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ASSESSMENT OF GAIT SPATIO-TEMPORAL PARAMETERS IN NEUROLOGICAL DISORDERS USING WEARABLE INERTIAL SENSORS

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Esame finale anno 2015

A mia madre e mio padre,

A mia sorella

"Tell me and I forget,

teach me and I may remember,

involve me and I learn".

(B. Franklin)

Summary

Movement analysis carried out in laboratory settings is a powerful, but costly solution since it requires dedicated instrumentation, space and personnel. Moreover, it cannot be used to observe the variability in performing everyday life movements. Recently, new technologies such as the 'inertial sensors' are becoming widely accepted as tools for the assessment of human motion in clinical and research settings. Inertial sensors are relatively small and inexpensive, they require low power to operate and can therefore be wearable and used outside the laboratory. The magnetic and inertial measurement units (MIMU) which integrate multiple sensors (triaxial accelerometer, triaxial gyroscope and triaxial magnetometer) are the most promising sensing units for human movement analysis carried out both inside and outside a laboratory setting. They are relatively easy-to-use and potentially suitable for estimating gait kinematic features, including spatio-temporal parameters.

The objective of the research conducted and reported in this PhD thesis regards the development and testing in clinical contexts of robust MIMU based methods for assessing gait spatio-temporal parameters applicable across a number of different pathological gait patterns.

First, considering the need of a solution the least obtrusive as possible, the validity of the single unit based approach was explored. A comparative evaluation of the performance of various methods reported in the literature for estimating gait temporal parameters using a single MIMU unit attached to the trunk first in normal gait and then in different pathological gait conditions was performed. The analysis was conducted in terms of accuracy, sensitivity and robustness of the tested methods with respect to a gold standard. A comparison between the results obtained for different methods and the different subjects groups was also carried out. It was shown that the use of a single MIMU is prone to different amounts of errors when applied to pathologic gait patterns.

The second part of the research headed then towards the development of new methods for estimating gait spatio-temporal parameters using shank worn MIMUs on different pathological subjects groups. In addition to the conventional gait parameters, new methods for estimating the changes of the direction of progression were explored. Finally, a new hardware solution and relevant methodology for estimating inter-feet distance during walking was proposed.

Results of the technical validation of the proposed methods at different walking speeds and along different paths against a gold standard were reported for each study and showed that the use of two MIMUs attached to the lower limbs associated with a robust method guarantee a much higher accuracy in determining gait spatio-temporal parameters.

Finally, an application of the developed methods was presented. The values obtained for the gait parameters were used to improve the set-up of a rehabilitation tool with the goal of enhancing gait symmetry in a group of hemiparetic subjects.

The results obtained in this work lead to the conclusion that the proposed methods could be reliably applied to various abnormal gaits obtaining in some cases a comparable level of accuracy with respect to normal gait. The proposed approach was validated on four different groups of pathological subjects (Parkinson's disease, Huntington's disease, Post-stroke, TBI), however we could expect that for pathologies implying similar alterations to the gait patterns the proposed methods may also be used in clinical assessment.

Keywords: Inertial sensors, Wearable sensors, Gait analysis, Spatio-temporal parameters, Elderly, Parkinson's disease, Huntington's disease, Stroke, Traumatic brain injured, Gait patterns, Abnormal gait, Biomechanics, Validation, Direction of progression, Inter-feet distance

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List of Publications and Awards

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2. **D. Trojaniello**, A. Cereatti, E. Pelosin, A. Mirelman, J.M. Hausdorff, L. Avanzino, U. Della Croce: Estimation of step-by-step spatio-temporal parameters of normal and impaired gait using shank-mounted magneto-inertial sensors: application to elderly, hemiparetic, parkinsonian and choreic gait. J Neuroeng Rehabil 2014, 11:152.

3. **D. Trojaniello**, A. Cereatti, U. Della Croce: Accuracy, sensitivity and robustness of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk. Gait Posture 2014, 40:487–92.

