed in chapter 8.

2 Methods

2.1 Prototype SAF Complex with embedded sensors

Existing and commercially available SAF prostheses were instrumented with lightweight kinetic and kinematic sensors and conditioning electronics to record signals in natural condition without disturbing the subjects.

In first prototype (P1), three foot-sensitive resistors (FSRs, model 402, Interlink) were laminated on a Dynastar[2] foot structure at contact points with the ground (fig. 2).

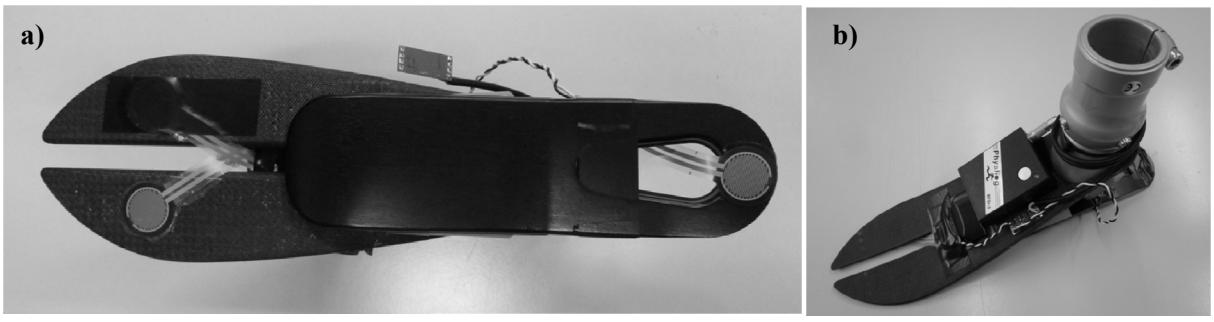

Figure 2 –FSR lamination under Dynastar sole (a), and instrumented prototype P1 with FSRs and inertial sensors (b)

FSRs were connected to a small board containing the amplifying circuit to record forefoot and hindfoot signals. As the resistance decrease with the force, the 2 forefoot sensors were mounted in parallel. A Physilog III module, containing 3D accelerometers (+/-3g) and 3D Gyroscopes (+/- 600°/s) was then attached to the upper side of the foot structure using double-sided velcro. FSR's were connected to the Physilog module to record synchronously signals at 200Hz.

A 1D111 ankle[3] (allowing a certain amount of planti and dorsi-flexion thru bumpers) and a Dynastep[4] foot were then used in a second prototype (P2) instrumented with Strain Gauges measuring Vertical Force and Sagital Torque in addition to Inertial Sensors (fig. 3.a). Physilog system records wirelessly the data from both force and inertial sensors at 200Hz, and a small external battery was used to power the strain gauges.

[2] http://orthopaedics.proteor.com/product,1153-energy-return-feet,1461-dynastar.php
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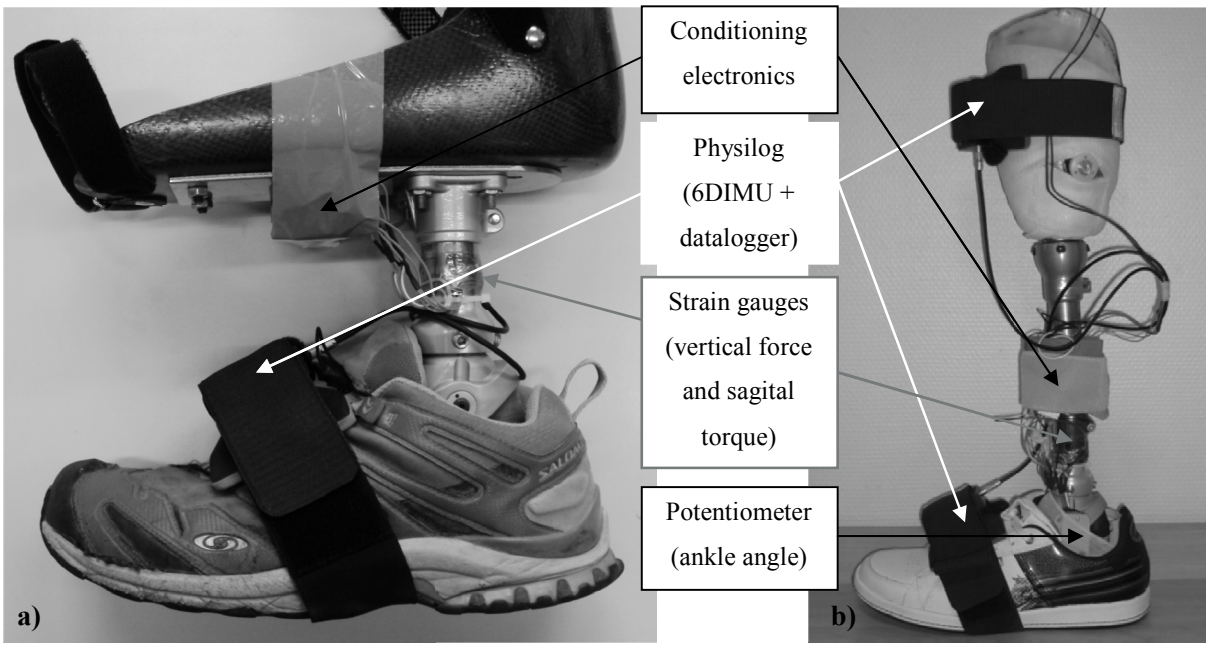

Figure 3 - Instrumented Prosthesis Prototypes with embedded force and inertial sensors for healthy subjects P2 (a) and amputee subjects P3 with additional potentiometer (b)

Both P1 and P2 were fixed below orthoses that can be worn by normal healthy subject simulating amputee gait (fig. 3.a).

Finally a third prototype (P3) was developed, consisting of a 1D11 ankle instrumented with 2 IMUs on foot and shank combined with strain gauges measuring vertical force and sagittal torque and a potentiometer providing the ankle joint angle. Two Physilog modules that are synchronized wirelessly records the data of both kinetic and kinematic sensors at 200Hz. P3 allows the ambulatory recording of the gait of trans-tibia amputee subjects on either right or left side, by adapting the length of prosthetic pylon to subject's height (fig. 3.b).

In those instrumented prototypes, inertial sensors were fixed on shoe without specific alignment. Preliminary alignment of inertial signals was therefore done using a method adapted from chapter 4, so that accelerometers (respectively gyroscopes) measure frontal, lateral and vertical (respectively yaw, roll, pitch) axes of foot. The gain and offset of strain gauges were also adjusted during level walking to measure forces in percentage of bodyweight and ankle joint moment in Nm [1], [14]. Finally, ankle angle potentiometer was calibrated using manual measure of maximal ankle range (~33.4° of plantiflexion).

2.2 Measurement setup for Daily-activity scenarios

5 healthy subjects were first recruited inside university staff members to walk with orthoses. Right orthosis was fixed above P2, while the left one was fixed above P1. After subjects had some time to get

acquainted with the locomotion with the orthoses combined with prostheses, they were asked to move freely inside an environment featuring slope, stairs, and flat surfaces for about 20 minutes (fig. 4). Measurements were filmed using a classical video camera to manually label subject's activity. Measurements took place at EPFL (Lausanne, Switzerland), with slopes between 5% (~3°) to 28% (~15°). In addition, one subject was asked to perform other activities such as taking Metro or the lift, as well as crossing obstacles, in order to verify that algorithm were not sensitive to such movement artifacts.

a)  b) 

Figure 4 - Examples of situations recorded during measurement protocol on healthy subjects with P1, P2 combining orthoses and instrumented prostheses in slope down (a) and stairs down (b) locomotion

A second measurement protocol was conducted with 5 amputee subjects. Measurements took place in C.E.R.A.H.[5] (Paris, France). Each subject was first asked to repeat pure single activities of level, stairs and slope locomotion. Subjects also performed a *"Daily-Life"* scenario, including a succession of level, incline and stairs locomotion as well as sit-to-stand transitions. In this protocol, the environment was controlled in the sense that each ramp and stairs remains identical between trials, so that the variations observed are only due to subjects changes. The approximate path of a subject during the daily-life scenario in the measurement area with the activity label convention is given in fig. 5.

For both protocols, each strides' activity was manually labeled on video at a time frame during stance phase prior to the swing phase.

[5] Centre d'Etudes et de Recherches sur l'Appareillage des Handicapées, Paris, France.

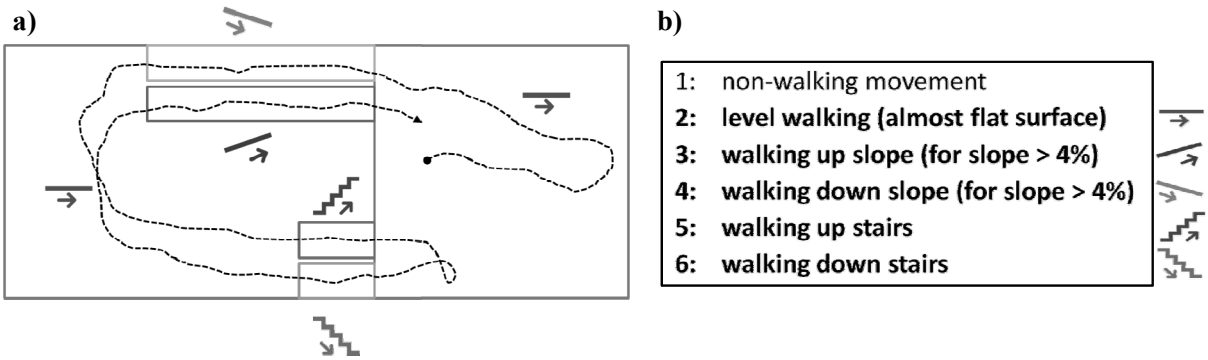

Figure 5 – (a) Schematic view of typical walking path of an amputee subject during daily-life locomotion scenario performed with P3 in CERAH (Paris, France). (b) activities label convention.

2.3 Temporal Detection of walking phases

For the purpose of triggering the control of an active prosthesis in real-time, it is necessary to detect the different gait events, so that the system knows the current walking phase (or state) at each time frame. This paragraph presents methods for detecting in real-time static phases and walking phases of gait in amputee in real-time based on instrumented SAF prosthesis.

2.3.1 Static phases detection

The interest of static phase detection is to be able to shut down the system in order to save energy when it is possible. The main idea is to being able to awake fast, and slowly return to Standby in case of long-term inactivity.

Therefore, three states are necessary (fig. 6):

- *Standby* state (default state), where the microcontroller and most of the sensors except accelerometer can be switched off to save energy.
- *Awake* state is activated in case the acceleration norm is above a threshold of 1.1 g. (which can be detected with an analog circuit). In that case, all components are switched on and are operating, including microcontroller and other sensors.
- *PreStandBy* state, in case acceleration norm falls below the 1.1g threshold, all components are still operating. Then, if acceleration norm remains below the threshold more than 2 sec., the system switches back to *StandBy* state, otherwise it goes back to *Awake* state.

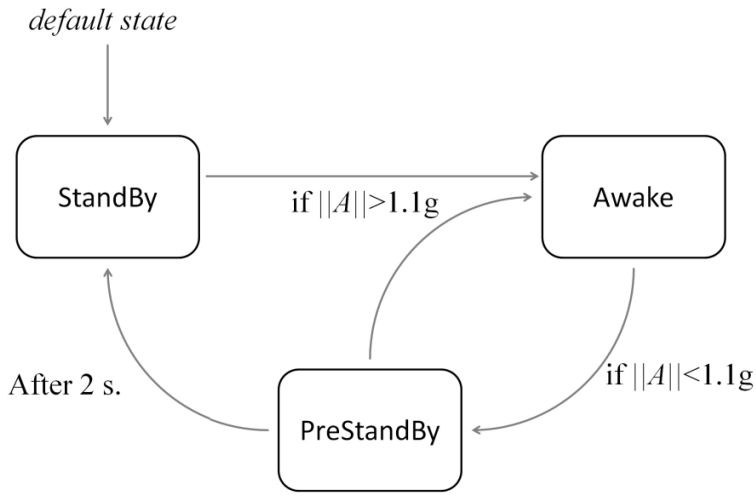

Figure 6 - State flow chart with state and transition rules for Static Phase Detection. ||*A*|| is the Euclidean norm of 3D accelerometer signal

2.3.2 Walking phases detection

Gait cycle is usually segmented between Swing and Stance phase. However, as in temporal analysis (chapter 3), more subdivisions were considered in order to bring additional temporal resolution and robustness. To detect walking phases in real-time independently of activity, we hypothesize that successive walking states are observed in any type of forward locomotion, namely unloading of the foot (referred as Toe-off in normal gait), swing of the leg (thus the foot) to go forward, loading of the foot (referred as Heel-strike in normal gait), and a relatively motion-less period when the foot is stable on the ground.

Therefore, gait cycle was divided in 4 main successive states characterized as follow:

"*Initial contact*" (IC), is reached at the beginning of Stance Phase, when a certain amount of vertical force is sensed on the prosthesis.

"*MidStance*", also referred as foot-flat (FF), is reached when in addition to the force, the motion of the foot as measured by gyroscope is low. As default state, MidStance is also reached automatically after a certain time of loading.

"*Terminal contact*" (TC), is reached right after the end of Stance phase, when the foot freely moves in the air, i.e. there is no more force exerted on the prosthesis.

"*MidSwing*" (MS), is reached approximately at the middle of swing phase when a peak of angular velocity is detected

While integrating inertial signals during long period, such as to estimate orientation angle from angular velocity, there is an important drift which is a source of constantly increasing error. To avoid that issue during walking, integration of foot inertial signal can be done only between two successive motionless periods [15], [16]. First hypothesis was that signals should be integrated during swing phase only and reset to static values during stance. However, in healthy subjects, at the end of stance phase, the foot has already started to rotate around metatarsal joint. In our measurements with prostheses, we also observed that the end of stance phase was characterized by an important motion of the foot even if prostheses were still in contact with the ground. That can be explained by the deformation of the prosthetic foot structure during stance, whereas it is explained by the rotation of metatarsal joint in non-amputee subjects. So, a more adequate hypothesis is that inertial signals should be integrated as soon a significant motion is detected. Therefore a new intermediate state, referred as "*Heel-off*" (HO) [17], was added between *MidStance* and *Terminal Contact* into walking phase detection algorithm.

Finally, timing conditions were also used in the transition rules of the state machine. It avoids successive wrong transitions between states when the signal stays around the necessary condition. Threshold values for detecting loading (between FF/HO and TC) were set to a slightly higher value than for detecting unloading (between TC/MS and IC). Again, this avoids detecting too rapid and false successive transitions between states. In addition, the *Midstance* state was delayed by implementing a prior *PreMidStance* state with a fixed duration, because inertial signals presents noisy signals due to Heel-strike during early stance phase, which could lead to wrong estimation of inclination if *Midstance* if detected too early.

A shortcut between MidStance and Terminal Contact was added to be robust to the case where terminal contact would occur without heel-off motion. This was observed in some subjects during stairs locomotion. Other direct transitions are also implemented in the model for robustness purposes.

The final Walking Phase Detection algorithm, including PreMidStance, Midstance (FF), Heel-off (HO), Terminal Contact (TC), Midswing (MS) and Initial contact (IC) states, was implemented in a state-flow chart (fig. 7).

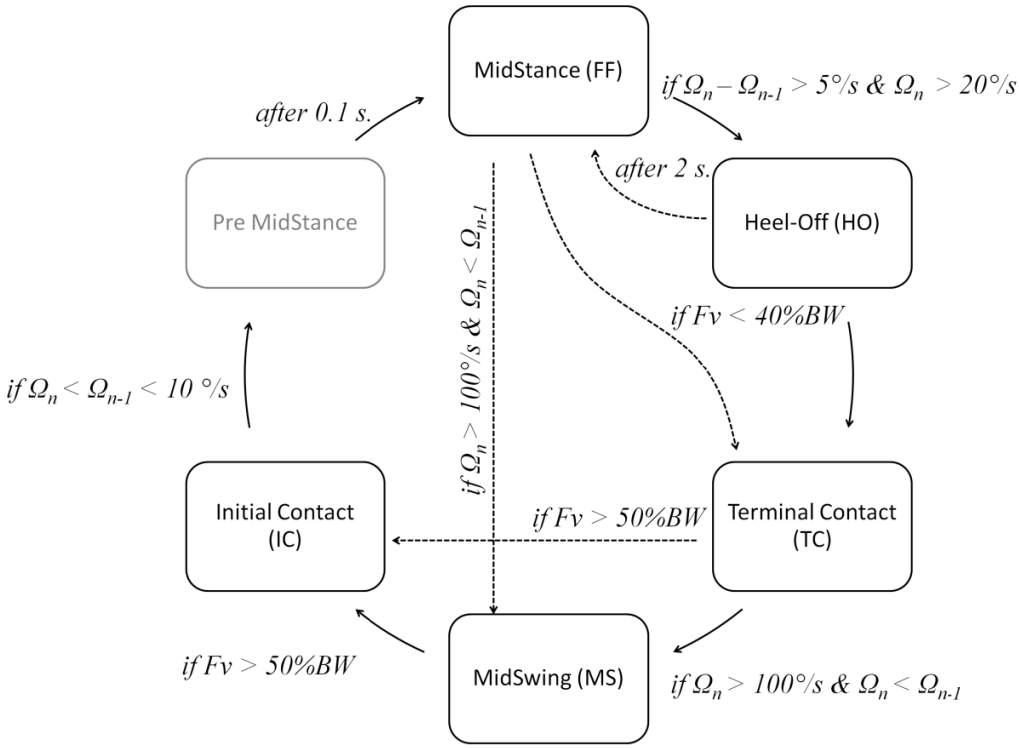

Figure 7 –Real-time walking phase detection state-flow chart, with the different states and successive transitions during a normal gait cycle (plain lines). Ω_n is the sample at time *n* of pitch angular velocity measured by gyroscope in °/s, and F_v is the sample of vertical force estimated from straine gauges in % of Bodyweight. Alternative transitions (dashed line) are implemented for robustness purposes.

State transitions are further used to trigger the real-time feature extraction algorithm.

2.4 Kinematics estimation

A real-time method for 2D foot kinematics estimation during walking was adapted 3D foot kinematics estimation method of chapter 4 and the one proposed by Sabatini et al. [15]. A *StrapDown* boolean variable, indicating whether inertial signals should be integrated or reset is set using the output of the walking phase detection algorithm and static phase detection algorithm. The *Strapdown* integration is computed only during non-static period after *Heel-off* or *Terminal contact*.

2.5 Features extraction

To quantify and characterize locomotion activities, features were extracted based on various *metrics* from different *signals* at different *time* events. Using the instrumented SAF prosthetic system and the algorithm of previous paragraphs, kinetic and kinematic signals measured or estimated and detected time events are as follow:

- *Signals*: all raw sensor signals and output signals of kinematic estimation algorithm are used, namely Pitch Angular Velocity, Pitch Angle, Frontal Acceleration, Vertical Acceleration, Frontal Speed, Vertical Speed, Frontal Displacement, Vertical Displacement, Vertical Force, Sagital Torque
- *Time events*: all events detected by walking phase detection algorithm are taken into account, namely Heel-Off, Terminal Contact, MidSwing, Initial Contact, and MidStance.

First, value of signal at each time event were extracted and constituted an initial set of 52 raw features at each gait cycle. Minimum and maximum values of each signal for the whole gait cycle were also extracted.

Second, *dependant* features were extracted by measuring the value of one signal when a specific criterion on another signal was met. In particular, a torque observer state flow was introduced, sending a flag when torque value was above a threshold and all signal values were measured at this instant. The choice of those dependant features was based on empirical observations of Leg angle versus torque signals which qualitatively discriminate slope and level activities. In addition, *non-linear features* were computed by combination (such as division or multiplication) of existing features. The ratio between Torque and Leg Angle was computed as well as the ratio between vertical and frontal displacement.

Common spatio-temporal parameters of gait are actually included in the extracted features with the present method. For example, the stride length is by definition the amount of forward displacement between two MidStance events.

Overall, a set of 153 features is extracted at each gait cycle using those criteria, and the extraction method was finally implemented in a SIMULINK model to work in real-time (fig. A.3-5 in annexes).

3 Results

3.1 SAF prosthesis instrumentation

Instrumented prostheses were able to record autonomously the signals of 5 healthy subjects wearing the orthoses, and 5 trans-tibia amputees with during measurement protocol including level walking, slope and stairs locomotion. Amputee subjects reported that the system was not disturbing them. The force and inertial signals were successfully measured with the proposed instrumented SAF prosthetic system, and the real-time processing and analysis of signals were simulated on the PC.

3.2 Sensitivity and specificity of real-time walking phase detection

The output of walking phase detection algorithm is illustrated on fig. 8.

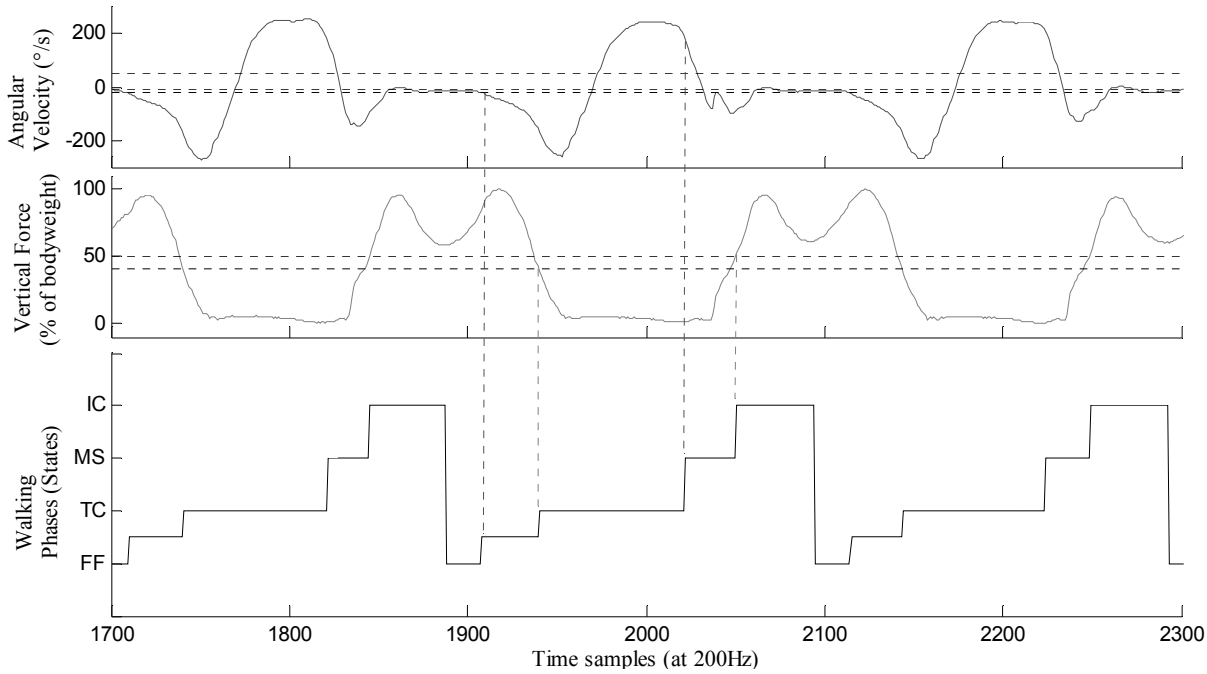

Figure 8 - Output of walking phase detection algorithm based on the fusion of angular velocity and vertical force signals

Sensitivity (SNS) and Specificity (SPC) of the algorithm for detecting each of walking phases in the different activities was assessed on the measurements with healthy subjects using the following formulas:

N = total number of gait cycles recorded

True Positive (TP) = number of phases detected correctly

False Positive (FP) = number of phases detected wrongly

SNS = TP / N, given in %

SPC = 1- FP/N, given in %

From past studies [18], we know that *Midswing* event detected in real-time by the positive peak of pitch angular velocity, is the most robust parameters for detecting gait cycles. It was therefore taken as reference to validate the sensitivity and specificitw of walking phase detection algorithm.