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1. A. Cereatti, **D. Trojaniello**, U. Della Croce: Accurately measuring human movement using magneto-inertial sensors: techniques and challenges, *accepted to* 2nd Annual IEEE International Symposium on Inertial Sensors and Systems, Hawaii, USA, March 2015

2. **D. Trojaniello**, A. Cereatti, E. Pelosin, A. Mirelman, J.M. Hausdorff, L. Avanzino, U. Della Croce: Stride-by-stride gait spatio-temporal parameters estimate from shank-worn IMU recordings: validation on parkinson, choreic, hemiparetic and healthy elderly subjects, 24th SIAMOC-23th ESMAC, Rome, Italy, October 2014 *Best Methodological Paper Award*, Gait & Posture (*in press)*

3. **D. Trojaniello**, A. Cereatti, A.K. Bourke, K. Aminian, U. Della Croce, A wearable system for the measurement of the inter-foot distance during gait, 20th IMEKO TC4 International Symposium Benevento, Italy, September 2014, ACTA IMEKO pp. 765-769

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5. **D. Trojaniello**, A. Cereatti, A. Ravaschio, M. Bandettini, U. Della Croce: Assessment of gait direction changes during straight-ahead walking in healthy elderly and Huntington Disease patients using a shank worn MIMU, Engineering in Medicine and Biology Society (EMBC), 36th Annual International Conference of the IEEE, Chicago, USA, August 2014, vol. pp.2508,2511, 26-30

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Awards

1. ELSEVIER BEST METHODOLOGICAL STUDY AWARD, ESMAC-SIAMOC Conference, Rome, Italy, October 2014: **D. Trojaniello**, A. Cereatti, E. Pelosin, A. Mirelman, J.M. Hausdorff, L. Avanzino, U. Della Croce: *Stride-by-stride gait spatio-temporal parameters estimate from shank-worn IMU recordings: validation on parkinson, choreic, hemiparetic and healthy elderly subjects*

2. ELSEVIER BEST METHODOLOGICAL STUDY AWARD, SIAMOC Conference, Pisa, Italy, September 2013: **D. Trojaniello**, A. Cereatti, U. Della Croce: *Accuracy, sensitivity and specificity of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk*

3. YOUNG INVESTIGATOR AWARD - BTS Bioengineering, SIAMOC Conference, Pisa, Italy, September 2013: **D. Trojaniello**, A. Cereatti, U. Della Croce: *Accuracy, sensitivity and specificity of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk*

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Glossary

IMU = Inertial Measurement Unit

MIMU = Magnetic and Inertial Measurement Unit

GE = Gait Events

IC = Initial Contact

FC = Final Contact

HD = Huntington's Disease

PD = Parkinson's Disease

TBI = Traumatic Brain Injury

DoP = Direction of Progression

GDC = Changes in gait direction

IFD = Inter-Feet Distance

GCS = Global Coordinate System

LCS = Local Coordinate System

IRR = Infra-Red Range sensor

PPV = Positive Predictive Value

Chapter 1

Introduction

1.1. Motivation and general introduction

In the last decades, the scientific literature and the clinical practice have proven that the instrumented measurement of the gait patterns is a crucial tool for determining gait related issues and relevant treatments. Movement analysis in controlled environments such as motion analysis laboratories is a useful, but expensive tool. More importantly, it does not reveal aspects of gait related to the variability in the everyday life. Recently, along with stereo-photogrammetric systems, which are regarded as the "gold standard" in gait analysis, new technologies such as the 'inertial sensors' are becoming widely accepted as tools for the assessment of human motion in clinical and research settings. Inertial sensors have many advantages compared to conventional systems such as low cost, small size, low power consumption and can be successfully used outside the laboratory. They allow for the measurements of kinematic data such as spatial and temporal parameters in daily life conditions at low cost and high reliability and therefore their use could be helpful in the planning of a motor rehabilitation program. Recent sensing hardware developments have made available magnetic and inertial measurement units (MIMU) which allow for wearable sensor solutions to human motion analysis obtained by integrating multiple sensors (accelerometers, gyroscopes and magnetometers). The literature offers various methods based on the use of either a single unit, often positioned on the trunk, or two units, mounted on both lower limbs, mostly validated on the gait of healthy subjects and/or of a single pathologic population. However, the large signal variability over different abnormal gaits and the deviations of signals features from those typical of normal gait (often due to impairments and consequent compensatory strategies) require great fine tuning efforts for clinical applications. Therefore, the validity of clinically suitable MIMU-based methods for the estimate of spatio-temporal parameters is still an open issue.

1.1.1. Human gait

Human gait refers to the most common type of locomotion (i.e. any of a variety of movements that results in progression of the body's centre of mass from one place to another), achieved by alternating the motion of the lower limbs. The other leg is in swing phase for creating a new step forward [1]. Normal gait is characterised by the ability of: a) supporting an upright position; b) maintaining balance during locomotion and c) generate a new step forward [2]. This should be done by minimizing the energy expenditure and limiting the joint loading. The gait cycle is used to describe the complex activity of walking, or our "gait pattern". It describes the motion from a placement of the heel on the ground to the following contact of the same heel.

In normal gait, lower limbs during a gait cycle perform the same sequence of motions with a time shift of half the duration of the cycle. In pathologic gait both sequence and regular alternation of limbs are modified, symmetry is often lost, with consequences on energy consumption, joint loads and balance.

1.1.2. Motor impairments related to neurological disorders

Among the various neurological disorders, the thesis focuses especially on the study of Parkinson's disease, Huntington's disease and post-stroke gait abnormalities.

Parkinson's Disease can cause a *festinating gait*. In this gait, the patient has rigidity and bradykinesia. The patient walks with slow little steps (shuffling gait) and may also have difficulty initiating steps. The patient may show an involuntary inclination to take accelerating steps, known as festination [3].

Huntington's Disease may result in *choreiform gait*. The subject walks performing irregular, jerky, involuntary movements in all extremities resulting in variable cadence, increased velocity and stride length [4].

Post stroke gait is characterized by a unilateral weakness on the affected side, arm flexed, adducted and internally rotated (*hemiparetic gait*). The ipsilateral lower limb is in extension with plantar flexion of the foot and toes. When walking, the patient holds his or her arm to one side and drags his or her affected leg in a semicircle (circumduction) due to weakness of distal muscles (foot drop) and extensor hypertonia in lower limb. With mild hemiparesis, loss of normal arm swing and slight circumduction may be the only abnormalities. The

resulting gait is very asymmetric and much slower than normal gait, characterized by a longer time spent on a double limb support [5].

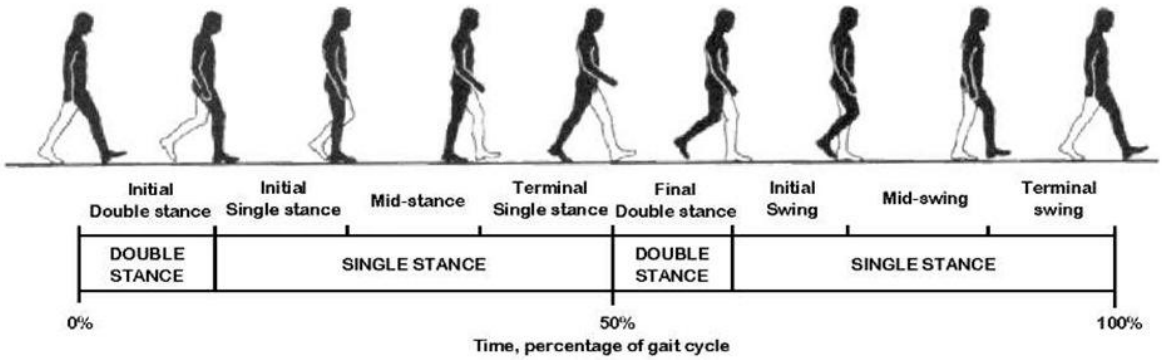
1.1.3. Clinical gait analysis

To date, gait has been analysed in a dedicated laboratory for both research and clinical applications. In clinics, the most interesting results have been obtained in analysing the gait of individuals with central nervous disorders associated with spasticity, especially children with cerebral palsy. To prevent deformity and increase mobility, various medications, non-surgical therapy regimens, bracing, assistive devices, and/or orthopaedic and neurosurgical procedures are prescribed for these children. By periodically repeating a clinical gait analysis, the correct number and selection of surgical procedures can be chosen.

In this context, a complete gait analysis consists in estimating and providing a clinical interpretation of patterns and values of biomechanical variables.

Spatio-temporal parameters. They characterize the phases of gait defined by the contacts of the feet with the ground within a single gait cycle. Such phases are: stance and swing for a single limb or single support and double support when both limbs are analysed (Fig. 1.1). Their durations are typically called gait temporal parameters. Other temporal parameters such as the cadence can be simply obtained from them. Spatial parameters are also determined from the distances of the feet at contact time: stride length and step length. Gait speed can also be obtained from the ratio of the distance of two consecutive foot contacts and the time past between them.