Results for each subject and each activity are reported in table I.

TABLE I - TRUE POSITIVE (TP), SENSITIVITY (SNS), FALSE POSITIVE (FP) AND SPECIFICITY (SPC) OF WALKING PHASE DETECTION VERSUS ACTIVITIES: NON-WALKING (1), LEVEL WALKING (2), SLOPE ASCENT (3), SLOPE DESCENT (4), STAIRS ASCENT (5), STAIRS DESCENT (6).

activity	N	Heel-off				Terminal Contact				Initial contact				MidStance			
		TP	SNS (%)	FP	SPC (%)	TP	SNS (%)	FP	SPC (%)	TP	SNS (%)	FP	SPC (%)	TP	SNS (%)	FP	SPC (%)
1	6	4	50	9	-22	4	50	5	22	4	50	2	78	4	50	5	33
2	1190	1190	100	9	99	1190	100	9	99	1190	100	9	99	1190	100	11	99
3	120	120	100	2	98	120	100	2	98	120	100	1	99	120	100	4	97
4	343	343	100	0	100	343	100	1	100	343	100	2	99	343	100	4	99
5	119	119	100	3	97	119	100	2	98	119	100	1	99	119	100	2	99
6	92	91	98	1	98	91	98	3	96	91	98	2	97	91	98	3	96
Walking	1864	1863	99.9	15	99.2	1863	99.9	17	99.1	1863	99.9	15	99.2	1863	99.9	24	98.7
Overall	1870	1867	99.8	24	98.7	1867	99.8	22	98.8	1867	99.8	17	99.1	1867	99.8	29	98.4

Overall the 1870 recorded cycles, we obtain really high sensitivity (>99.9% for all phases) and specificity (>98.4% for all phases). Moreover we cannot see differences in the performances of the algorithm for a specific activity or subject, indicating that the walking phase detection algorithm is robust to activity and subject change. Only the non-walking activity (#1) shows poor sensitivity and specificity but sample size in small in that category and that was not the main focus of the present work.

3.3 Real-time Kinematics estimation

2D foot kinematics was obtained in all performed activities using the real-time adapted algorithm. We qualitatively observed that although there was no drift modeling and correction within the gait cycle due to real-time constrain, vertical displacement at the end of the gait cycle was positive (respectively negative) while going up (respectively down), and close to 0 during level walking. Moreover, pitch angle during motionless periods was congruent with slope angle (fig. A.6 in annexes).

3.4 Comparison of features

The output of features extraction algorithm is illustrated by the example of pitch angle signal in fig. 9.

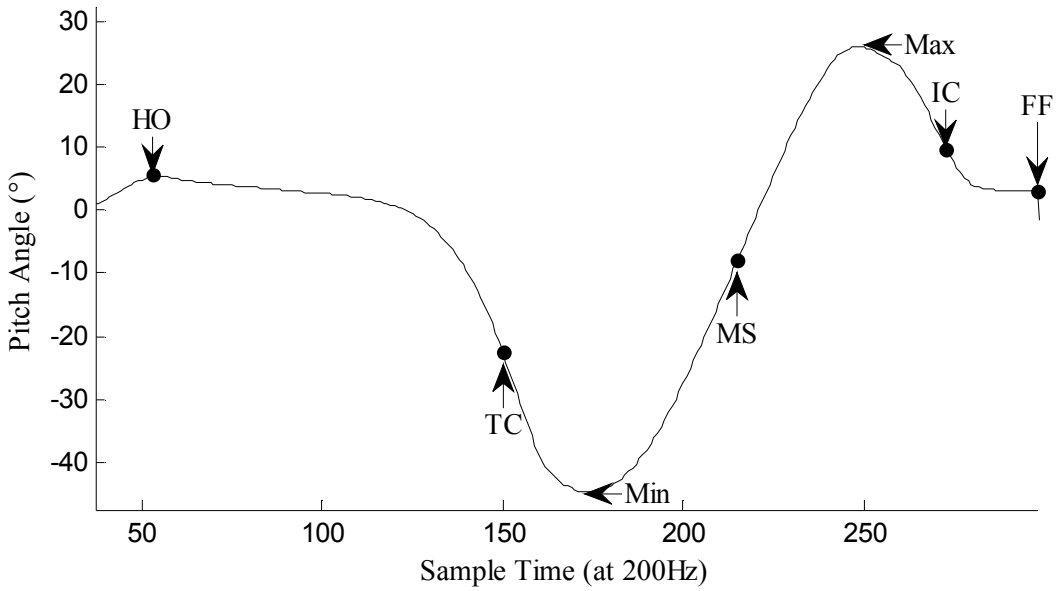

Figure 9 –Pitch Angle with seven subsequent features extracted in real-time,comprising value at Heel-Off (HO), value at Terminal Contact (TC), value at Midswing (MS), value at Initial Contact (IC), value at Midstance (FF), maximum (Max), and Minimum (Min).

Using the recorded signals from instrumented prostheses, median and inter -quartile range (IQR) were calculated for each feature among the datasets of each activity (table A.I in annexes). That provides an insight into the average value of each feature as well as its inter-subject and intra-subject variability. Statistical comparison between datasets from each activity was done using a two-sided Wilcoxon rank sum test. Median, IQR and p-values are reported in Annexes. To deeper investigate locomotion pattern, rank-sum test was also calculated in pair wise comparison of activities. Fig. 10 provides a subset of the most significant results obtained in the different activities, selected as the main representative examples. Values are reported in percentage of the mean obtained during level walking, so that parameter changes among activity can be compared with each other.

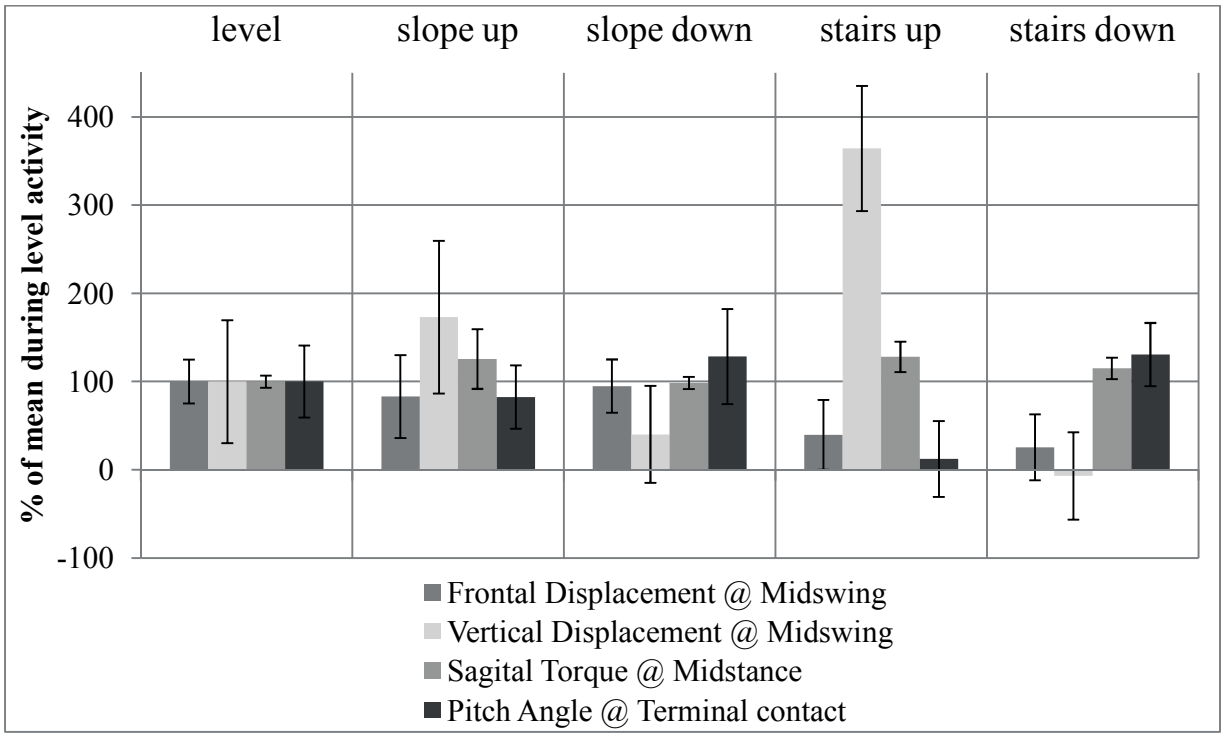

Figure 10 - median+/-IQR among all subjects recorded cycles (N=1870) for a subset of features expressed in % of mean measured during level activity. All parameters show significant differences (*p-value* <0.01) in various activities compared to level walking

Results show that vertical displacement estimated at MidSwing is higher in slope and stairs up activities, and lower in slope and stairs down compare to level walking. Frontal displacement is comparable between level and slope locomotion, but is diminished in stairs walking. Ankle joint torque measured by strain gauges at MidStance shows particular increase in slope up and stairs up activity, whereas Pitch angle at terminal contact is strongly decreased in stairs up activity.

4 Discussion

Overall, this chapter showed that most of the concept introduced in temporal (chapter 3) and spatial (chapter 4) gait analysis were adaptable to real-time application. The only limitation comes from the drift resetting strategy which cannot be optimized such as to measure foot clearance. However, the results obtained in kinematics estimation and resulting extracted features showed that performances were acceptable to significantly discriminate the kinematics of activities including level walking, slope ascent, slope descent, stairs ascent, and stairs descent. The validation of those real-time methods in terms of accuracy and precision against a reference should be further analyzed if applications of those real-time methods are foreseen for clinical gait analysis.

Physilog III was used as a practical system to conduct the measurement and to realize a prototype in fast delay for data logging and inertial signals sensing, and real-time processing of signals was simulated offline. Nevertheless, the developed algorithm was designed to work with any other equivalent sensor configuration. The use of lower sampling frequency such as 100Hz is also a realistic alternative to reduce power consumption without affecting too much the performances of the algorithm. In this study, the preliminary alignment of sensor's axis to foot or SAF prosthesis axis, as well as the calibration of force, moment and angular sensors, was done offline. In future practical application in real-time active prosthetic device, two solutions are possible, either based on factory calibration and alignment, or based on online implementation of alignment methods and calibration protocols presented.

Walking phase detection method yielded excellent performances which were only quantified in healthy subjects with orthoses. Comparable performances were also observed with amputee subjects. It shows that orthotic devices were good alternatives for simulating amputee gait, and that our criteria for state temporal transitions were robust to the different types of activities and subjects.

Features extracted directly from raw inertial signals without any processing showed statistical differences in some cases (notably at MidSwing), but they were less robust to characterize activities since their inter-subject variability was big. Speed however seems to be a good tradeoff as it requires one less integration than displacement in its estimation process, and thus is less prone to drift errors. Globally, most of the features were showing highly significant differences between each other. Kinematic features were most suited for finding differences during swing phase of gait (at MidSwing and Initial contact), whereas Kinetic features, and especially Torque, were most suited during stance (at MidStance, Heel-off and Terminal contact). Those results obtained quantitatively show a good potential in characterizing unambiguously the different activities, and results were in accordance with common sense and literature.

The perspective of this study would be to test the real-time implementation of the methods into prototype prosthesis by implementing the proposed method into a micro-controller. Then it would open the door of the active control a prosthetic Shank-Ankle-Foot complex to adapt the behavior of the prosthesis to the terrain.

Finally, the presented methods could be further adapted to be used for prosthetic knee. However, in that case, the kinematic estimation phase should be adapted as it is using the particular foot motion to reset the drift periodically. Other application requiring real-time detection of phases and/or estimation of kinematics with capability of foot sensing could also benefit from that research, notably functional electrical stimulation [19] or active rehabilitation devices [20]

5 Conclusion

An instrumented prosthesis, including Force sensors, a potentiometer, inertial measurement unit and a datalogger was developed and successfully used on 5 amputee subjects performing different locomotion including level walking as well as stairs and ramps. Algorithm capable of detecting in real-time the walking phases and estimating 2D foot kinematics of the subject has been designed and implemented into a real-time simulation program. The walking phase detection algorithm is based on the fusion of force and inertial signals. It showed excellent robustness to all subjects and various types of locomotion recorded on the amputee subjects tested in this study. A feature extraction algorithm has been finally designed and implemented, which is able to compute a wide range of parameters describing the kinetic and kinematic of the amputee subject. The algorithm includes signal processing method combined with the output of walking phase detection to extract parameters of interest. Within those parameters, we found significant difference between different types of locomotion.

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Chapter 8

Foot Signature

1 Introduction

A signature (from Latin: signare, "to sign") is usually a handwritten (and sometimes stylized) depiction of someone's name, or nickname, that a person writes on documents as a proof of identity and intent. Signature is not always similar and can show some variability from time to time, but it still remains repeatable to unambiguously identify a person and to a certain extent, its character. One never has to think about the way he is writing his signature, it became innate. Similarly, some characteristics of walking, e.g. cyclic and alternate movement are also innate, and foot trajectory pattern presents some similarities with a hand-written signature (fig. 1). That led us to define "*foot signature*" as the foot trajectory pattern during one gait cycle. Therefore, the following research questions arouse:

- How can we technically characterize and quantify "*foot signature*"?
- To what extent "*foot signature*" could be used as an unambiguous assessment of locomotion?

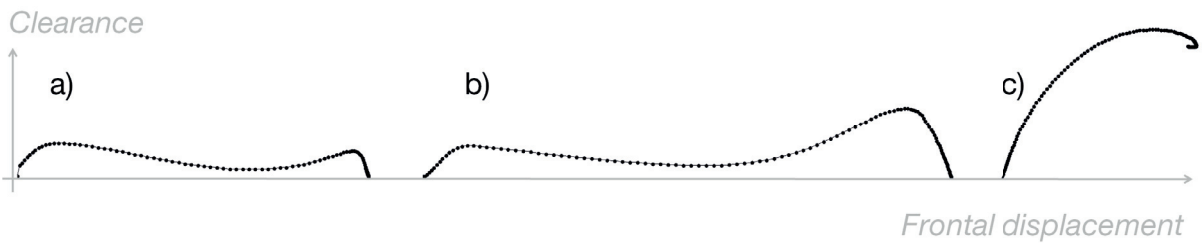


Figure 1 - Example of experimental "foot signatures" provided by 3D toe trajectory obtained using foot-worn inertial sensors in CP child during level walking (a), healthy adult during level walking (b), amputee during stair climbing (c).

In the previous chapters, a system based on foot-worn inertial sensors was designed and validated to measure 3D foot trajectory and orientation during gait in natural condition, and to extract specific parameters which quantify foot movements' characteristics. That demonstrated that the quantification of

foot signature can be done using foot-worn sensors and a subset of specific parameters obtained from the fusion of the methods described in chapters 3 to 7.

The identification of foot signature for each individual is an ambitious aim but more related to other scientific domains such as biometry than biomechanics. Here we aim to investigate the potential application of foot signature for studying gait changes related to the type of activity and disease. Two approaches are then presented and discussed in this chapter:

- using *intra-subject* paradigm, we assume that different types of locomotion show different foot signatures. This is typically illustrated in stairs climbing (fig 1. c), which foot signature is characterized by a bigger clearance and shorter frontal displacement that in level ground walking (fig 1. b). That approach is further developed in section 2 and applied to the real-time recognition of locomotion activity in amputee subjects using instrumented ankle-foot prosthesis.
- using *inter-subject* paradigm, we assume that each mobility disease shows a different foot signature during gait at self-selected walking speed in free condition. This is typically illustrated in children with Cerebral Palsy (fig 1. a), where foot signature is characterized by a lower toe clearance at the end of the gait cycle, and shorter frontal displacement. In order to characterize mobility disease, that approach is extended to the comparison of foot signature obtained using foot-worn sensors on a large sample of subjects from age 7 to 77, including PD and CP subjects.

The overall methodology proposed in this chapter is depicted in the diagram in fig. 2.

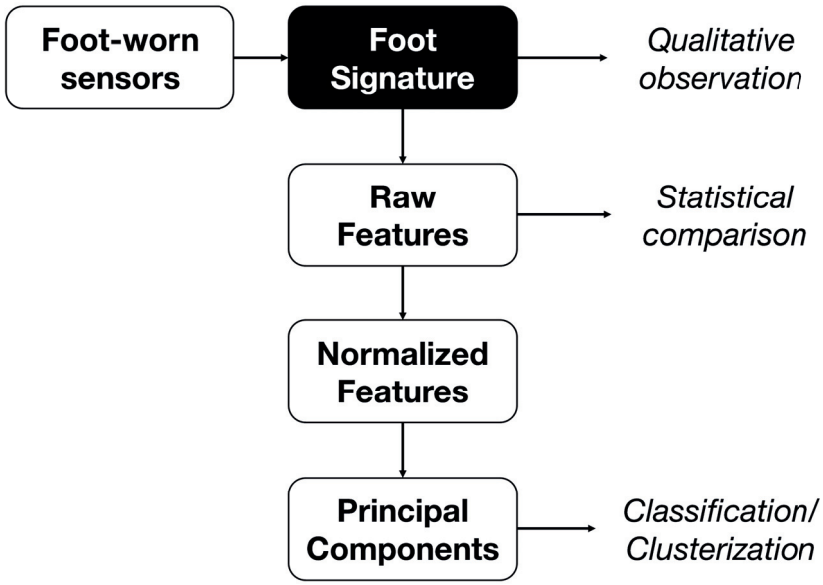


Figure 2 - Block diagram showing the use of foot signature for observation, comparison, and classification of gait activities and mobility diseases.

Foot signature, i.e. 3D foot trajectory during one gait cycle, constitutes the guideline of this chapter. Foot signatures are estimated using foot-worn sensors and can be qualitatively observed as in fig.1. To further analyze foot signature changes among various activities and mobility diseases, this chapter presents the use and statistical comparison of raw features, e.g. parameters, which are subsequently extracted from foot signatures. Finally, machine learning classification tools are also used based on normalized features and principal components (PC).

2 Real-time recognition of locomotion activity*

In this section, foot-signature is used for intra-subject comparison of locomotion activities. Systems and methods presented in chapter 7 have already shown to be capable of estimating the foot kinetics and kinematics from instrumented ankle-foot prosthesis during various locomotion including walking on level ground, incline and stairs, and observing differences of foot signature between those activities (fig. 3).

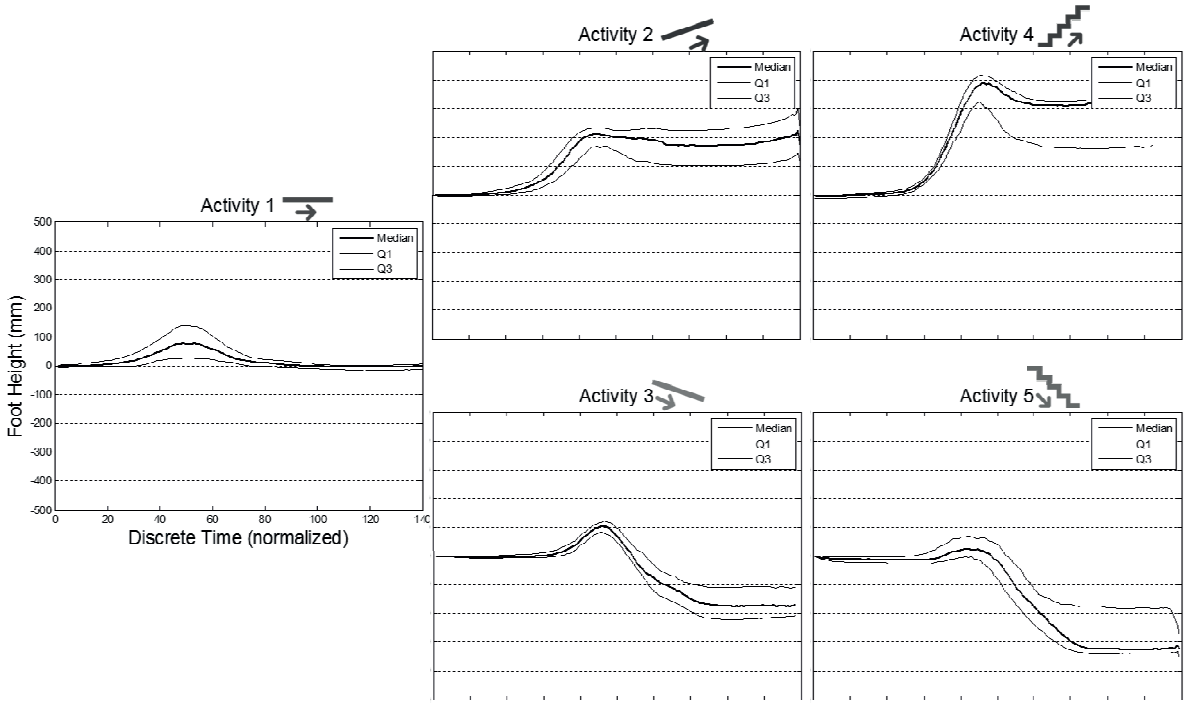


Figure 3 - Median +/- Interquartile range of vertical component of Foot signature measured in amputee subjects (chapter 7) during various activities including level walking, slope and stairs ascent and descent.

In addition, the detection of walking phases and the extraction of parameters at each cycle already provide a real-time quantification of raw features of foot signature.

This section aims to apply the general methodology presented in the introduction, based on raw features normalization and principal components analysis, to recognize locomotion activity from any type of foot signature recorded using foot-worn sensors on subjects with or without mobility disease. It is illustrated with the data which was collected during the study of amputee subjects (chapter 7). To recognize different types of locomotion, referred as *activities*, our objectives can therefore be summarized as:

* Patent pending, PROTEOR, *2012.*

- Establish a pattern model for each activity, based on a transformation and selection of relevant parameters extracted from foot signature, referred as *features* (in accordance with data mining terminology). This is done on a subset of recorded data, referred as *training data*.
- Recognize activities at each gait cycle, by classifying the extracted features, referred as *testing data*, with the model.
- Assess the performance of the recognition algorithm by comparing the recognized activities to the real activities performed by the subject.

A factor analysis is also proposed to identify the most relevant features of foot signature that can be extracted in real-time during locomotion.

Constraints for the algorithm can be summarized as:

- ability to recognize at least 5 main walking activities: level walking, slope up and down, stairs up and down (Additional activities such as sitting could be considered in the future)
- robustness to inter-subject variability
- implementability on an embedded micro-controller to work in real-time (typically the code and algorithm must be translatable to C)
- understandability for the user, with the possibility for further tuning and modification. It means an expert classification method is preferable to a "black box" method which behaviour cannot be interpreted.

2.1 Method

2.1.1 Features normalization

With the method of chapter 7 using the signal measured on instrumented prosthesis, 153 raw features are extracted at each gait cycle. Prior to classification, it is important to normalize the features dataset so that they are equally considered. Two types of normalization are considered. Using linear normalization (L-norm), each feature *i* range in [-1 1] after normalization using the following equations:

$$l=min(FEATURES(:,i)),\ u=max(FEATURES(:,i)), \qquad (1)$$
$$FEATURES\_L\text{-}Norm(:,i)=2*(FEATURES(:,i)-(u+l)/2)/(u-l)$$

With Standard Score normalization (S-norm), each feature *i* has a mean of 0 and STD of 1:

$$mu=mean(FEATURES(:,i)),\ sigma=std(FEATURES(:,i)), \qquad (2)$$
$$FEATURES\_S\text{-}Norm(:,i)=(FEATURES(:,i)-mu)/sigma$$

Linear normalization might be strongly influenced by an outlier, but will perfectly match ranges between data features. Standard Score is based on the distribution of data, so if the number of training data is

sufficient, it is less influenced by outliers. However, the data features will not perfectly fall into the same range (fig. 4).

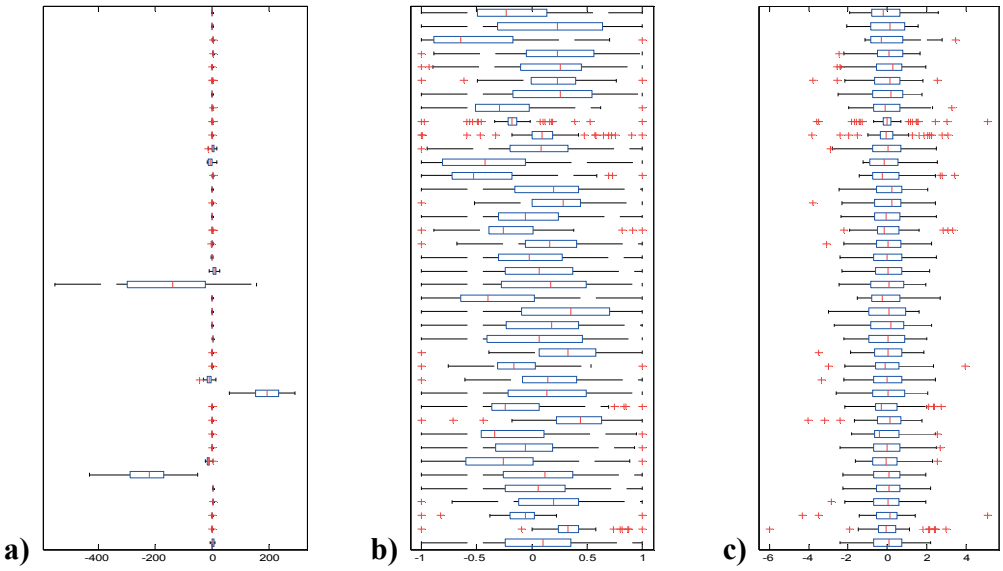


Figure 4 - Box plot of raw features set (a), and after normalization with L-Norm (b) and S-Norm (c).

2.1.2 Principal component analysis

Some features might be correlated to each other, for example this is the case for the vertical displacement at midswing and initial contact. In order to consider this dependency between features, data reduction using Principal Components Analysis (PCA) was applied to the dataset [1]. The diagram of fig. 5 shows the % of variance explained versus the number of principal components taken into account. The first 10 principal components explain nearly 90% of the variance of the data.

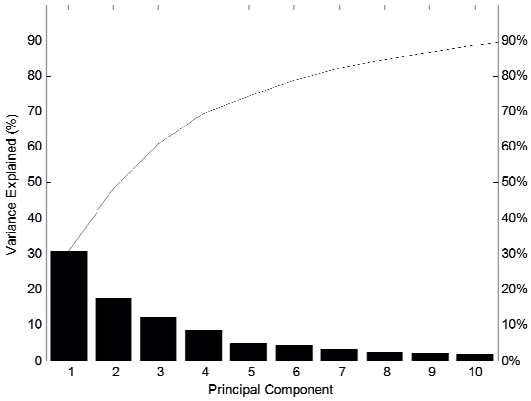


Figure 5 - Variance Explained versus number of principal components among the dataset of all extracted features

2.1.3 Activity Classification

Two approaches for activity classification are presented. The first approach is using common statistical machine learning techniques on the set of principal components as input features. Such methods have

been used in a wide range of application in literature, and demonstrated good performances for specific classification problems. Consequently, they were considered a reference for our study. In addition, the method presented here consists in using principle components as the inputs for a classifier, which has demonstrated significantly better classification performance compared to using original features as the inputs [2]. The second approach consists in defining expert rules on extracted features, based on prior knowledge and observations to manually classify activities. It presents the advantage of being interpretable, easily adjustable and tunable to a subject, and allows having criteria that match realistic biomechanical hypotheses. Its performances on a per-subject basis are finally compared with the first reference approach, based on the data recorded on 5 amputee subjects.

2.1.3.1 Training and Testing Data

For classification purpose, most of machine learning techniques require a certain amount of data to be used for training the classifier. In literature, it is common to split collected data with a certain percentage between training and testing data. In this study, using the measurements performed on amputee subjects during the study of chapter 7, *training* data was constituted from separate trials of pure activities, whereas *testing* data was constituted from daily-activity scenario including the succession of activities.

2.1.3.2 Reference methods

Different reference methods, including Linear Discriminant Analysis (LDA), K-nearest neighbor (KNN), and Decision Tree (TREE) are briefly presented in this section and were considered for this study. Such methods consist in classical data mining tools that have respectively demonstrated good classification performance in past studies focusing on speech recognition [2], text categorization [3], and activity classification [4], [5]. LDA [6], consists in defining linear boarders in the space of features for each activity. The algorithm can be adjusted with different distance measures. An improvement can consist in using Support Vector Machines, which constructs a hyperplane or set of hyperplanes in a high-dimensional space used for classification. A good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class [6]. KNN method [7], consists in counting the majority number of training neighbor of a tested sample within a defined area. Again, this algorithm can be tuned by changing the number of neighbor to take into account, and the type of distance measure which is used to define the area around the tested sample. The decision tree [8], consists in a simple yet powerful classification technique applying successive comparisons of single features to reach terminal states (called leafs). Different path can lead to the same results.

2.1.3.3 *Expert method*

Expert classification, also referred as rule-based classification, implies to have hypotheses on criteria to distinguish activities from each other. In this approach, the set of extracted features is used without prior normalization or PCA. So, to reduce the dimensionality of input features, it is necessary to identify which features are particularly relevant. Two methods are proposed to select the relevant features. The first is based on decision tree, and the second on empirical observation of feature space.

2.2 Results

2.2.1 Reference methods

Reference classification methods were applied on the set of principal components of normalized features extracted from foot signatures. LDA is illustrated on the first two principal components (fig. 6.a.), whereas KNN with 3 neighbors (KNN3) using Euclidean distance on 2D principal component space is illustrated on fig 6.b. An example of decision tree generated on nine principal components is given in fig. 6.c. Tree can be pruned (fig. 6.d), i.e. reducing the number of terminations to a near-optimal value.

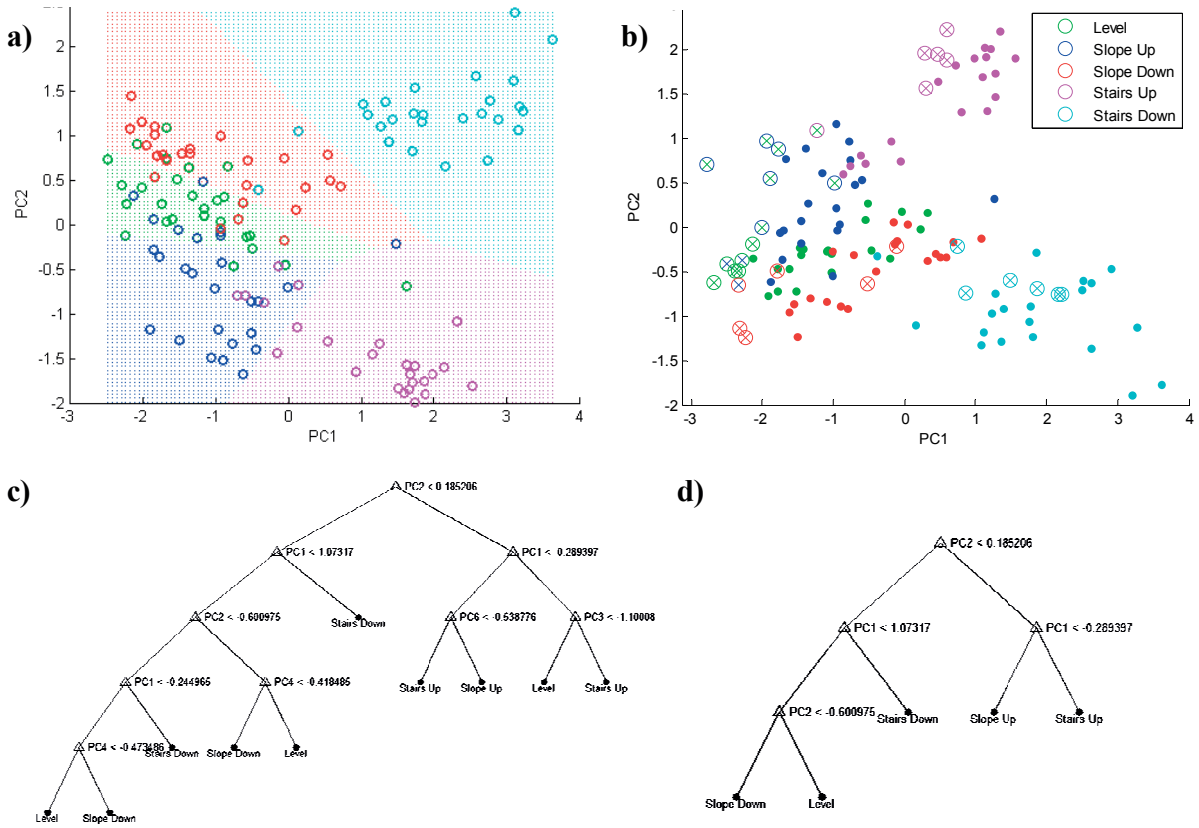


Figure 6 - Illustration of reference activity classification methods of Linear Discriminant Analysis (a), K-nearest neighbor (b), full decision tree (c), and pruned decision tree (d) on a reduced set of principal components (PC)

2.2.2 Expert method

2.2.2.1 Features space investigation using decision tree

By using the decision tree method described previously on the whole set of features, the algorithm automatically generates a classification tree that can be pruned to get only one termination per activity in order to identify relevant features. A tree was then automatically generated for each subject's training data. This investigation provides a good insight into the 153 features space, and provides the four most relevant features selected on the criteria that they appeared in at least 2 per-subject generated trees. These four features are further used in the expert method.

The list of features identified as relevant was then:

- to @ FF: the torque at midstance
- PI @ HO: the pitch orientation at Heel-off
- DV @ FF: the vertical displacement at foot-flat
- a1 @ FF: the frontal acceleration value

Using this restricted list of features, per-subject tree and their coefficients were generated, as in the example of fig. 7. Generated trees obtained for all other subjects are given in fig. A.7-10 in annexes.

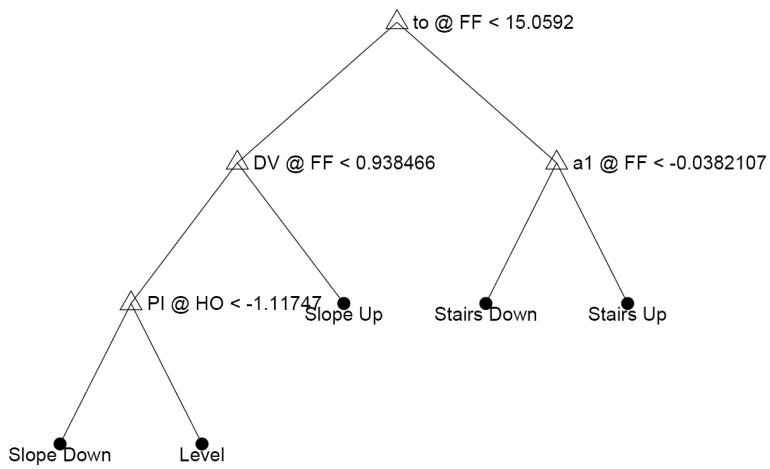


Figure 7 – Expert classification tree of activities for subject 9 using ankle torque (to), vertical displacement (DV) and frontal acceleration (a1) signals at Midstance (FF), and pitch angle signal at heel-off (PI@HO).

2.2.2.2 Feature space investigation using qualitative observations

Based on a-priori hypothesis obtained from literature, other relevant features were identified. Further observation of those features in the training set allowed confirming their pertinence for discriminating activities (fig. 8).

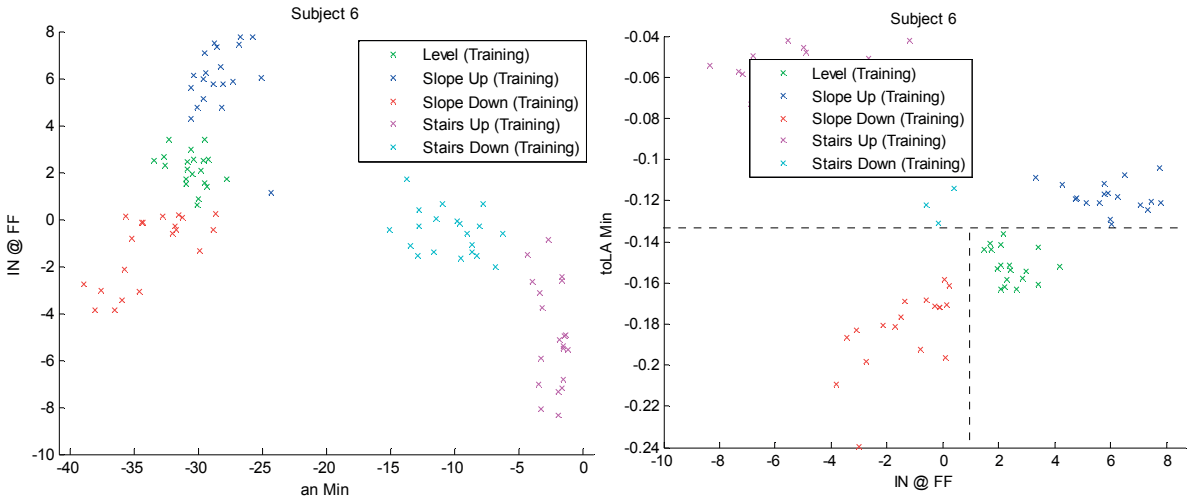


Figure 8 - Qualitative observation of activity-discriminant features including inclination angle at Midstance (IN@FF), minimum of ankle angle (anMin), and minimum of torque/leg angle ratio (toLAMin) in amputee subjects.

Out of our observations on the different subjects, an empirical list of particularly relevant parameters was identified as:

- anMin: minimum value of ankle angle
- DV@MS: the vertical displacement of the foot at midswing
- IN@FF: the foot inclination at midstance (i.e the slope angle is foot is flat-landed)
- toLA Min:the minimum value of the ratio between Torque and Leg angle

This list is obviously non-exhaustive and features can be easily exchanged with the other highly correlated ones. For example, the inclination at foot-flat is computed from acceleration value, so those two metrics are strongly associated and can replace each other as input of the expert classification method. Moreover, according to the results of the PCA, we know that less than 10 independent features are needed to explain 90% of the Variance of data.

Finally, the list of features included features obtained from decision tree and qualitative observation. The expert method was based on the decision tree algorithm which was run again to set automatically the optimal per-subject threshold based on Training data. The expert method (*Optimal Tree)* is then implemented in SIMULINK for real-time simulation.

2.2.3 Comparison of classification Performance

For reference classification methods (LDA, KNN3, TREE) and expert method (Optimal Tree), the confusion matrix was established by counting the number of training and testing data assigned to each

activity by the algorithm against the reference video-labeled activity. The confusion matrix was computed both in absolute values and in percentage of sample for each activity. The diagonal values of the confusion matrices represent the correctly classified samples. The global average error (AE) and the correct rate of classification (CR) were computed on the relative confusion matrix (CM_pct) and the absolute confusion matrix (CM):

$$AE=100\text{-}average(diag(CM\_pct)) \qquad (3)$$
$$CR=100*sum(diag(CM)) \,/\, total\ number\ of\ samples$$

If the number of samples is the same for each activity, then $CR=1\text{-}AE$.

The global average error rate decreases and rapidly converges when the number of principal components increases (fig. 9). In consequence, it was decided to use only nine principal components. Table I provides the performance assessment of the different methods for both training and testing data.

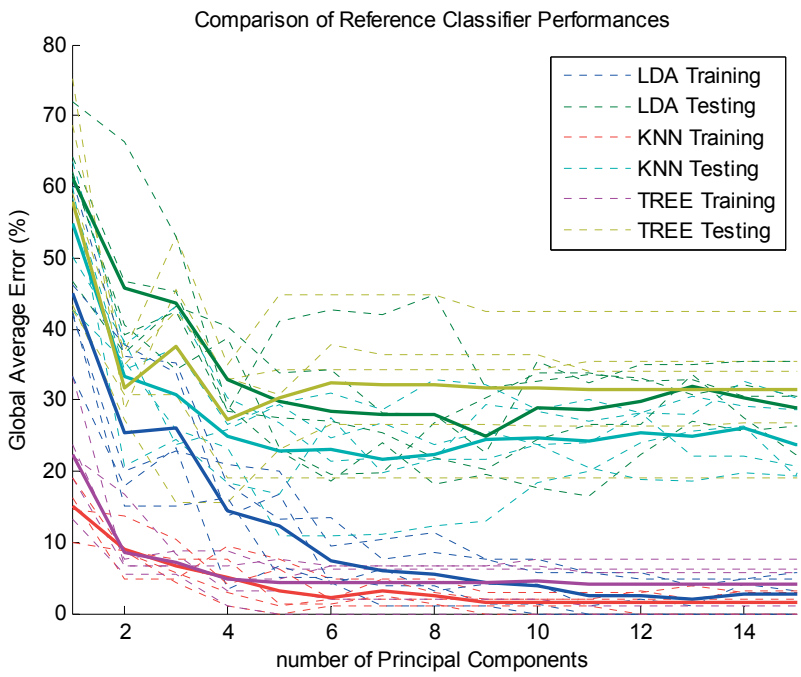


Figure 9 – Per-subject (dashed line) and Mean (plain line) classification performance measured by global average error versus number of principal components used.

TABLE I – COMPARATIVE ACTIVITY CLASSIFICATION PERFORMANCE (CONFUSION MATRICES) OF REFERENCE METHOD (LDA, KNN3, TREE) AND EXPERT METHOD (OPTIMAL TREE) ON TRAINING AND TESTING DATA FROM 5 AMPUTEE SUBJECTS.

		Training Data							Testing Data						
LDA	%	Average Error (%)		classified as					Average Error (%)		classified as				
		1.4		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	24.0		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*100*	97.6	0.0	2.4	0.0	0.0	activity: Level	*100*	46.0	18.2	30.9	1.3	3.6
		Slope Up	*100*	2.4	97.6	0.0	0.0	0.0	Slope Up	*100*	26.4	71.4	0.0	0.0	2.2
		Slope Down	*100*	2.4	0.0	97.6	0.0	0.0	Slope Down	*100*	1.8	2.2	96.0	0.0	0.0
		Stairs Up	*100*	0.0	0.0	0.0	100.0	0.0	Stairs Up	*100*	6.7	6.7	0.0	80.0	6.7
		Stairs Down	*100*	0.0	0.0	0.0	0.0	100.0	Stairs Down	*100*	0.0	0.0	13.3	0.0	86.7
	Samples	Correct Rate (%)		classified as					Correct Rate (%)		classified as				
		98.6		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	57.8		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*83*	81	0	2	0	0	activity: Level	*302*	142	52	94	4	10
		Slope Up	*83*	2	81	0	0	0	Slope Up	*44*	11	32	0	0	1
		Slope Down	*83*	2	0	81	0	0	Slope Down	*48*	1	1	46	0	0
		Stairs Up	*83*	0	0	0	83	0	Stairs Up	*15*	1	1	0	12	1
		Stairs Down	*83*	0	0	0	0	83	Stairs Down	*15*	0	0	2	0	13
KNN 3	%	Average Error (%)		classified as					Average Error (%)		classified as				
		1.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	20.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*100*	97.6	0.0	2.4	0.0	0.0	activity: Level	*100*	46.2	29.7	17.4	1.0	5.8
		Slope Up	*100*	1.2	97.6	0.0	0.0	1.2	Slope Up	*100*	11.7	83.9	0.0	0.0	4.4
		Slope Down	*100*	1.4	0.0	98.6	0.0	0.0	Slope Down	*100*	10.5	2.2	87.3	0.0	0.0
		Stairs Up	*100*	0.0	0.0	0.0	100.0	0.0	Stairs Up	*100*	0.0	13.3	0.0	80.0	6.7
		Stairs Down	*100*	0.0	0.0	0.0	1.2	98.8	Stairs Down	*100*	0.0	0.0	0.0	0.0	100.0
	Samples	Correct Rate (%)		classified as					Correct Rate (%)		classified as				
		98.6		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	58.3		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*83*	81	0	2	0	0	activity: Level	*302*	141	86	55	3	17
		Slope Up	*83*	1	81	0	0	1	Slope Up	*44*	5	37	0	0	2
		Slope Down	*83*	1	0	82	0	0	Slope Down	*48*	5	1	42	0	0
		Stairs Up	*83*	0	0	0	83	0	Stairs Up	*15*	0	2	0	12	1
		Stairs Down	*83*	0	0	0	1	82	Stairs Down	*15*	0	0	0	0	15
TREE	%	Average Error (%)		classified as					Average Error (%)		classified as				
		1.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	39.1		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*100*	97.6	2.4	0.0	0.0	0.0	activity: Level	*100*	35.9	38.5	15.5	3.0	7.0
		Slope Up	*100*	1.2	98.8	0.0	0.0	0.0	Slope Up	*100*	13.6	66.1	4.7	2.2	13.3
		Slope Down	*100*	3.8	0.0	96.2	0.0	0.0	Slope Down	*100*	27.3	10.0	62.6	0.0	0.0
		Stairs Up	*100*	0.0	0.0	0.0	100.0	0.0	Stairs Up	*100*	0.0	6.7	0.0	53.3	40.0
		Stairs Down	*100*	0.0	0.0	0.0	0.0	100.0	Stairs Down	*100*	0.0	0.0	13.3	0.0	86.7
	Samples	Correct Rate (%)		classified as					Correct Rate (%)		classified as				
		98.6		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	45.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*83*	81	2	0	0	0	activity: Level	*302*	113	112	48	8	21
		Slope Up	*83*	1	82	0	0	0	Slope Up	*44*	6	29	2	1	6
		Slope Down	*83*	3	0	80	0	0	Slope Down	*48*	13	5	30	0	0
		Stairs Up	*83*	0	0	0	83	0	Stairs Up	*15*	0	1	0	8	6
		Stairs Down	*83*	0	0	0	0	83	Stairs Down	*15*	0	0	2	0	13
Optimal Tree	%	Average Error (%)		classified as					Average Error (%)		classified as				
		5.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	12.7		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*100*	96.5	0.0	2.4	1.1	0.0	activity: Level	*100*	92.0	2.2	2.9	0.6	2.3
		Slope Up	*100*	11.7	83.3	3.5	0.0	1.4	Slope Up	*100*	15.6	84.4	0.0	0.0	0.0
		Slope Down	*100*	7.2	0.0	92.8	0.0	0.0	Slope Down	*100*	20.0	0.0	80.0	0.0	0.0
		Stairs Up	*100*	0.0	0.0	0.0	100.0	0.0	Stairs Up	*100*	6.7	0.0	0.0	93.3	0.0
		Stairs Down	*100*	0.0	0.0	0.0	0.0	100.0	Stairs Down	*100*	13.3	0.0	0.0	0.0	86.7
	Samples	Correct Rate (%)		classified as					Correct Rate (%)		classified as				
		94.5		Level	Slope Up	Slope Down	Stairs Up	Stairs Down	89.6		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
		activity: Level	*83*	80	0	2	1	0	activity: Level	*302*	278	7	9	2	6
		Slope Up	*83*	10	69	3	0	1	Slope Up	*44*	7	37	0	0	0
		Slope Down	*83*	6	0	77	0	0	Slope Down	*48*	10	0	38	0	0
		Stairs Up	*83*	0	0	0	83	0	Stairs Up	*15*	1	0	0	14	0
		Stairs Down	*83*	0	0	0	0	83	Stairs Down	*15*	2	0	0	0	13

2.2.4 Application to real-time classification of activity

Finally, the use of an expert tree implemented in SIMULINK was assessed on one subject to verify its practical usage and the real-time flow of classification output (fig. 10 and table II).

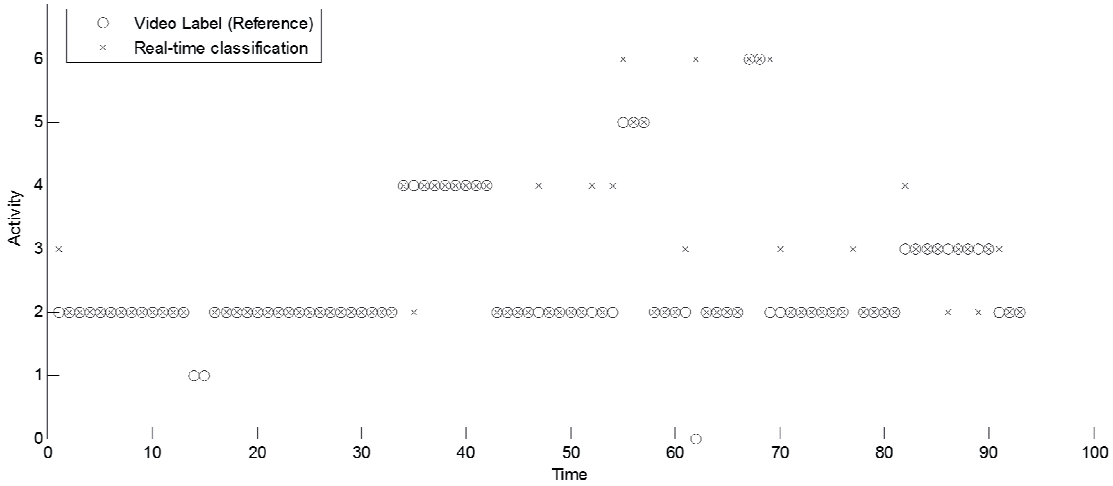


Figure 10 - Real-time activity recognition from expert tree on one subject

TABLE II - CONFUSION MATRIX FOR REAL-TIME EXPERT RECOGNITION OF ACTIVITY (SUBJECT 6)

EXPERT TREE (SUBJECT 6)				classified as				
		Average Error (%)						
		18.0		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
%	activity	Level	*100*	87.9	6.1	4.5	0.0	1.5
		Slope Up	*100*	22.2	66.7	11.1	0.0	0.0
		Slope Down	*100*	11.1	0.0	88.9	0.0	0.0
		Stairs Up	*100*	0.0	0.0	0.0	66.7	33.3
		Stairs Down	*100*	0.0	0.0	0.0	0.0	100.0
		Correct Rate (%)						
		85.4		Level	Slope Up	Slope Down	Stairs Up	Stairs Down
Samples	activity	Level	*66*	58	4	3	0	1
		Slope Up	*9*	2	6	1	0	0
		Slope Down	*9*	1	0	8	0	0
		Stairs Up	*3*	0	0	0	2	1
		Stairs Down	*2*	0	0	0	0	2

2.3 Discussion

We observe excellent and comparable performance of all classification methods on training data with a minimal performance of correct classification for the expert method (Optimal Tree) of 94.5%, slightly under reference methods (LDA, KNN3, TREE), obtaining each 98.6 % of correct classification. This shows that reference classification methods yielded excellent performances on training data constituted of pure activities.

Regarding testing data, composed of a succession of activity in daily-life scenario, Optimal Tree, which can be seen as the best possible expert tree for a subject, provide better performances (Average Error 12.3%, Correct Classification Rate 89.6%) than the reference methods. This can be explained by the over-fitting of the reference methods to the training data. Reference methods perform well to classify training data but are not robust to slight modifications that occur with testing data. Indeed, during the daily-life protocol, subjects are performing transitions between activities which are not specifically labeled in the training dataset. For example, the foot signature of the first step of stair climbing following level walking remains similar to the one of level walking, and thus the features that appear in the first selected principal components might be unable to discriminate those two activities.

A limitation of this comparative study comes from the fact that the number of collected samples was small. In particular, the number of sample for stairs activity was limited to 3 steps per subject. Yet, the results show that the use of an expert method to classify the extracted features from foot signature is possible for recognition of activities in real-time, with comparable performances to the reference methods. A complete evaluation of its performance would require a bigger number of subjects.

An opportunity for further improvement is to better identify the important misclassifications in order to avoid risky situation. Three approaches are then possible to avoid such situation:

- the manual tuning of the thresholds to prioritize certain path of the decision tree
- the instruction to the subject to pay attention to his locomotion pattern in order to respect the decision tree criteria
- the use of a cost matrix during threshold optimization on training data, i.e. each classification branch will not have the same weight, and we can prioritize some state based on assumptions.

Interestingly, the observation of the confusion matrix obtained by Optimal Tree shows that only level walking was misclassified with other activities. There are no other types of errors (every term except the diagonal, the first line and first column are null in confusion matrices of table I). One could observe that the misclassified samples are not the same through reference methods, and notably, KNN3 is the only method confusing stairs with the other activities. Other reference classification techniques such as neural networks could have been also considered, but the reference methods considered in this study already yielded excellent recognition performances. Moreover, neural networks reveal little information about their classification mechanism compare to decision tree, since they only provide a black box of weights [9].

3 Characterization of Mobility Disease

This section aims at inter-subject comparison of foot signatures. From the results obtained in chapters 3 to 6, we have seen that the following parameters significantly discriminate subjects with reduced mobility against control subjects:

- In *temporal analysis* (Chapter 3), a longer stance and foot-flat on arthritic ankle
- In *spatial analysis* (Chapter 4), a lower stride velocity and maximal heel clearance in elderly subjects
- In *turning analysis* (Chapter 6), a longer turning phase duration during TUG and higher variability in stride velocity and a longer path length during gait in PD subjects in ON and OFF state, a smaller stride velocity and heel-strike pitch angle on affected side of CP children during straight walking gait.

Indices for assessing overall gait deviations have been reported in literature under the generic term "gait analysis summary measure". Notably, the Gillette Gait Index (GGI) is a summary measure incorporating 16 clinically important kinematic and temporal parameters [10]. It has been mostly validated in children with cerebral palsy, but also evaluated in adults with gait abnormalities [11]. Yet, those methods require dedicated laboratories and have not been applied to compare various populations.

Following the methodological concept introduced in fig. 2, this section aims to compare foot signature in various populations with mobility diseases, through statistical comparison of subsequent extracted gait parameters (e.g. features), and then to improve the discriminative power using normalization and principal components analysis. Finally, a method is proposed for using a subset of principal components in an index measure constituted by a visual foot signature map.

3.1 Method

3.1.1 Measurements Database

In the frame of the present thesis work, and based on the measurement protocols that were performed in the studies of chapters 3 to 6, a wide range of gait data has been collected using foot-worn inertial sensors on 1854 subjects with various mobility disease (Table III). All those measurements have been performed at self-selected walking speed using the exact same sensor configuration with 6D-IMUs attached to the foot. Parts of those data were performed in laboratory setting and used for the technical validation of parameters described in chapters 3 to 6. The remaining data includes clinical trials that were performed in free living condition outside of the laboratory, typically in hospital corridors.

TABLE III - MEASUREMENT DATABASE OF FOOT SIGNATURE USING FOOT-WORN INERTIAL SENSORS

Population	Group Label	study	Gait Tasks	Sample Size
Control adults & elderly	-	*Spatial Validation*	fo8, U-turn, 5m gait	20
Europe Community-dwelling elderly	-	Clinical trials	6 minutes walking test	70
Control adults	**25-39**	*Clearance Validation*	fo8, U-turn, 5m gait	12
Lausanne Community-dwelling elderly	**65+**	Clinical trials	TUG, 20m gait under single task, cognitive and motor dual task	673
	71+			983
PD ON/OFF medication & age-matched controls	**PD**	*Turning validation*	TUG	21
		Clinical trials	40m gait, 200m gait	
Ankle OA treatments & age-matched controls	-	*Temporal Validation*	50m gait test	40
CP childs & age-matched controls	**16-**	*Spatial/Turning validation*	fo8, U-turn, 5m gait	35
		Clinical trials	200m gait test	

The following groups of subjects were thus considered in the following with different conditions:

- Older community-dwelling persons with age over 65 years (**65+**) and 71 years (**71+**), who performed a 20m gait trial at self-selected speed in the following conditions: single task walking (**ST**), walking while counting backward (**DTc**), walking while carrying a glass of water (**DTm**) and walking while carrying a glass of water and counting backward(**DTcm**).
- People with Parkinson's disease (**PD**), who performed a 2*20m (e.g. 40m) gait and a 4*50m (e.g. 200m) gait test under **ON** and **OFF** medication.
- Children under the age of 16 year (**16-**), including controls and children who were followed in tertiary outpatient neurorehabilitation unit for Cerebral palsy and whom were graded GMFCS I (**CP I**) or graded GMFCS II (**CP II**).
- Control adults with age between 25 and 39, recruited among students and colleagues, with no previous gait pathology, who performed short walking trial on 5m in laboratory setting. This group was originally only used for technical validation but we used the results in clearance analysis to get some reference data.

All measurements protocols received approval from local ethical comity.

The gait parameters were automatically extracted from foot-worn sensors signals at each gait cycle using the methods described in chapters 3 to 6, leading to get for each trial of each subject the exhaustive list of common and original parameters classified in three categories as follow:

- Temporal parameters:
    - Gait cycle time, Cadence, Swing and Stance in percentage of gait cycle, Load, Foot-flat and Push in percentage of stance, total Double-support in percentage of gait cycle.
- 3D Spatial parameters:
    - Stride Velocity (walking speed), Stride Length, Swing width, 3D Path length in percentage of Stride Length, Peak swing angular velocity, Foot pitch angle at terminal contact (Toe-off) and initial contact (Heel-strike).
- Clearance parameters:
    - Maximal Heel Clearance, Minimal Toe Clearance, 1st and 2nd Maximal Toe Clearance, Toe and Heel clearance Area, Foot velocity at Minimal Toe Clearance

3.1.2 Descriptive statistics

Walking trials recorded in each population were analyzed with the same algorithm. The first three and the last three strides, corresponding to gait initiation and termination were discarded from the analysis. During long-term measurement including pivot, turning strides were also discarded using a threshold of 20° on turning angle [12], [13]. The remaining gait cycles were considered as steady-state gait and their mean, standard deviation (STD), and coefficient of variation (mean/STD) were calculated for each trial and subject.

3.1.3 Reference parameters of foot signature in older adults

Among elderly subjects, data from 65+ and 71+ groups during Single Task were putted together, leading to a sample of 1490 subjects measured in the same condition on a 20m gait task. Reference gait values were computed from the mean and STD of gait parameters extracted on foot signature on a representative sample of subjects with age between 65 and 77 years. Moreover, average walking speed is the easiest gait parameters that can be simply estimated from measuring the time taken by a subject to walk a known distance. It has been shown in literature that this provide an indicator of frailty in elderly. It is therefore interesting to see whether the other gait parameters, that are estimated using foot-worn sensors and proposed method, are directly associated with walking speed or not

For the quantitative description of parameters distribution, measures of skewness and kurtosis were considered, as respective numerical analysis of the asymmetry and the “peakedness” of data distribution. A pure normal distribution corresponds to a skewness and kurtosis of 0.

The correlation coefficient (R), as a measure of linear association, was computed between the set of mean stride velocity and all the other parameters estimated for each subject. Variability value of parameters

were taken as CV for most parameters except in the case of Minimal toe clearance and Swing width, for which STD was used instead since they are close to 0.

3.2 Results

This section presented the statistical comparison of foot signature parameters in each population group during steady-state walking at self-selected speed.

3.2.1 Temporal Analysis

Fig. 11 provides the results of temporal analysis, obtained in the different groups of subjects using foot-worn sensors.

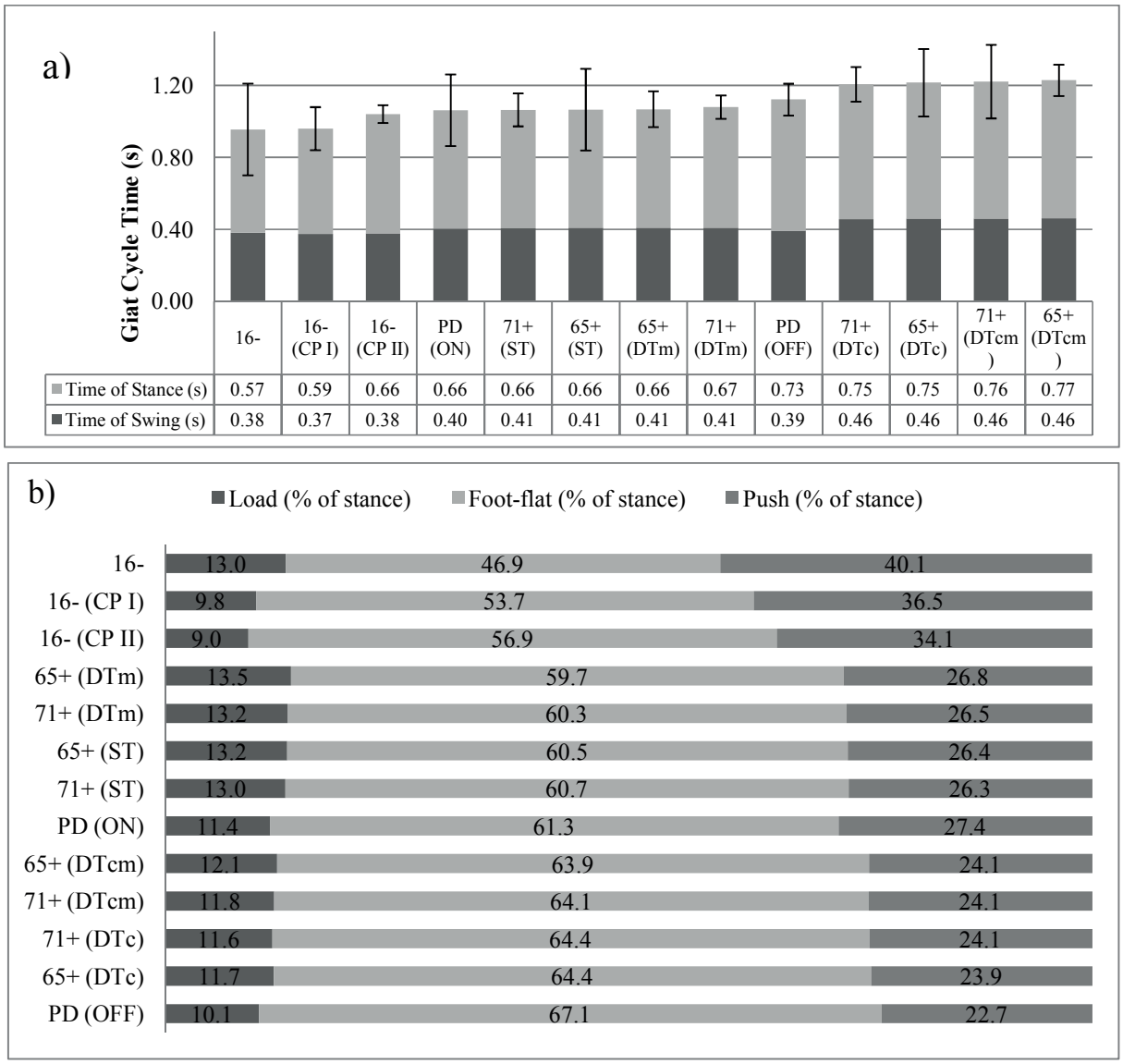
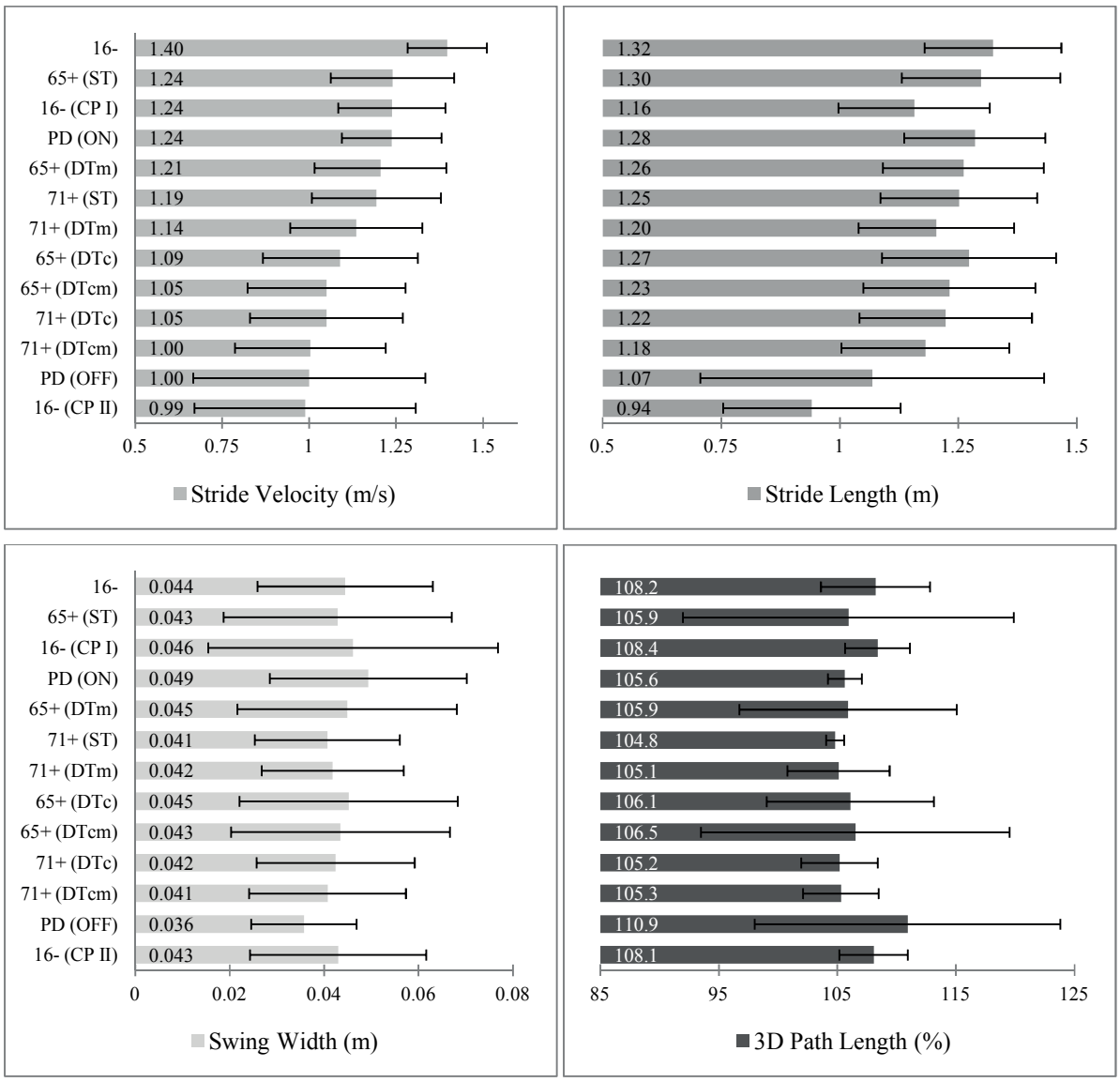


Figure 11 - comparison of subjects groups using mean+/-STD of sorted gait cycle time (a) and mean of inner stance phases ordered by foot-flat ratio (b)

Children show a smaller gait cycle time and a shorter foot-flat than any other groups, although it tends to be longer in CP condition. PD subjects have comparable gait cycle time to age-matched elderly populations but tend to have a longer foot-flat, especially in OFF condition. Regarding elderly subjects, we could see comparable results for the group 65+ and 71+ for all temporal parameters. Moreover, there is no clear influence of motor dual task (DTm) on temporal gait parameters, whereas it is affected by cognitive dual task (DTc and DTcm), which shows longer gait cycle time and foot-flat.

3.2.2 Spatial Analysis

Fig. 12 provides the results of spatial analysis, obtained in the different groups of subjects using foot-worn sensors, and sorted by increasing walking speed.



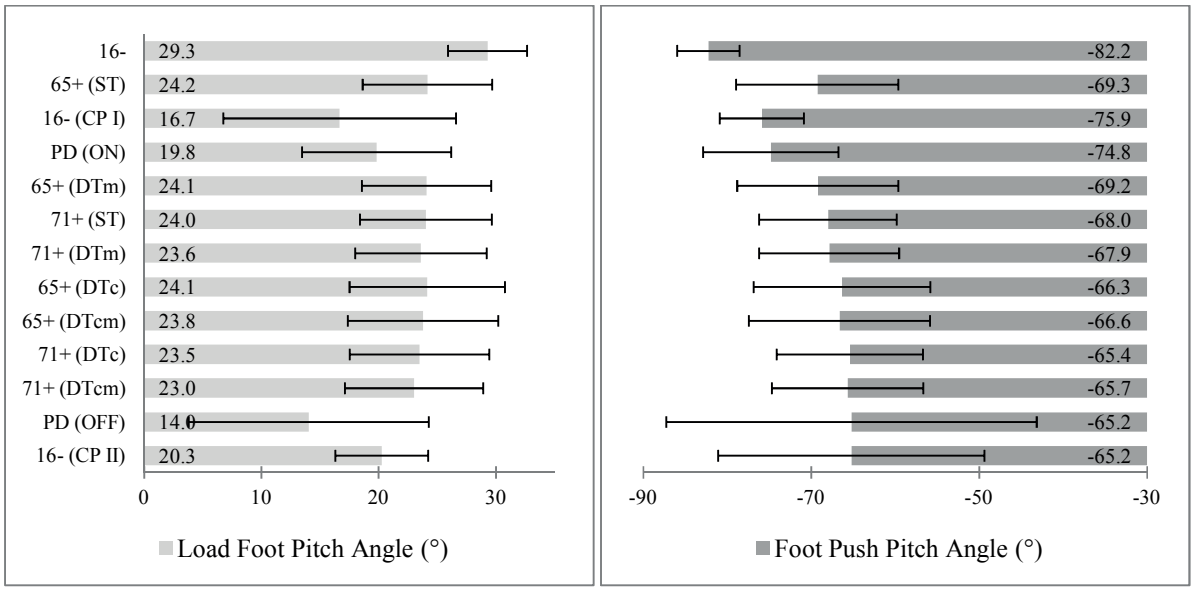


Figure 12 - comparison of mean+/- STD of gait parameters in subjects groups ordered by self-selected wlaking speed

Among the different groups of subjects, the patients with strong neurological disorders (PD OFF and CP II) show the slower walking speed, with high dispersion within the group though. On average, the younger our sample subjects are, the faster they walk at self-selected speed. Contrary to temporal analysis, the influence of both motor and cognitive dual task is visible in spatial analysis with a decrease of speed with task complexity. Interestingly, we can see that PD subject in ON state and CP child with moderate symptoms have comparable walking speed than 65+ elderly subjects. The comparison of 65+ and 71+ elderly subjects groups shows that the influence of 5 years of aging is equivalent to adding a motor task, with comparable speed between 71+ ST and 65+ DTm group.

The results obtained in fig. 12 also allow observing the various factors that lead to speed changes through the other gait parameters. The most remarkable ones are the diminished Load foot pitch angle (i.e. heel-strike) in neurologic populations (CP and PD).

3.2.3 Clearance Analysis

The measurement of shoe size, and thus the clearance analysis, was only done on 16-, 25-39, 65+ and 71+ groups of subjects. Results of the three main clearance parameters, namely maximal heel and toe clearance, and minimal toe clearance, are shown in fig. 13 for the different age groups.

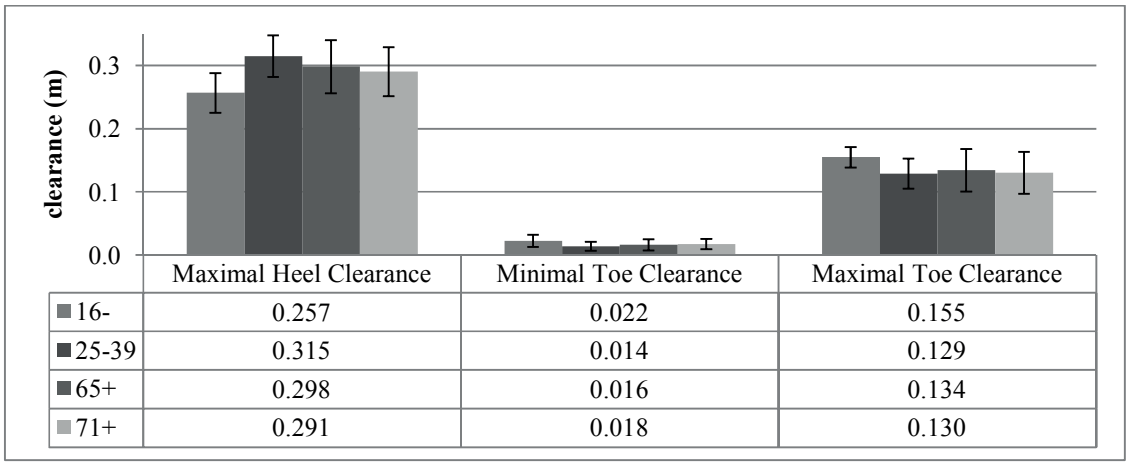


Figure 13 – Mean+/- STD of Foot Clearance parameters comparison with age groups

Assuming a reference foot clearance pattern with 25-39 years old group, we can see that children have a lower maximal heel clearance, which can be easily explained by their lower height. In addition, children show a higher minimal and maximal toe-clearance, which can be interpreted as a non-mature control of clearance during gait, contrary to adults 25-39. On the other side, elderly subjects show a tendency to decrease maximal heel clearance and increase minimal toe clearance. A decrease in maximal heel clearance can be interpreted as a lack of force for lifting the foot, notably due to a decrease in knee or hip muscles power, which is even more noticeable in older group 71+. The increase of minimal toe clearance in 65+ and even more in 71+ subjects can be interpreted as a safety strategy used to avoid tripping.

In order to refine the analysis of foot clearance in elderly, and to investigate it as a risk factor for falls or indicator of frailty, comparative analysis between single and dual-task conditions were done (fig. 14).

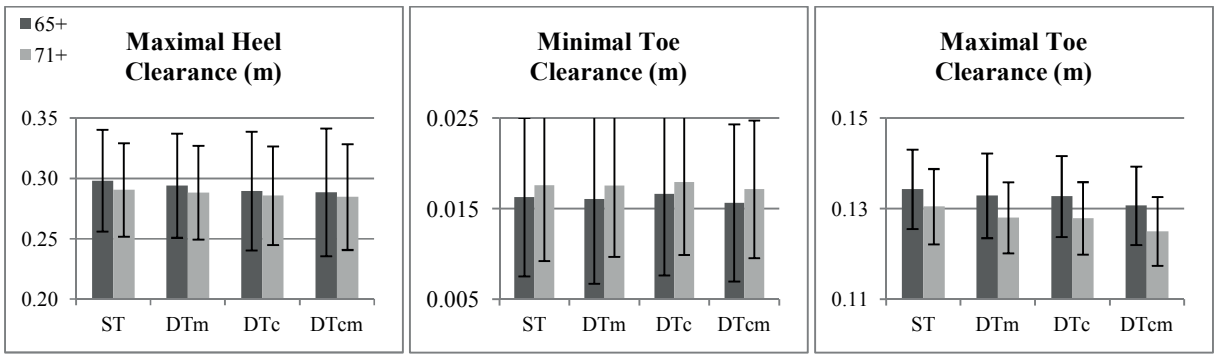


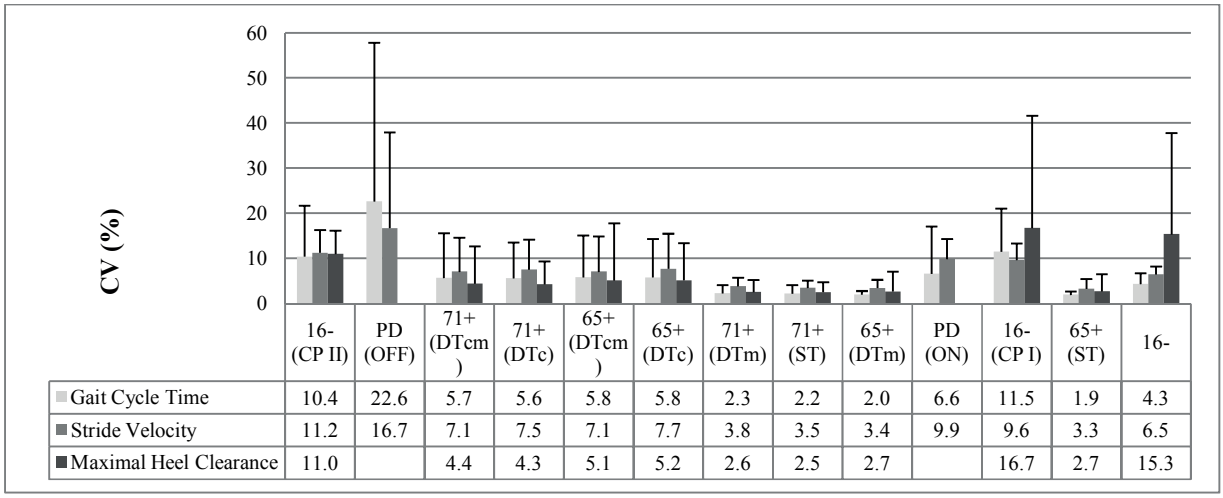
Figure 14 - Comparison of mean+/-std of foot clearance parameters during 20m gait tests in elderly subjects 65+ and 71+ under single and dual-task condition

Results shows that the differences between 65+ and 71+ group of subjects are not dependent of dual-task complexity, with always reduced maximal heel and toe clearance and increase minimal toe clearance in

older subjects. Low fluctuations can be observed on foot clearance among the different conditions, but we can observe a reduction of maximal heel and toe clearance with task complexity. For minimal toe clearance, there is a slight tendency for an increase in DTc and decrease in DTcm, compared to ST.

3.2.4 Variability Analysis

Gait variability expresses the stride-to-stride fluctuations in walking. It was quantified by standard statistics based on mean and standard deviation of gait parameters, through the coefficient of variations expressed by the ratio between the STD of parameter and its mean. Results of variability analysis for one typical parameter in each category (Temporal, Spatial, and Clearance) are given in fig. 15.



	16- (CP II)	PD (OFF)	71+ (DTcm)	71+ (DTc)	65+ (DTcm)	65+ (DTc)	71+ (DTm)	71+ (ST)	65+ (DTm)	PD (ON)	16- (CP I)	65+ (ST)	16-
Gait Cycle Time	10.4	22.6	5.7	5.6	5.8	5.8	2.3	2.2	2.0	6.6	11.5	1.9	4.3
Stride Velocity	11.2	16.7	7.1	7.5	7.1	7.7	3.8	3.5	3.4	9.9	9.6	3.3	6.5
Maximal Heel Clearance	11.0		4.4	4.3	5.1	5.2	2.6	2.5	2.7		16.7	2.7	15.3

Figure 15 - Coefficient of variations (CV) of main temporal (Gait cycle time), spatial (Stride velocity), and clearance (Maximal heel clearance) parameters among the different groups of subjects ordered by walking speed))

Results show strong changes of gait variability parameters in our different group of subjects, increasing together with severity of motor symptoms of mobility diseases. In particular, variability is strongly increased in PD OFF and CP groups, and associated with a cognitive dual task in elderly. It is particularly interesting to observe that PD ON group has much higher gait variability than other elderly subjects groups, whereas the average value of gait parameters such as walking speed and stride length were comparable between those groups. That confirms gait variability parameters provide additional discriminative information to the common average parameters.

3.2.5 Gait parameters distribution among older adults

This section presents the distributions of the various gait parameters extracted from foot signature of older persons.

The shape of a probability distribution allows finding an appropriate distribution to model the statistical properties of a population. The shape of the distribution can be from different kinds, the most common being the normal (or gaussian) function. For testing the normality of the distribution of all gait parameters obtained on our sample of elderly subjects, we performed the Jarque-Bera goodness-of-fit test of composite normality. That tests whether the data comes from an unspecified normal distribution. Results yielded that all that the null hypothesis ("the data are normally distributed") cannot be rejected at the 5% significance level, so all distribution of gait parameters obtained with foot worn sensors on foot signature were close to normal.

Histograms of the most common (gait cycle time and stride velocity) and original (foot-flat ratio and foot clearance) parameters distribution are provided in fig. 16 using 50 classes.

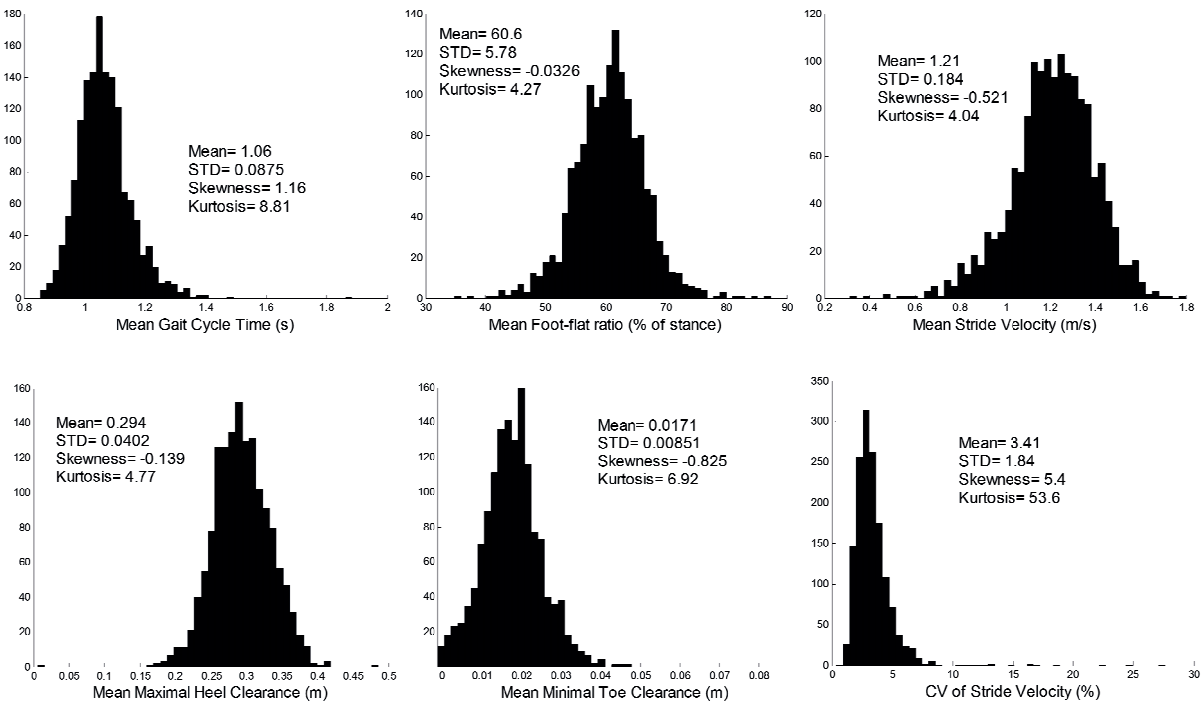


Figure 16 - Gait parameters distribution and shape statistics among a representative sample of 1490 elderly subjects

None of the observed parameters shows a strong asymmetry around mean except the CV of stride velocity with a skewness of 5.4. Such a positive skew indicates that the tail on right side (upper values) is longer than the left side (lower values) and the bulk of the values lie to the left of the mean. Regarding kurtosis, all the parameters shows a strong peakedness with values above 3, i.e. the value of Laplace distribution, also known as the double exponential distribution. That means a more acute peak at the mean than normal distribution, and that is especially the case for CV of stride velocity, and least the case for mean stride velocity.

3.2.6 Association of gait parameters with walking speed in older adults

Table IV provides the correlation coefficients of the various gait parameters extracted from foot signature of elderly subjects with walking speed.

TABLE IV - CORRELATION COEFFICIENTS OF MEAN AND VARIABILITY OF GAIT PARAMETERS EXTRACTED FROM FOOT SIGNATURE AGAINST MEAN WALKING SPEED. CORRELATION WITH ABSOLUTE VALUES OF R>0.5 ARE HIGHLIGHTED IN GREY, AS WELL AS SIGNIFICANT CORRELATIONS FOR P-VALUES < 0.001.

Statistics		Parameter	*R*	*p-value*
Mean	Temporal	Gait Cycle Time	-0.59	0.000
		Swing	0.49	0.000
		Stance	-0.49	0.000
		Cadence	0.57	0.000
		Load	0.49	0.000
		Foot-flat	-0.68	0.000
		Push	0.56	0.000
		total Double support	-0.52	0.000
	Spatial	Walking speed	1.00	0.000
		Stride Length	0.86	0.000
		Swing Width	-0.21	0.000
		3D Path Length	-0.13	0.000
		Peak Swing Angular Velocity	0.42	0.000
		Foot Pitch angle at Toe-off	-0.57	0.000
		Foot pitch angle at heel-strike	0.54	0.000
	Clearance	Maximal Heel Clearance	0.41	0.000
		Minimal Toe Clearance	-0.15	0.000
		1st Maximal Toe Clearance	0.07	0.009
		2nd Maximal Toe Clearance	0.48	0.000
		Toe Clearance Area	0.24	0.000
		Heel Clearance Area	0.22	0.000
		Foot velocity at Minimal Toe Clearance	0.95	0.000
Variability	Temporal	Gait Cycle Time	-0.16	0.000
		Swing	-0.33	0.000
		Stance	-0.26	0.000
		Cadence	-0.26	0.000
		Load	-0.18	0.000
		Foot-flat	0.18	0.000
		Push	-0.15	0.000
		total Double support	-0.03	0.205
	Spatial	Walking speed	-0.33	0.000
		Stride Length	-0.25	0.000
		Swing Width	-0.08	0.002
		3D Path Length	-0.12	0.000
		Peak Swing Angular Velocity	-0.22	0.000
		Foot Pitch angle at Toe-off	0.33	0.000
		Foot pitch angle at heel-strike	-0.44	0.000
	Clearance	Maximal Heel Clearance	-0.29	0.000
		Minimal Toe Clearance	0.17	0.000
		1st Maximal Toe Clearance	0.04	0.123
		2nd Maximal Toe Clearance	-0.31	0.000
		Toe Clearance Area	-0.01	0.577
		Heel Clearance Area	-0.12	0.000
		Foot velocity at Minimal Toe Clearance	-0.31	0.000

Most of the parameters shows significant correlations with speed except for those which correlation coefficient are close to 0. However, a low correlation with speed should not be interpreted as irrelevance of the parameter since it could express other gait features less influenced by speed. Considering an absolute threshold of R=0.4, we can see that parameters which are positively associated with speed are: *Swing ratio, Cadence, Load and Push ratios, Stride Length, Peak Swing Angular Velocity, Heel-strike pitch angle, Maximal Heel and Toe clearance and speed at minimal toe-clearance*. With the same threshold, the parameters which are negatively associated with speed are *Gait Cycle time, Stance ratio, foot-flat ratio, total double-support, Toe-off pitch angle, and heel-strike pitch angle CV*.

Interestingly, most of the other parameters, and especially all variability parameters as well as swing width, path length and minimal toe clearance, show little association with walking speed. We could then assume that they contain additional information for describing the gait characteristics. Finally, for the parameters that showed the stronger association with walking speed (R>0.5), linear and cubic regression were done in order to provide a model for the estimation of those parameters from the simple measure of walking speed in elderly subjects (fig A.11 in annexes).

3.3 Foot Signature Map

In previous sections, gait parameters extracted from foot signature have been compared between the various groups of subjects. Although such results provide an interesting and interpretable insight of gait performance, it is difficult to synthesize the information given by all the various parameters. So, a similar approach to recognition of locomotion activity is applied, in order to discriminate subjects groups based on a reduced and transformed set of features, using normalized features and principal components (fig. 2).

Since the sample size of recorded measurements varies from one group to another, a fixed number of 50 samples in each group were generated randomly from the mean and STD of each parameters, assuming normal distribution within the group. All features were then normalized and transformed using PCA.

By comparing the first two principal components in all groups of subjects whose foot signatures have been measured, we can establish a 2D diagram that shows differences between subjects groups, and which constitutes *the foot signature map.* This is illustrated in fig. 17 with a subset of groups 71+, PD subjects ON and children with or without CP, together with a cluster analysis performed using Gaussian Mixture models [14].

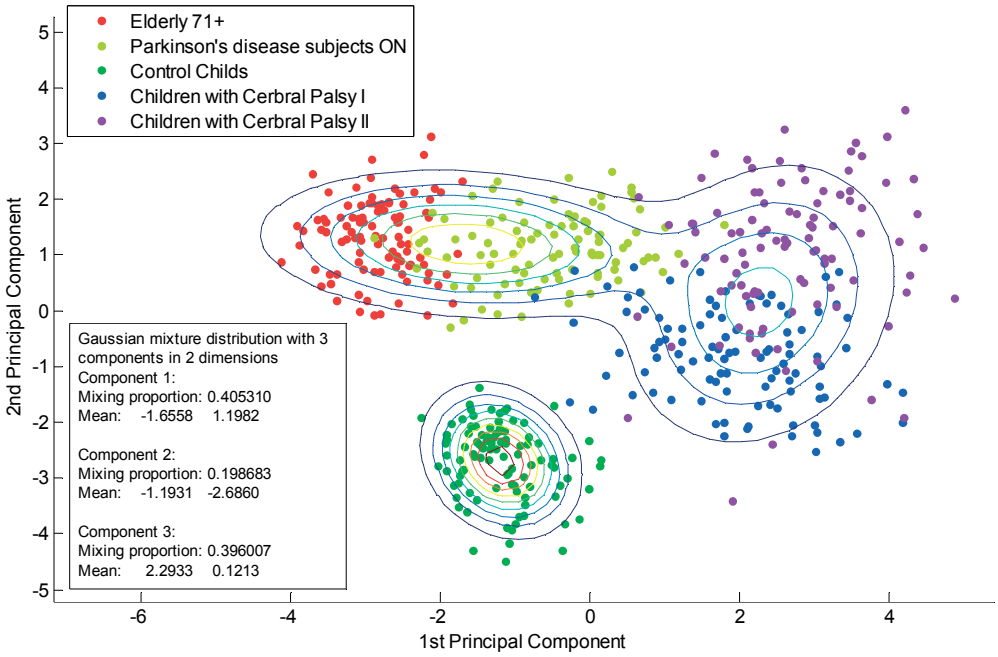


Figure 17 - Cluster analysis of 2D foot signature map using gaussian mixture model

Results show that three main clusters can be identified in the 2D foot signature map, one corresponding to control children, one to children with cerebral palsy, and one with Elderly subjects and PD subjects with ON medication. Interestingly, 71+ and PD ON subjects appeared in the same statistical cluster, but foot signature map allows to discriminate those group based on the 1st principal component axis.

Principal components analysis results show that contrary to walking activity classification, the first two principal components used to establish the foot signature map, only explain 25% of the variance of the dataset from foot signature of various mobility disease (fig. 18). Results show that 22 PC are needed to explain more than 90% of the variance.

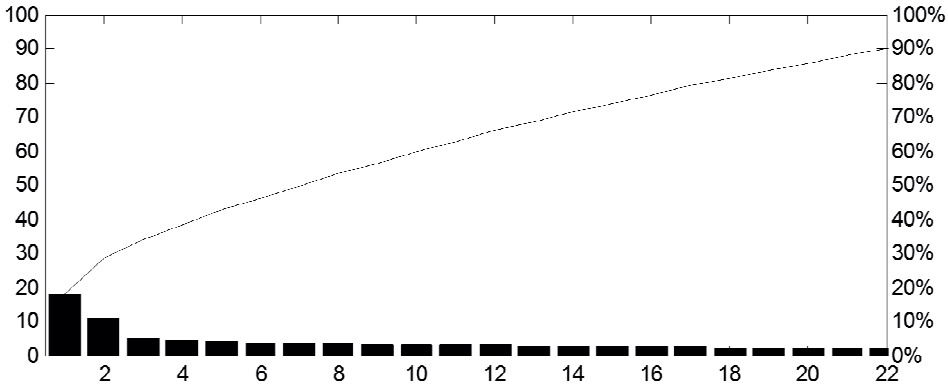


Figure 18 - Variance explained versus number of principal components of gait parameters among PD, 16-, CP, 65+ and 71+ groups of subjects

3.4 Discussion

We performed measurements using foot-worn inertial sensors during clinical trials obtained in free walking condition at self-selected speed, and including elderly subjects, people with Parkinson's disease and children with or without cerebral palsy. The application of the previously designed and validated algorithm from chapters 3 to 6, provided strong insight into the gait characteristics of those populations, by describing the statistical distribution of common parameters such as gait cycle time or walking speed, and also new parameters such as foot clearance, inner-stance phases and inter-cycle variability. To our knowledge, this is the first study including such amount of spatio-temporal gait parameters obtained with body worn sensors in more than 1800 subjects in free walking conditions.

As an opportunity for future investigations, we could subdivide the population group, and particularly the elderly group which has a large sample size, based on background data such as age or clinical score such as fear-of-falling and number of falls, to study their relationships with gait parameters, and notably foot clearance as in recent studies by [15]. That was not possible at the time of this thesis work since that data is being processed by our clinical collaborators, but it represents an interesting field of further research. In addition, the normalization of gait parameters to gender and/or height could provide a comparison of subjects groups which is independent of anthropometric data, as it was done in other recent studies [16]. The counterpart of such normalization is that results then become difficult to interpret with non-self-explanatory units.

The analysis of gait parameters association with walking speed demonstrated that the various original parameters which were introduced in this thesis provided additional information to what is commonly being measure with inertial sensors. Results obtained in our sample of subjects for self-selected walking speed were congruent to what is commonly reported in PD [17], CP [18], and adults and elderly subjects [19]. On the other hand, our statistical results including distributions and regression models can be used as reference gait data for other applications such as robotics or simulation.

The foot signature map obtained from 2 principal components of normalized features has shown interesting capabilities for separating populations, and can be used as an intuitive visual tool for clinical gait comparison. However, to really describe foot signatures variance among mobility diseases, we have seen that more principal components should be taken into account. Yet, few other limitations are still important to consider before its application to clinics:

- The validity of foot signature map relies on the amount of collected data used to establish the principal components coefficients. In our case, although there is a solid amount of data in elderly group, it was not the case in other pathologic groups. More measurements are needed to get

reference data in those remaining group of subjects and in other potentially interesting pathologic groups

- The direct interpretation of the axis of the foot signature map is not possible since they are constituted of linear combinations of gait parameters. That pitfall is of course common for all summary measure or scores established on different items.

4 Conclusion

The novel concept of foot signature, defined by the 3D foot trajectory during one gait cycle, has been introduced in this chapter. A general methodology for foot signature analysis was proposed based on the extraction of features, their normalization and the computation of principal components. We believe that the foot signature measured using foot-worn inertial sensors, and its subsequent features and principal components, have an interesting potential as a simple yet powerful gait assessment tool with true clinical significance and interpretability. It combines all the methods and finding of the previous chapter into a single unified concept. Its application to the real-time recognition of activity has shown excellent performances with correct classification rates of 89.6% using expert tree algorithm. Its application to discriminate mobility disease has provided reference gait data and statistical comparison among various groups of subjects. For a new subject, foot signature analysis procedure can be fully automatized, and clinician can therefore observe foot signature, compare it with reference data provided in this thesis, and see on foot signature map to which cluster the subject better fits in. That provides him an easy and fast gait assessment tool to support his clinical diagnosis, for instance following a medication treatment or rehabilitation intervention.

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Chapter 9

Conclusion

1 General results and main contributions

The research presented in this thesis consists in a multidisciplinary work involving electronics, signal processing and drift modeling, biomechanics and movement science, human experimental protocols, data analysis and statistics, and finally machine learning. By considering existing technology of inertial sensors, this thesis focused on gait analysis. Based on embedded wireless and wearable units worn on the foot, we propose a practical tool which is easy to use in clinics. The general result of this dissertation can be summarized as:

- *The design, technical validation, and clinical application of algorithmic methods for measuring objectively and quantifying foot signature with wearable sensors.* Foot signature was defined by analogy to hand-written signature by the 3D foot trajectory during one gait cycle. It was quantified and analyzed by extracting relevant gait parameters in subjects who suffer from various mobility diseases.

The main contributions of this work can be summarized as:

1. *The estimation of 3D foot kinematics from foot-worn inertial sensors, and its technical validation against optical motion capture reference*. The method is based on online calibration and alignment, detection of gait cycles and motionless periods, quaternion-based strap-down integration of inertial signal, and drift modeling. It provides automatic estimation of 3D foot orientation, velocities and trajectory patterns during unconstrained walking without the need for specific positioning of foot sensors. It was validated in terms of accuracy, precision, agreement and repeatability against reference system in children with cerebral palsy, people with Parkinson's disease ON and OFF medication, elderly persons, and healthy control subjects.

2. *The detection of main temporal events of gait using foot-worn inertial signals, and its validation against force measurements with pressure insoles*. The method is based on the detection of various characteristics of inertial signals and their derivate, such as peaks and flat regions. Results shows the most precise and accurate characteristics for detecting gait events of heel-strike, toe-strike, heel-off and toe-off, and provide objective quantification of subsequent gait phases, including swing, stance and inner-stance phases (load, foot-flat, push). It was validated during long-distance walking in control subjects and patients with osteoarthritis and ankle treatments.

3. *The extraction of common and original spatio-temporal parameters of gait from 3D foot kinematics estimated from foot-worn inertial sensors, its technical validation against optical motion capture, and its clinical validation against clinical scores and subjects' status*. The method is based on the fusion of temporal detection of gait events and the estimation of 3D foot kinematics, the modeling of sensor position on the foot, and the quantification of relevant metrics describing gait abnormalities. Spatio-temporal parameters provided include a precise and accurate estimation of common parameters such as stride velocity and stride length, with the advantage of being robust to turning condition or gait abnormality. Moreover, it provides new and original quantification of *circumduction* through parameters such as 3D path length and swing width, *turning* through turning angle, and *clearance* through parameters such as minimal and maximal toe and heel clearance. That allows estimating clinically relevant gait parameters and their inter-cycle variability during walking tests such as "6 minutes walking test" or "timed up and go test". It was successfully validated against reference and showed face validity against clinical diagnosis to compare children with cerebral palsy and people with Parkinson's disease against age-matched control subjects, and to compare healthy adults and elderly persons.

4. *The implementation of instrumented prosthesis system and algorithm to extract gait features in real-time during amputee locomotion*. The method is based on the fusion of force and inertial signals into a state-machine for walking phase detection and the real-time implementation of a 2D kinematic estimation algorithm. That provides a real-time estimation of various gait features such as vertical and frontal displacement or ankle torque during unconstrained locomotion of amputee subjects, and was successfully tested with a high robustness during activities including level walking, slope and stairs ascent and descent.

5. *The definition of foot signature concept and its quantification using parameters obtained from foot-worn sensors, applied to the recognition of locomotion activity of amputee subjects.* The method is based on both machine learning techniques and expert rule-based decision tree to classify activities from real-time extracted gait features obtained using instrumented prosthesis. The real-time expert classification provided is one of the first reported methods able to recognize locomotion activity after a single stride with performances up to 89.6% of correct classification. Furthermore, it presents the advantage of being adjustable and interpretable, contrary to "black box" systems such as neural networks. It could be further implemented into an active prosthetic device.

6. *The application of foot signature measurement and its quantification using parameters to provide reference gait data and discriminate various mobility diseases*. The method is based on statistical comparison, analysis of distributions, and principal components analysis of gait parameters measured by foot-worn sensors on a population of more than 1800 subjects, including children with and without cerebral palsy, adults, elderly persons and people with Parkinson's disease. The comparison of 1800 subjects with various mobility disease which is proposed is unique in the field, and provides a strong insight and reference data for common and original gait parameters, their variability, as well as their inter-dependant relationship and association with speed.

2 Improvement of algorithm performances

The potential limitations and possible improvements of methods presented in this dissertation have been discussed in respective chapters. Nevertheless, some general recommendation for further improvement can be formulated. One of the critical point which was identified as having a direct impact on the performance is the inertial sensor calibration. Indeed, since foot kinematics estimation relies on the integration of both gyroscopes and accelerometers signals, it is prone to error due to small deviation of the gain and offset of those sensors. Indeed, those errors can be corrected with specific hypothesis, such as the offset being null during static position, or zero-velocity update, but still it remains impossible to correct all sources of error including electronic noise and non-linear effects. Solution could come from better drift models, or with new sensors with better signal-to-noise ratios. Another important source of errors in each validation phase is how the reference itself is used. In fact, comparing 3D orientation or displacement measured by optical motion capture and foot-worn sensors rely on the knowledge of the relative position and orientation of markers to sensor module. That is a source of overestimation of differences between the two systems since they do not measure exactly the motion of the same points.

3 Sensor development and use of other technologies

Industry and manufacturing progress might continue reducing the size, weight and power consumption of MEMS sensors in the upcoming years, thus leading to miniaturized sensor units with equivalent, if not better, measurement specifications. That opens the doors to the integration of foot worn sensors into foot-wear such as shoe or socks. In addition, the use of wireless communication technology could improve the practical usage of sensors by streaming directly the data measured on the patient to the doctor's computer or hospital database. In fact with the automatic methods proposed in this thesis, data transfer remains the only step requiring manipulation in the process between the measurement on the subject level, and the outcome result at the clinician level. That raises the issue of data security though.

This work has shown that we were able to provide a good assessment tool for gait analysis from foot-worn inertial sensors. However, inertial sensors have limited performances for providing relative distances and orientations on a long-term basis due to drift, which justify the use of additional sensors on the shoe. Magnetic sensors have been extensively studied but suffer from being sensitive to environment, and strongly perturbed by any metallic material nearby, thus making impossible to apply them in daily activity or clinical environment. Yet, other technologies could be used such as Ultrasonic (US) and infrared (IR) telemetry. For example, we proposed recently, a novel method for ambulatory gait assessment using a micro-infrared camera based on Wiimote technology and IR LED-tracking, and its fusion with inertial sensor for estimating step parameters [1]. That study laid the first groundwork for ambulatory estimating relative step parameters during walking based on the fusion of portable IR-LED tracking with inertial sensors, and has a good opportunity for complementing inertial sensor technology in other applications for posture and gait research, since it could be adapted to other limbs.

4 Extension to other types of human locomotion

The present thesis focused on forward gait on level ground, turns, as well as incline and stair walking. Although being the most common and studied aspects of human locomotion, daily activity actually encapsulate other locomotion modalities such as running, side and backward walking.

Backwards walking (BW) is more challenging than natural forward walking (FW). BW test may reveal balance disorders, due to diminished visual feedback and modified motor scheme. Past studies showed changes in temporal parameters between FW and BW [2], and investigated age-related decrease in spatial parameters [3]. However, they investigated only a small number of subjects and used laboratory devices. We proposed recently, the use of foot-worn sensors to provide spatio-temporal parameters during a 5m BW test by adapting the methods presented in the present thesis [4]. In particular, changes between FW

and BW (i.e. the cost of BW) discriminated better young and elderly subjects groups than single FW test. Further studies with a higher number of subjects are needed to confirm these interesting findings.

The extension of the present method to running gait has been also investigated in the study of people with hip resurfacing [5]. In fact in patients with hip resurfacing, whether or not regular sporting activity should be limited or even prohibited because of the risk of implant loosening has been discussed early in the 80s by [6] and is still discussed nowadays [7]. Being independent of type of motion, the strapdown integration algorithm was directly adapted to running. However, temporal detection of gait event was redesign since foot-strikes during running were different than during walking. Particularly, whether an acceptable motionless condition during running stance is met for updating drift model should be further investigated to validate the method and potentially identify pathologic and healthy running patterns in the future.

5 Clinical perspectives

Some clinical application of foot-worn sensors and dedicated algorithm for foot signature estimation and quantification have been already presented in this thesis, such as the characterization of gait parameters in elderly and the relationship with walking speed. Yet, several other clinical applications of the present work can be foreseen, as well as the application of those methods to other populations with gait abnormalities.

First, the use of real-time walking detection can be used as a tool to trigger active rehabilitation device or real-time feedback systems. In fact, a simplified version of the presented algorithm for real-time walking phase detection only based on a single gyroscope has been successfully used to trigger actuators of a shoe providing chaotic perturbation to elderly subjects [8]. The method was successfully used in more than 90 elderly subjects trained during 4 weeks (twice a week) by this instrumented shoe. Preliminary results show some decline in fearful subjects with the instrumented shoe while confident subjects improve. While results about the specific effect of the shoe should be interpreted cautiously, it is likely that this training shoe should target specific population of elderly.

Second, although the interplay between new parameters such as swing width and foot clearance and classic parameters such as gait speed has been investigated in this study, several major gaps remain in our knowledge about the clinical significance of those parameters. For instance, the association between foot clearance while walking over ground and prospective falls has not yet been evaluated in a large sample of older people. Similarly, the relationship between foot clearance and fear of falling, a prevalent factor associated with gait performance and falls in older people, has never been evaluated previously. Finally, we have found that the effect of dual tasking didn’t induce significant changes of foot clearance in elderly

subjects. Nevertheless, investigating more deeply the extent to which dual-tasking conditions could affect foot clearance in certain subgroup such as fallers will certainly extend our knowledge about mechanisms linking dual-tasking and an increased risk of falling in older people.

Finally, the system and methods presented in this thesis could be further used as a practical tool for routine clinical gait assessment and have a strong impact by providing a simple yet powerful tool for objective and quantitative gait assessment. For instance, foot signature parameters obtained in CP child can provide information about the effect of Botox injection interventions. Moreover, clinician could be interested in the evolution of foot signature and related parameters pre/post orthopedic surgery or any rehabilitation intervention. Since our methods have been validated and provide outcome measures automatically, the next step toward a large scale clinical application of this research is a commercially available product with data management solution and clear user interface.

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[6] L. Dubs, N. Gschwend, and U. Munzinger, "Sport after total hip arthroplasty.," *Archives of orthopaedic and traumatic surgery. Archiv für orthopädische und Unfall-Chirurgie*, vol. 101, no. 3, pp. 161-9, Jan. 1983.

[7] N. Fouilleron, G. Wavreille, N. Endjah, and J. Girard, "Running activity after hip resurfacing arthroplasty: a prospective study.," *The American journal of sports medicine*, vol. 40, no. 4, pp. 889-94, Apr. 2012.

[8] K. Aminian et al., "Foot worn inertial sensors for gait assessment and rehabilitation based on motorized shoes," in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, 2011, pp. 5820-5823.

Annexes

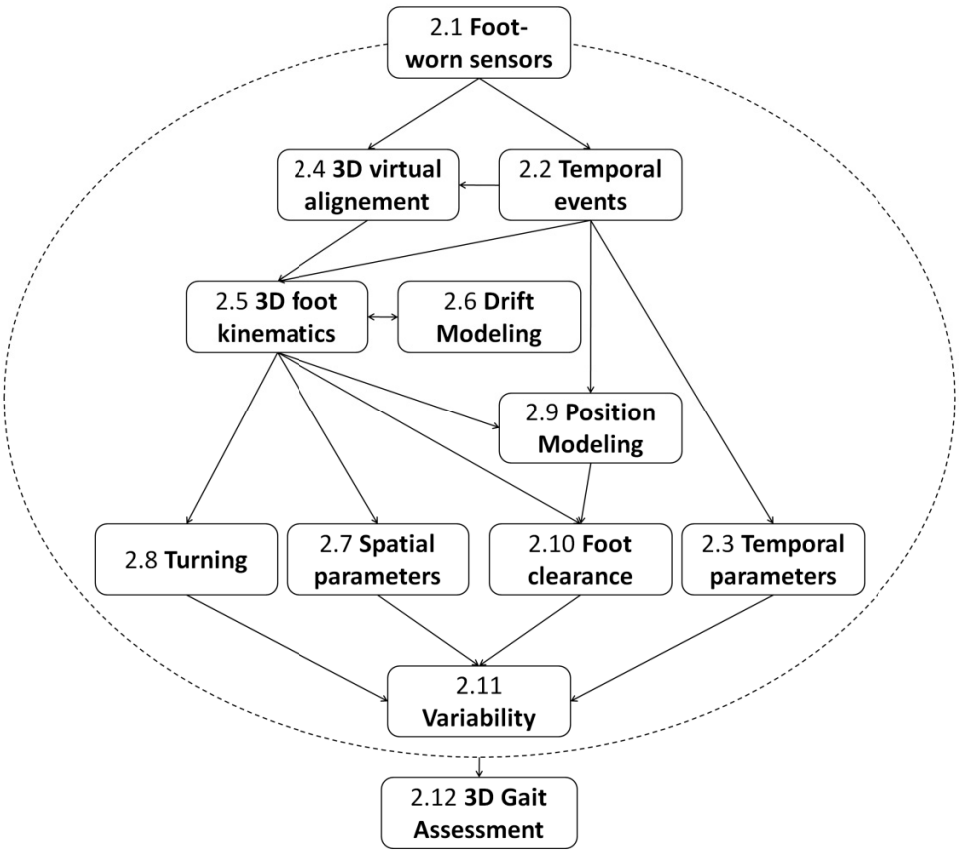


Figure A.1 - Block Diagram of system and methods for 3D gait assessment using foot-worn sensors. ***Patent WO2012007855 submitted by EPFL, 2012***

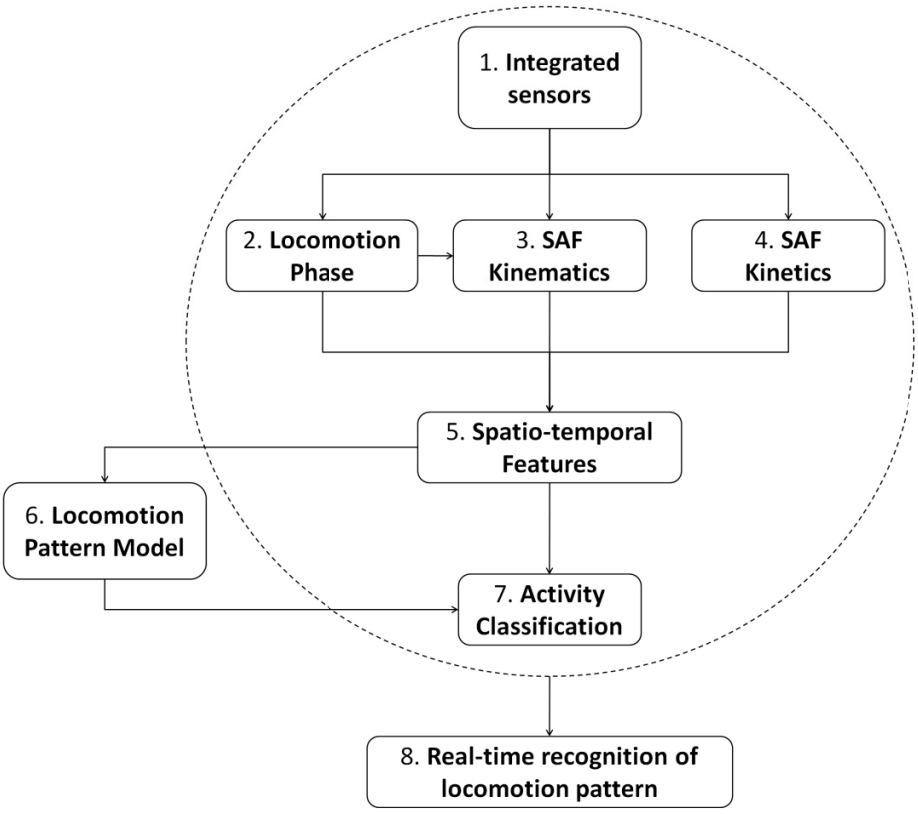


Figure A.2 – Block Diagram of system and methods for real-time recognition of locomotion activity using instrumented prosthesis. ***Enveloppe Soleau submitted by PROTEOR, 2011.***

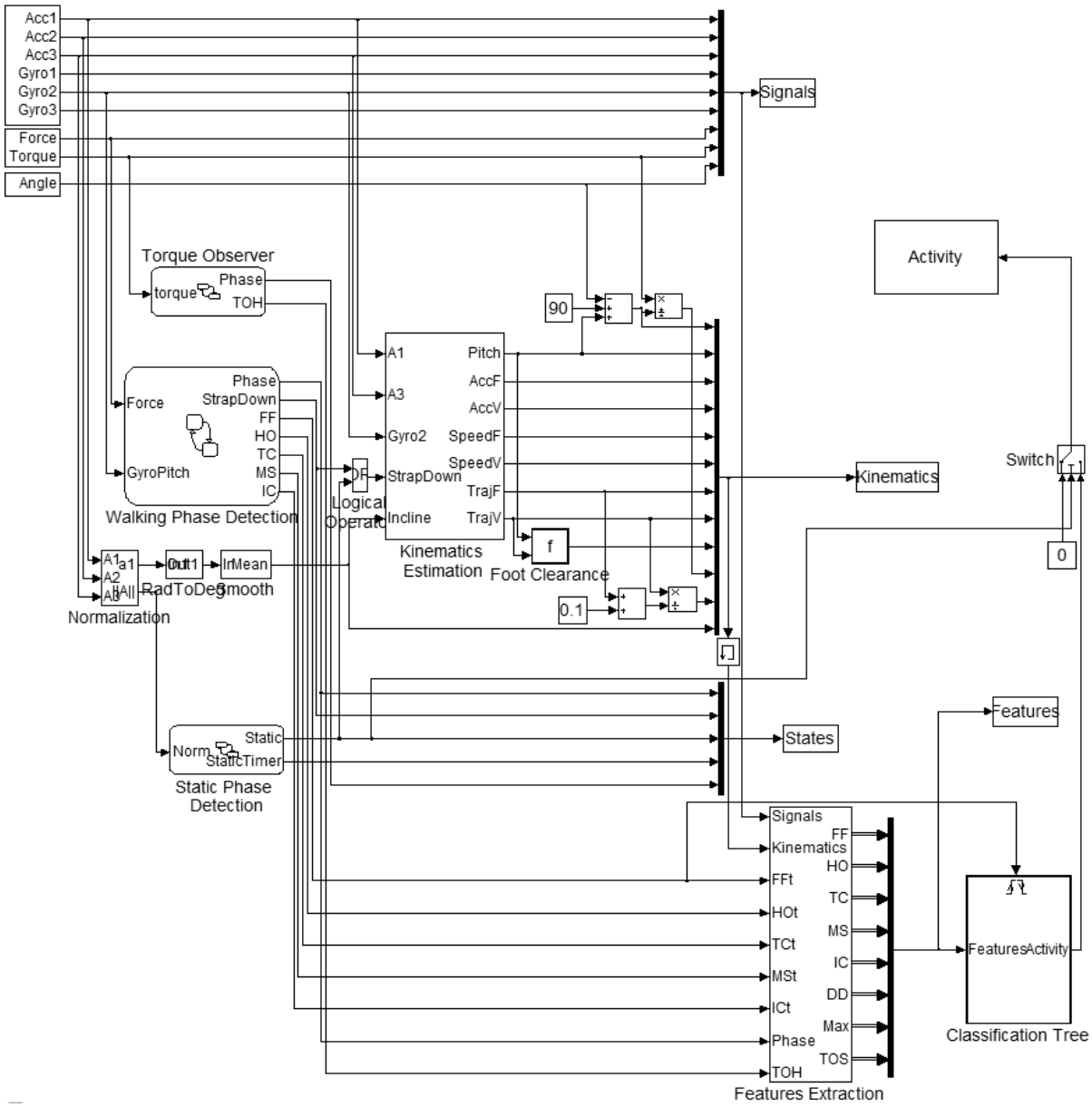


Figure A.3 SIMULINK model for real-time features extraction and classification of activity based on instrumented prosthesis

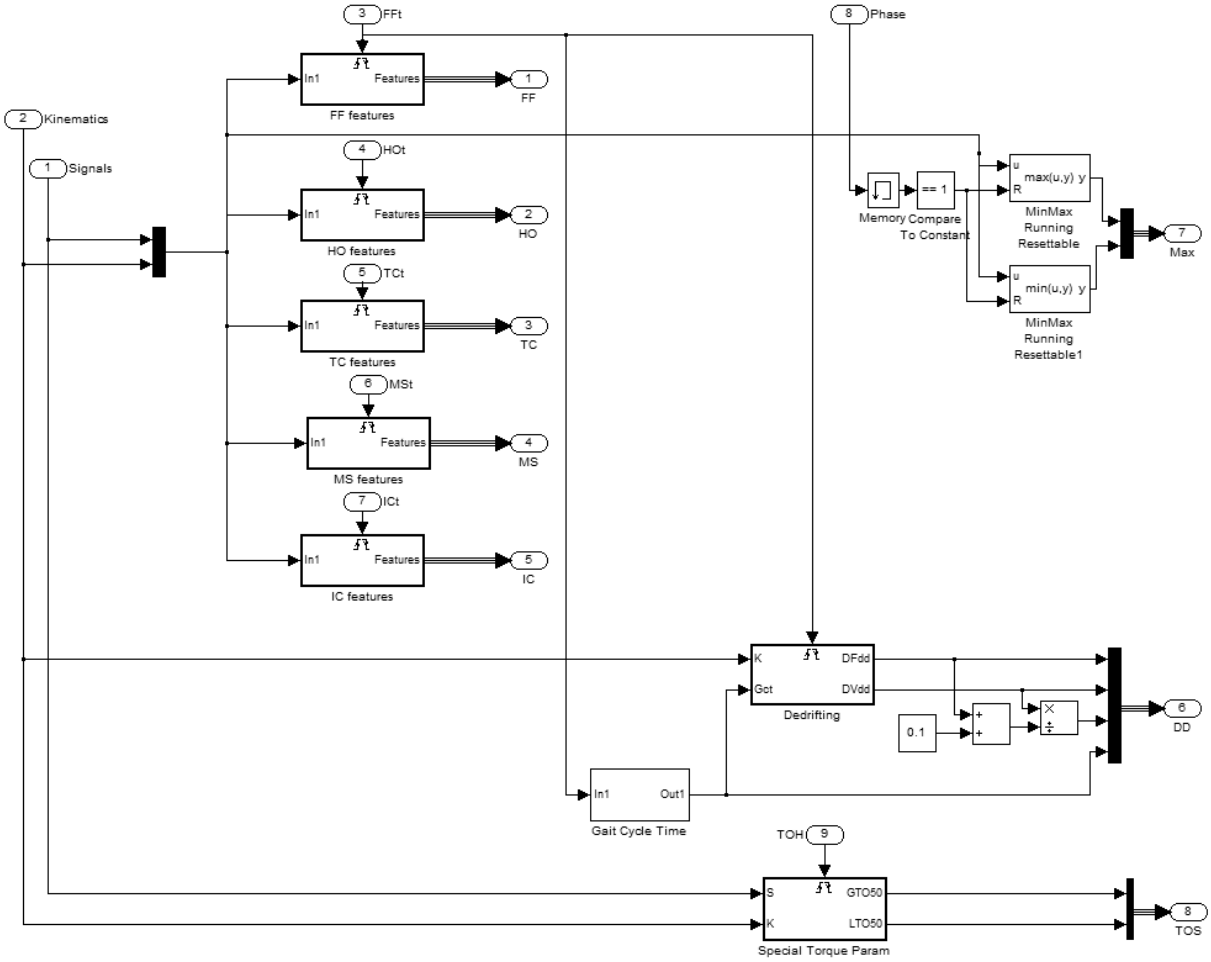


Figure A.4 – Real-time features extraction SIMULINK block from model of fig. A.3

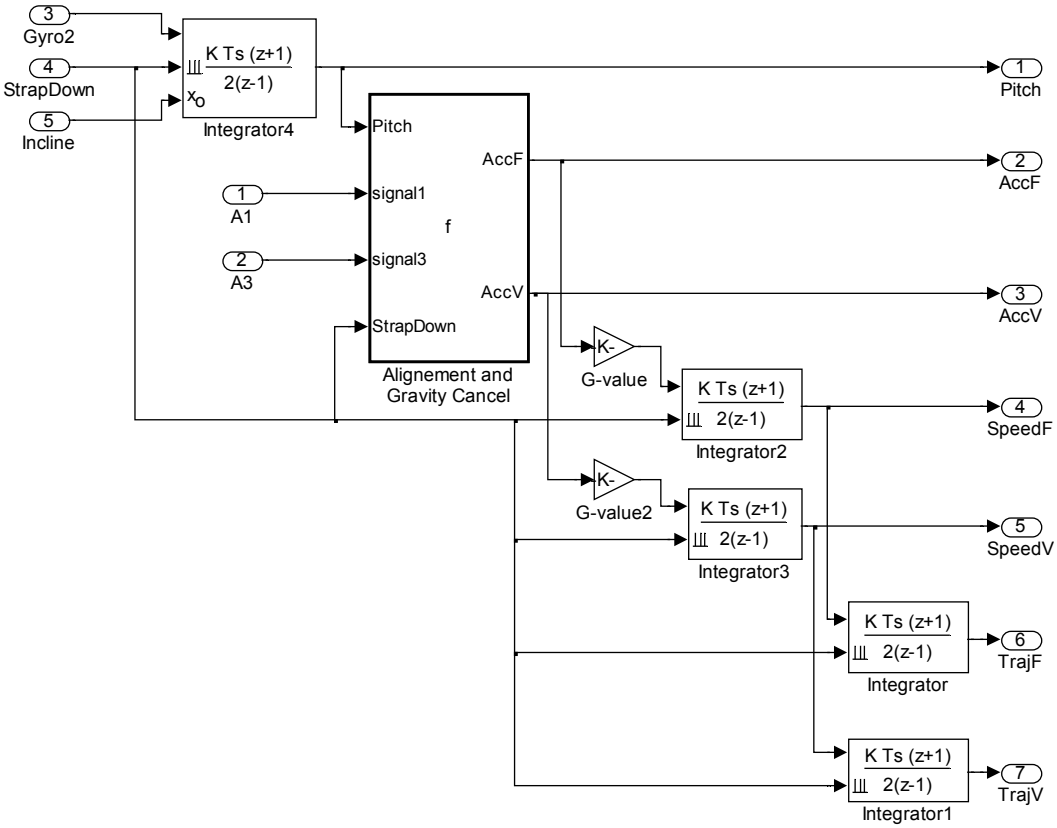
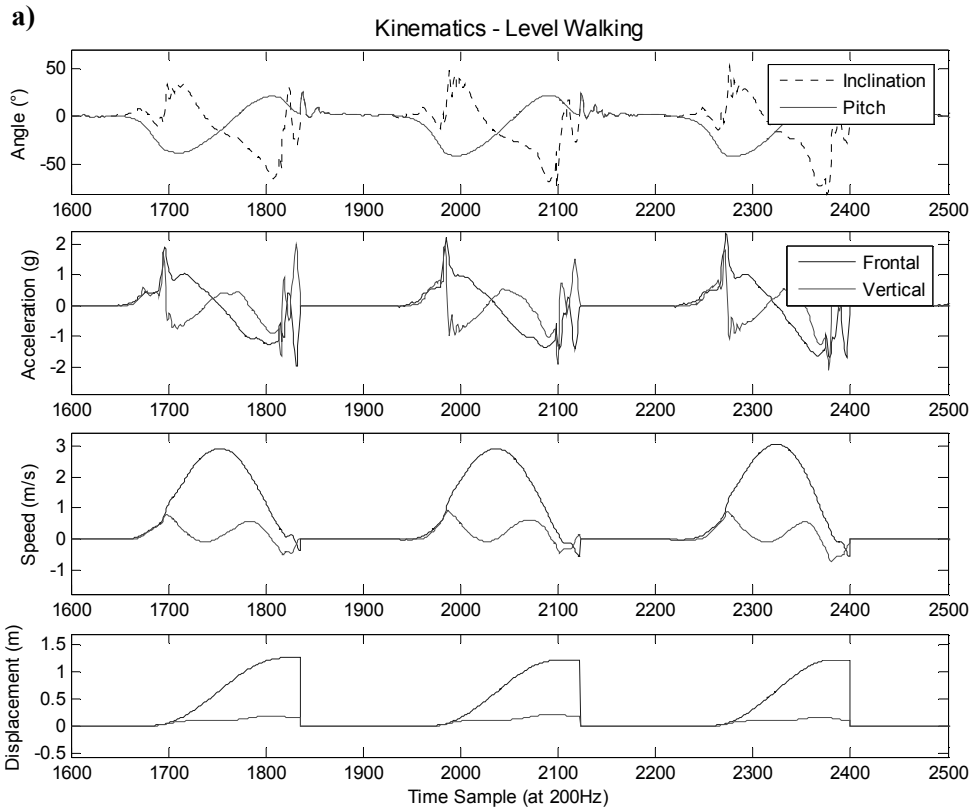
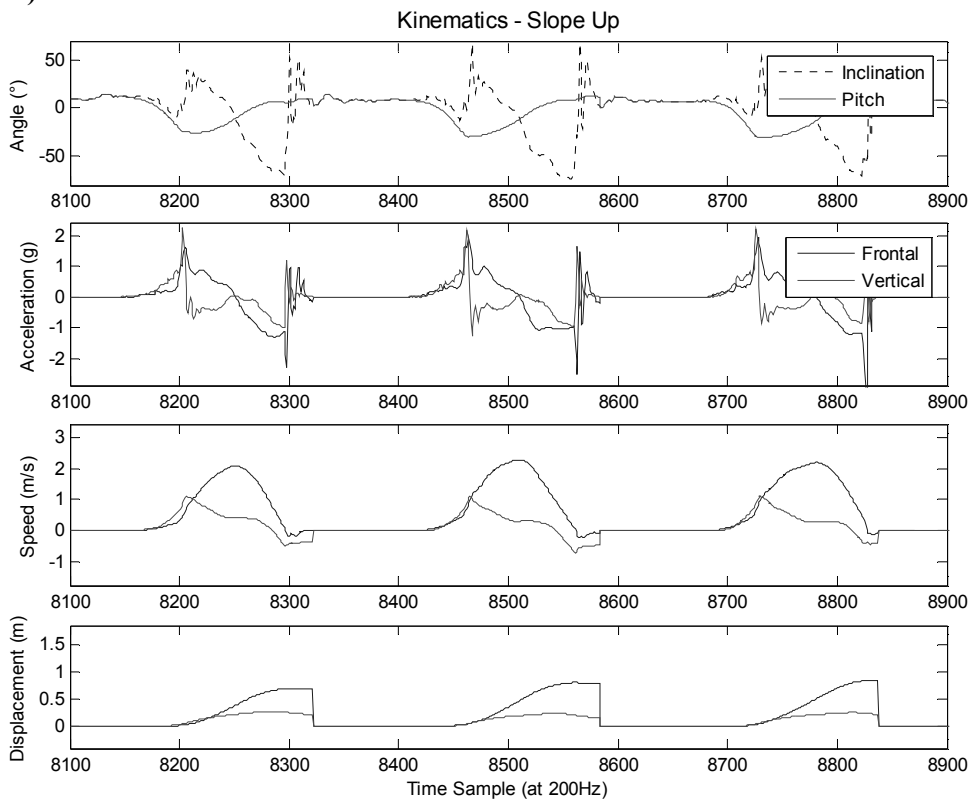


Figure A.5 – Real-time 2D kinematics estimation SIMULINK block from model of fig. A.3

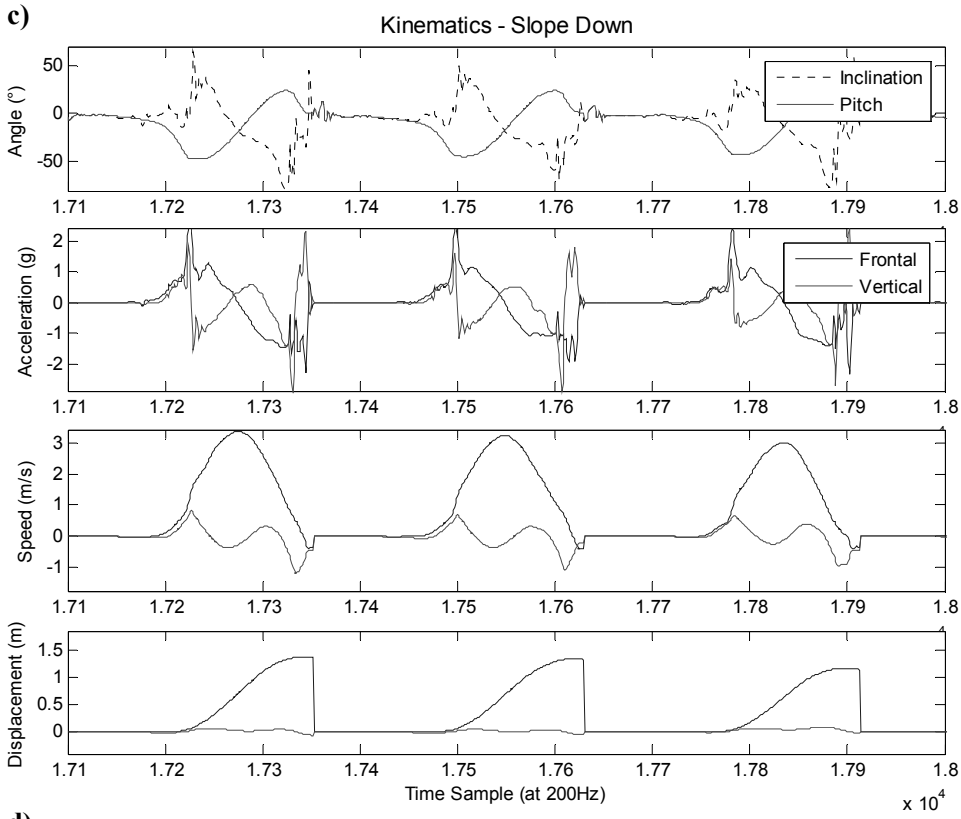
a)


Kinematics - Level Walking
Angle (°)
Inclination
Pitch
Acceleration (g)
Frontal
Vertical
Speed (m/s)
Displacement (m)
Time Sample (at 200Hz)

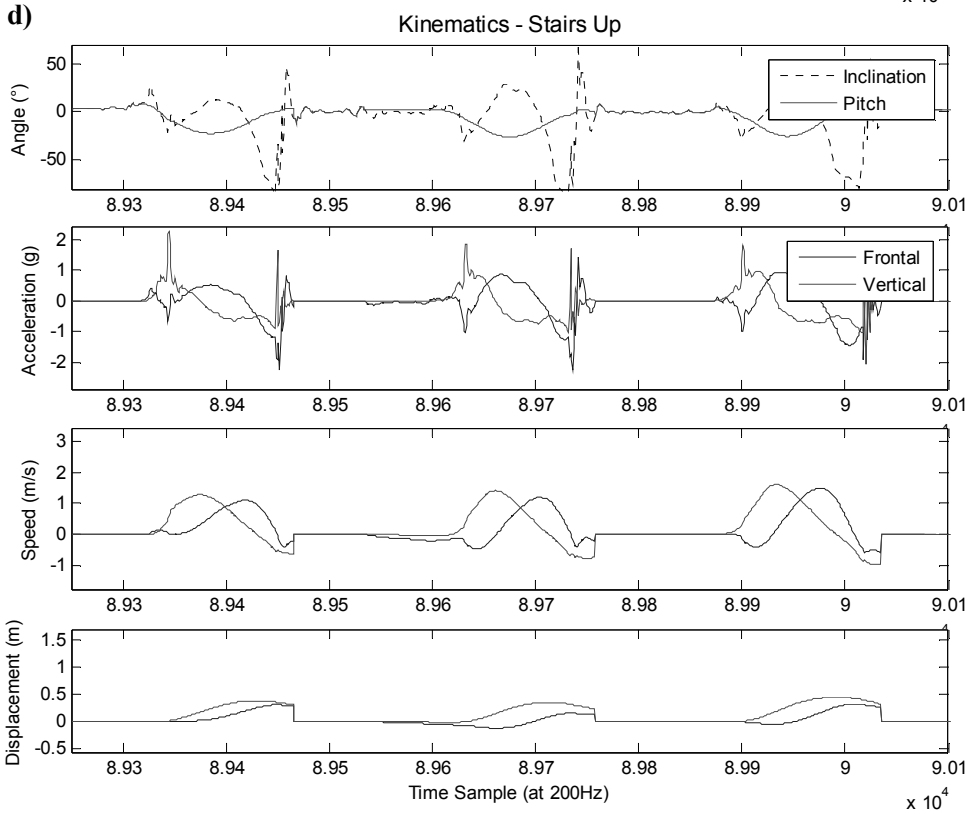
b)


Kinematics - Slope Up
Angle (°)
Inclination
Pitch
Acceleration (g)
Frontal
Vertical
Speed (m/s)
Displacement (m)
Time Sample (at 200Hz)

c)


Kinematics - Slope Down
Angle (°)
Inclination
Pitch
Acceleration (g)
Frontal
Vertical
Speed (m/s)
Displacement (m)
Time Sample (at 200Hz)
x 10^4

d)


Kinematics - Stairs Up
Angle (°)
Inclination
Pitch
Acceleration (g)
Frontal
Vertical
Speed (m/s)
Displacement (m)
Time Sample (at 200Hz)
x 10^4

e)

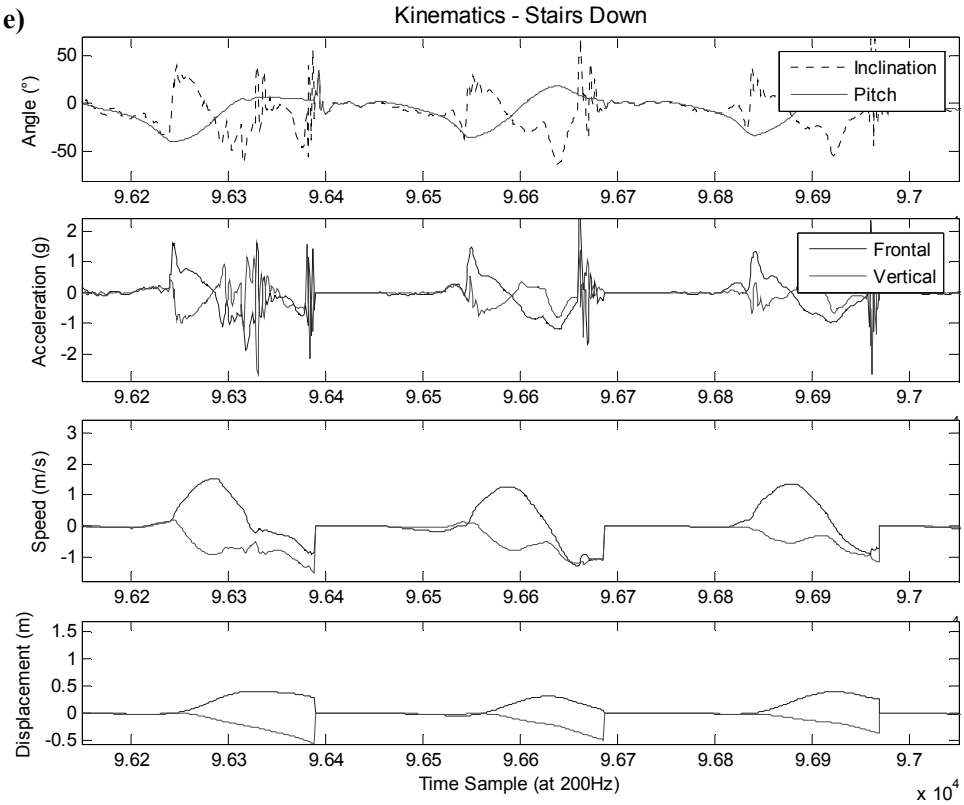


Figure A.6 - Orientation, Accelerations, Speeds and Displacement assessed by kinematic estimation algorithm based on inertial sensors for the different activities including level walking (a), slope ascent (b), solpe descent (c), stairs ascent (d) and stairs descent (e)

TABLE A.I - STATISTICAL COMPARISON OF FEATURES EXTRACTED ON PITCH ANGULAR VELOCITY (G), PITCH ANGLE (P), FRONTAL ACCELERATION (AF), VERTICAL ACCELERATION (AV), FRONTAL SPEED (SF), VERTICAL SPEED (SV), FRONTAL DISPLACEMENT (DF), VERTICAL DISPLACEMENT (DV), VERTICAL FORCE (VF), SAGITAL TORQUE (ST), FROM EACH ACTIVITY.

event		Heel-off									
	Signal	G	P	AF	AV	SF	SV	DF	DV	VF	ST
Median											
Activity	**2**	-20.93	2.57	0.01	-0.03	0.00	0.00	0.00	0.00	2.43	2.19
	3	-20.89	5.99	0.00	0.00	0.00	0.00	0.00	0.00	2.48	2.39
	4	-20.72	-2.44	0.00	-0.02	0.00	0.00	0.00	0.00	2.35	2.03
	5	-20.82	3.51	0.01	0.00	0.00	0.00	0.00	0.00	2.49	2.17
	6	-20.69	1.32	0.00	-0.02	0.00	0.00	0.00	0.00	2.26	2.01
IQR											
Activity	**2**	1.38	3.40	0.02	0.03	0.00	0.00	0.00	0.00	0.18	0.23
	3	1.26	4.67	0.02	0.02	0.00	0.00	0.00	0.00	0.20	0.27
	4	1.01	2.84	0.01	0.02	0.00	0.00	0.00	0.00	0.18	0.24
	5	1.63	4.38	0.03	0.03	0.00	0.00	0.00	0.00	0.31	0.31
	6	0.99	2.39	0.02	0.02	0.00	0.00	0.00	0.00	0.27	0.22
p-values											
Compared Activities	**2 vs 3**	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2 vs 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2 vs 5	0.08	0.00	0.11	0.00	0.11	0.00	0.11	0.00	0.21	0.13
	2 vs 6	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	3 vs 4	0.02	0.00	0.19	0.00	0.19	0.00	0.19	0.00	0.00	0.00
	3 vs 5	0.18	0.00	0.26	0.01	0.26	0.01	0.26	0.01	0.25	0.00
	3 vs 6	0.06	0.00	0.21	0.00	0.21	0.00	0.21	0.00	0.00	0.00
	4 vs 5	0.96	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00
	4 vs 6	0.77	0.00	0.58	0.89	0.58	0.89	0.58	0.89	0.00	0.03
	5 vs 6	0.96	0.00	0.06	0.00	0.06	0.00	0.06	0.00	0.00	0.00

event		Terminal Contact									
	Signal	G	P	AF	AV	SF	SV	DF	DV	VF	ST
Median											
Activity	**2**	-301.85	-16.80	0.56	0.62	0.34	0.25	0.02	0.01	1.53	1.85
	3	-264.57	-13.84	0.40	0.56	0.26	0.29	0.01	0.01	1.52	1.83
	4	-262.20	-21.58	0.50	0.48	0.33	0.17	0.01	0.00	1.52	1.83
	5	-127.52	-2.08	0.25	0.35	0.09	0.07	0.00	0.00	1.52	1.80
	6	-186.52	-21.96	0.30	0.17	0.12	0.06	-0.01	0.00	1.52	1.83
IQR											
Activity	**2**	60.19	6.86	0.25	0.29	0.13	0.11	0.01	0.00	0.03	0.20
	3	55.52	6.03	0.22	0.27	0.13	0.11	0.01	0.00	0.02	0.21
	4	74.61	9.06	0.27	0.27	0.18	0.15	0.01	0.01	0.02	0.26
	5	62.67	7.21	0.24	0.32	0.14	0.09	0.01	0.00	0.03	0.16
	6	42.81	6.01	0.29	0.30	0.22	0.11	0.04	0.01	0.02	0.11
p-values											
Compared Activities	**2 vs 3**	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.08	0.39
	2 vs 4	0.00	0.00	0.01	0.00	0.10	0.00	0.00	0.00	0.01	0.36
	2 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.00
	2 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.01
	3 vs 4	0.28	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.91	0.08
	3 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.01
	3 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.64	0.06
	4 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39	0.26
	4 vs 6	0.00	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.17
	5 vs 6	0.00	0.00	0.07	0.00	1.00	0.05	0.00	0.00	0.75	0.63

event		MidSwing									
	Signal	G	P	AF	AV	SF	SV	DF	DV	VF	ST
Median											
Activity	**2**	226.83	-7.13	-0.31	0.45	2.94	0.08	0.71	0.11	1.14	1.49
	3	165.14	-7.94	-0.26	0.11	2.34	0.21	0.59	0.18	1.13	1.49
	4	220.52	-10.00	-0.24	0.46	2.77	-0.15	0.68	0.04	1.14	1.48
	5	150.20	-16.99	-0.20	-0.44	1.51	-0.12	0.28	0.38	1.17	1.52
	6	149.44	-17.09	0.12	-0.15	1.22	-0.36	0.18	-0.01	1.11	1.51
IQR											
Activity	**2**	42.57	9.67	0.40	0.25	0.54	0.38	0.18	0.07	0.17	0.06
	3	54.12	11.51	0.30	0.26	0.80	0.31	0.34	0.09	0.10	0.13
	4	37.12	8.22	0.35	0.29	0.67	0.27	0.22	0.06	0.26	0.08
	5	52.52	9.36	0.22	0.39	0.82	0.45	0.28	0.07	0.09	0.09
	6	93.67	19.98	0.60	0.56	0.68	0.53	0.27	0.05	0.09	0.07
p-values											
Compared Activities	**2 vs 3**	0.00	0.07	0.17	0.00	0.00	0.00	0.00	0.00	0.98	0.00
	2 vs 4	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.00	0.09	0.06
	2 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.01
	3 vs 4	0.00	0.07	0.19	0.00	0.00	0.00	0.09	0.00	0.20	0.00
	3 vs 5	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.41
	3 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.02
	4 vs 5	0.00	0.00	0.13	0.00	0.00	0.45	0.00	0.00	0.08	0.00
	4 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.14
	5 vs 6	0.16	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01

event		Initial Contact									
	Signal	G	P	AF	AV	SF	SV	DF	DV	VF	ST
Median											
Activity	**2**	-203.49	12.21	-0.81	0.51	0.01	-0.52	1.13	0.13	1.57	1.42
	3	-17.53	10.05	-0.26	0.01	-0.01	-0.42	0.95	0.20	1.57	1.64
	4	-226.87	9.38	-0.51	0.17	0.22	-0.60	1.12	0.02	1.57	1.41
	5	34.21	0.42	-0.21	0.01	-0.19	-0.39	0.43	0.31	1.58	1.67
	6	-40.19	5.83	0.07	0.05	-0.61	-0.70	0.37	-0.29	1.50	1.54
IQR											
Activity	**2**	140.45	7.02	1.19	1.04	0.57	0.33	0.19	0.12	0.04	0.05
	3	160.32	8.35	1.27	0.97	0.55	0.25	0.37	0.12	0.03	0.34
	4	148.08	5.72	1.03	0.88	0.50	0.35	0.31	0.08	0.04	0.07
	5	96.15	6.97	1.14	0.65	0.94	0.31	0.44	0.08	0.04	0.20
	6	65.42	4.84	1.37	1.15	0.89	0.36	0.44	0.15	0.16	0.12
p-values											
Compared Activities	**2 vs 3**	0.00	0.00	0.00	0.00	0.89	0.00	0.00	0.00	0.41	0.00
	2 vs 4	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.01	0.78
	2 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00
	2 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	3 vs 4	0.00	0.33	0.06	0.07	0.00	0.00	0.00	0.00	0.45	0.00
	3 vs 5	0.00	0.00	0.82	0.55	0.00	0.95	0.00	0.00	0.55	0.21
	3 vs 6	0.03	0.00	0.00	0.71	0.00	0.00	0.00	0.00	0.00	0.00
	4 vs 5	0.00	0.00	0.06	0.19	0.00	0.00	0.00	0.00	1.00	0.00
	4 vs 6	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00
	5 vs 6	0.00	0.00	0.00	0.76	0.00	0.00	0.01	0.00	0.00	0.00

event		MidStance											
Signal		G	P	AF	AV	SF	SV	DF	DV	VF	ST	DFd	DVd
Median													
Activity	**2**	-8.69	5.13	-0.19	0.14	-0.40	-0.10	1.11	0.11	2.17	1.41	1.31	0.15
	3	-15.05	7.82	-0.12	0.05	-0.10	-0.31	0.94	0.18	2.13	1.77	0.97	0.31
	4	-9.84	0.43	-0.16	0.16	-0.20	-0.11	1.11	0.00	2.24	1.38	1.21	0.05
	5	-2.57	2.38	-0.01	0.02	-0.24	-0.37	0.43	0.28	2.06	1.80	0.50	0.45
	6	-9.22	1.54	-0.18	0.09	-0.56	-0.60	0.33	-0.35	2.26	1.62	0.67	0.08
IQR													
Activity	**2**	13.97	5.19	0.22	0.19	0.67	0.24	0.22	0.12	0.31	0.10	0.23	0.15
	3	8.84	6.73	0.19	0.07	0.67	0.32	0.39	0.11	0.45	0.47	0.43	0.23
	4	13.78	4.44	0.22	0.21	0.59	0.26	0.35	0.09	0.33	0.10	0.27	0.13
	5	21.92	6.42	0.30	0.06	0.86	0.36	0.52	0.08	0.40	0.24	0.28	0.11
	6	14.13	4.45	0.17	0.11	0.82	0.43	0.49	0.18	0.38	0.17	0.21	0.17
p-values													
Compared Activities	**2 vs 3**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	2 vs 4	0.38	0.00	0.03	0.24	0.00	0.02	0.98	0.00	0.00	0.00	0.00	0.00
	2 vs 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2 vs 6	0.59	0.00	0.90	0.00	0.01	0.00	0.00	0.00	0.08	0.00	0.00	0.00
	3 vs 4	0.00	0.00	0.01	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	3 vs 5	0.00	0.00	0.06	0.00	0.19	0.01	0.00	0.00	0.13	0.88	0.00	0.00
	3 vs 6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	4 vs 5	0.00	0.00	0.00	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	4 vs 6	0.31	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.72	0.00	0.00	0.35
	5 vs 6	0.00	0.20	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

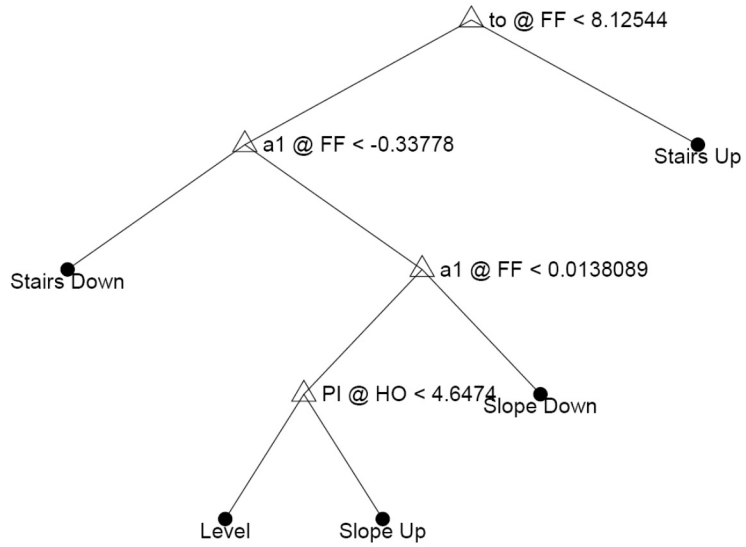


Figure A.7 - Optimal Tree, subject 6

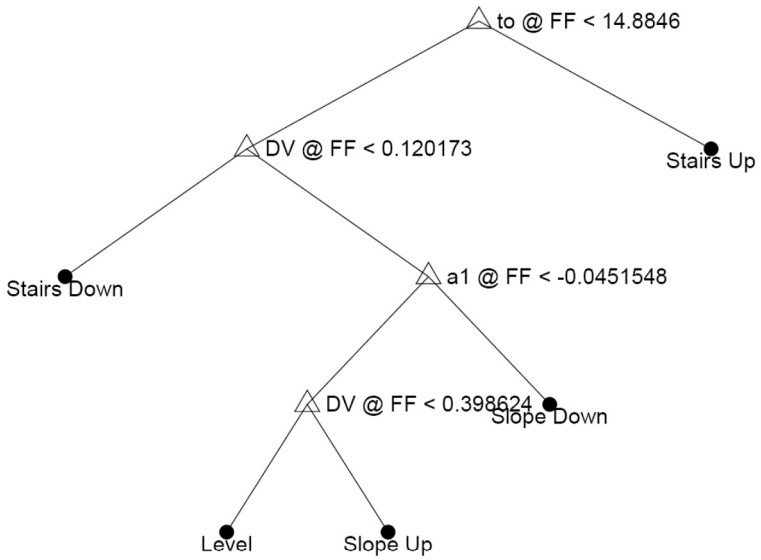


Figure A.8 - Optimal Tree, subject 7

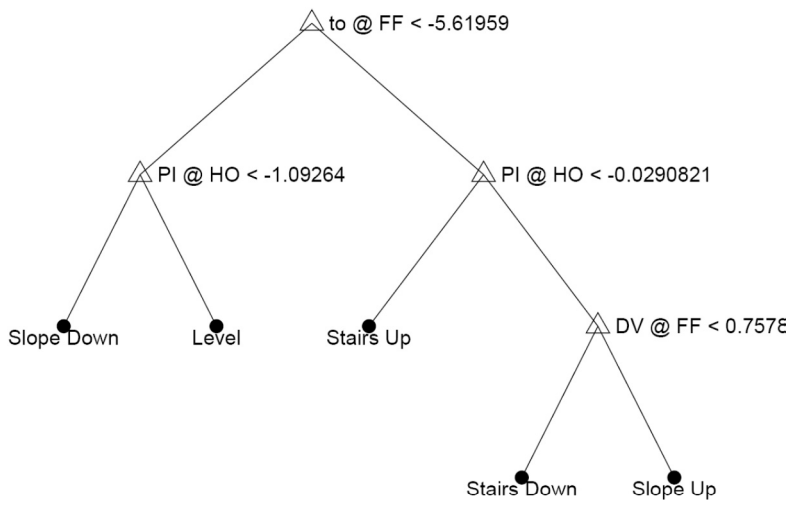


Figure A.9 - Optimal tree, subject 8

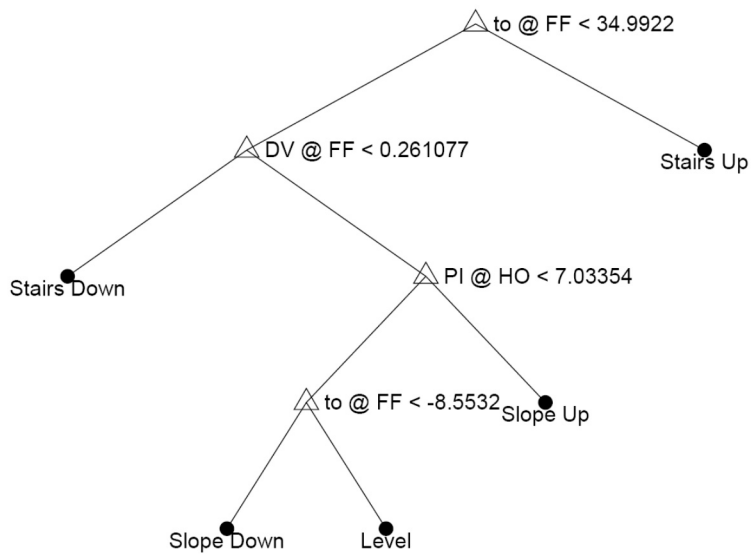
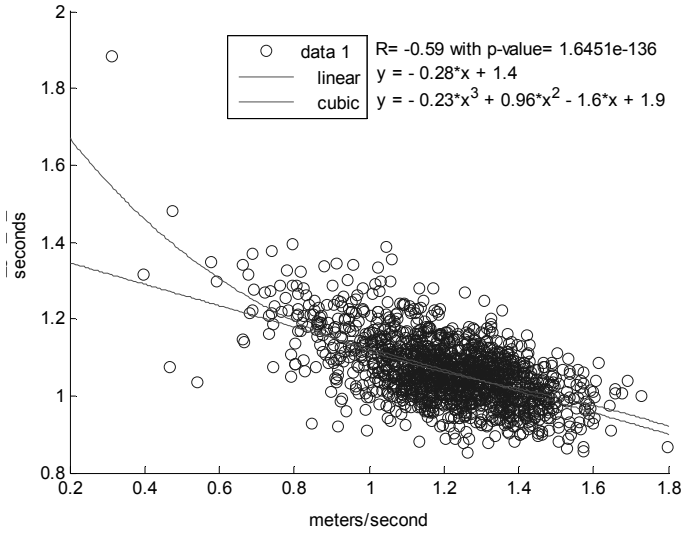
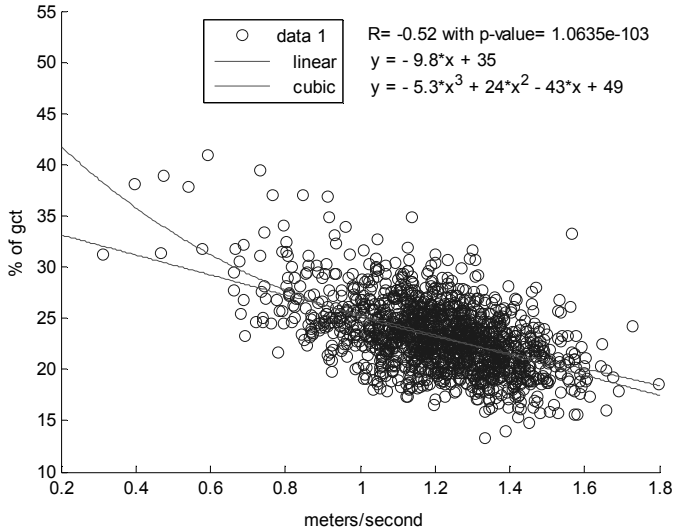


Figure A.10 - Optimal tree, subject 10

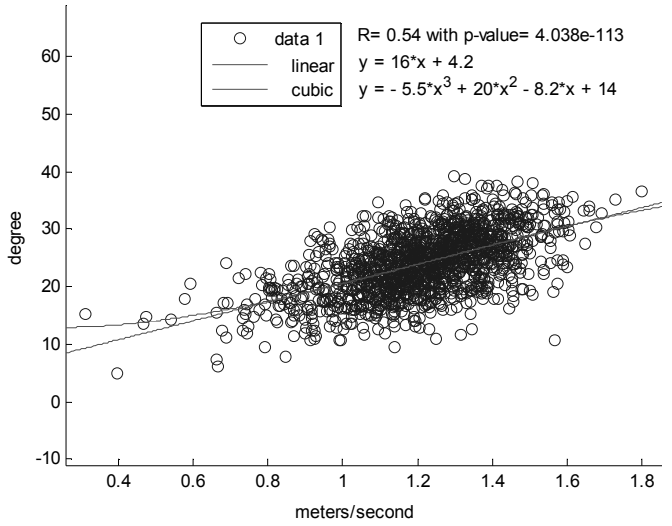
a)


data 1
linear
cubic
R= -0.59 with p-value= 1.6451e-136
y = - 0.28*x + 1.4
y = - 0.23*x^3 + 0.96*x^2 - 1.6*x + 1.9
seconds
meters/second

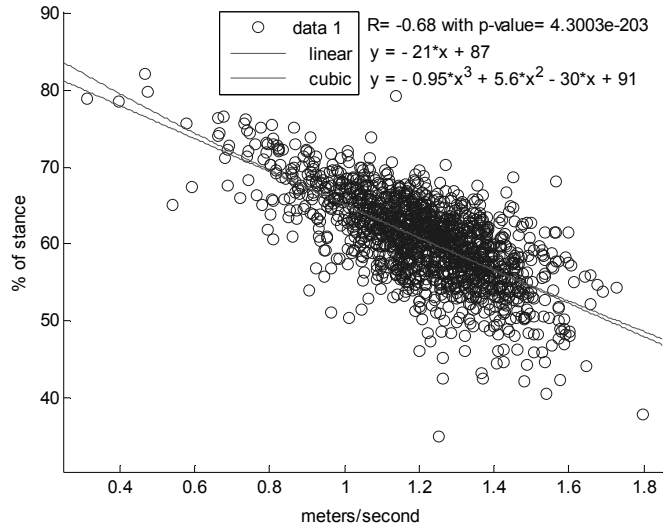
b)


data 1
linear
cubic
R= -0.52 with p-value= 1.0635e-103
y = - 9.8*x + 35
y = - 5.3*x^3 + 24*x^2 - 43*x + 49
% of gct
meters/second

c)


data 1
linear
cubic
R= 0.54 with p-value= 4.038e-113
y = 16*x + 4.2
y = - 5.5*x^3 + 20*x^2 - 8.2*x + 14
degree
meters/second

d)



e)

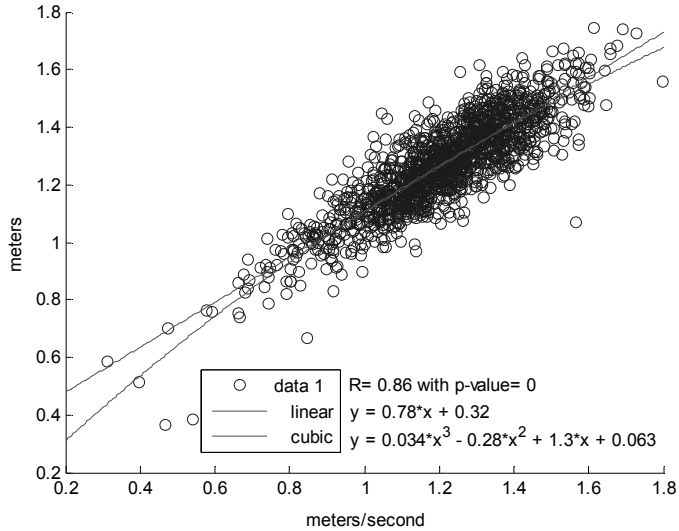


Figure A.11 - Correlation coefficients, Linear and cubic regressions of gait parameters, including gait cycle time (a), total Double support (b), Foot pitch angle at Heel-strike (c), foot-flat ratio (d), and stride length (e), with walking speed.

Curriculum Vitae

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Education

2008 - 2012: Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland
PhD student in Computer, communication and information sciences.
Thesis: *Assessment of foot signature using wearable sensors for clinical gait analysis and real-time activity recognition*

2006 - 2008: Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland
Master of Science in Micro-engineering
Major in Micro and Nanoscale systems.
Thesis: *Analysis of body movements during front crawl using inertial sensors*

2004 - 2007: Ecole Supérieure d'Electricité (SUPELEC) Paris, France
Engineering Degree in the field of electrical and computer engineering.

2002 - 2004: Lycée Berthollet Annecy, France
Preparatory school for "Grandes Ecoles" in mathematics and physics

2002: Lycée Anna de Noailles Evian, France
French scientific Baccalauréat with high honours (mention Très bien)

Working Experience

2008 - 2012: Laboratory of Movement Analysis and Measurements EPFL, Switzerland
Research Assistant and supervision of 10 bachelor/master theses
Teaching Assistant for the course "*Sensors in biomedical instrumentation*"

2007: Integrated Actuators Laboratory EPFL, Switzerland
Teaching assistant for electrotechnical laboratory course

2006: Technocentre RENAULT Guyancourt, France
Engineering internship: *Characterization and optimization of GPS navigation system*

2005, 2006: HONKE BANKYU BANKYU RYOKAN, Yunishigawa, Japan
Labor internship as clerk, cleaner and waiter in traditional Japanese inn "*Ryokan*"

2003, 2002: CONNEXION Thonon, France
Summer Job for delivery and setup of home appliance

Patents

Mariani, B., Aminian, K., EPFL
System and method for 3D gait assessment
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Publications

Mariani, B., Hoskovec, C., Rochat, S., Büla, C., Penders, J., Aminian, K.
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