FIGURE 1.1 GAIT CYCLE AND RELEVANT GAIT PHASES



Joint and segment kinematics. The human body is commonly modelled as a system of rigid bodies, each associated with a human body segment. Often, for gait studies only the motion of the lower part of the body is analysed. Therefore, the system of rigid bodies employed includes pelvis, thighs, shanks and feet, all considered as rigid bodies. The kinematics of each of the segments can be estimated from proper measurements and the joint kinematics (i.e. the kinematics of a segment with respect to the adjacent segment) can be mathematically obtained.

Joint kinetics. The estimate of joint kinetics is the results of the inverse dynamics applied to the system of rigid bodies employed for the analysis. By measuring the forces and moments exchanged by the system with the environment, once the inertial characteristics and the kinematics of the body segments involved is determined, the joint kinetics patterns during a gait cycle can be estimated.

All these biomechanical quantities are typically obtained with a variety of instrumentation to be operated in a dedicated laboratory.

1.1.3.1. Laboratory based systems

Various sensing technologies have been proposed to estimate step-by-step gait temporal and spatial parameters. Force platforms, instrumented mats, and footswitches are examples of devices sensing the contact of the foot with the ground. Motion analysis systems have also been used to estimate GE timings from body segment motion. To some degree, force platforms and instrumented mats suffer from the same limitations. They require extensive laboratory space, force subjects to walk in a specific environment and are relatively costly. Their main advantage is the possibility of estimating spatial gait parameters in addition to temporal parameters. Foot switches are portable and relatively inexpensive but may require extensive subject set up and can provide temporal parameters only. Motion capture systems capabilities go beyond the estimation of the gait spatio-temporal parameters, since they are devised for 3D point kinematics measurements.

Instruments such as stereo-photogrammetric systems and force platforms, are considered as the gold standard in the field of motion analysis for assessing joint kinematics and kinetics. A stereo-photogrammetric system consists of a set of cameras which allow for the reconstruction of the instantaneous 3-D position of markers located in a calibrated volume of operation. If markers are attached to specific locations on the subject's body, the rigid

body system kinematics can be fully estimated. Technology is based on either active or passive markers and uses the red and infrared light range. Force platforms are the standard instruments for the measurements of ground reaction forces, necessary for the estimate of joint kinetics. Force platforms can also provide accurate gait temporal parameters such as foot initial and terminal contact.

Measuring body movements in laboratory settings under controlled conditions allows getting precise, accurate and reliable measurements, and add quantitative and objective figures to the clinical gait assessment. Nevertheless, motion capture systems present also several disadvantages, such as the costly equipment and the need of technical expertise to operate. Another drawback is represented by the confinement of such a system inside the laboratory setting, where the volume of measurement is limited. This aspect can strongly influence the natural behaviour of the subjects and does not allow observing them in their everyday life.

1.1.3.2. Wearable magnetic and inertial sensors*

Magneto–inertial sensing is an emerging technology with a growing number of potential applications in human movement analysis. Several key factors are behind the success of this technology. First, MIMUs are self-contained systems and hence their functioning is independent of the specific "built environment". Second, since these sensors are heavily used in the consumer electronics market products, their price keeps dropping while their performance improves. Lastly, the move from wearable measurement systems to pervasive systems made possible by the MEMS/NEMS technology opens up new perspectives for motor performance assessment and monitoring.

The specific 9-axis configuration of MIMUs is widely adopted by various manufacturers since it allows for the estimation of the pose in the 3D space by combining the good dynamic response of the gyroscope, with the drift-free inclination and heading estimates provided by the accelerometers and magnetometers in static conditions. Since the global coordinate system (GCS) definition is only based on the estimated gravity and the local magnetic north directions, its origin results undefined. An alternative to this configuration, it is represented by inertial measurement units (IMU) which integrate only accelerometers and gyroscopes.

* This paragraph is based on

A. Cereatti, D. Trojaniello, U. Della Croce: ***Accurately measuring human movement using magneto-inertial sensors: techniques and challenges***, accepted to 2nd Annual IEEE International Symposium on Inertial Sensors and Systems, Hawaii, USA, March 2015

MIMU ORIENTATION AND POSITION BASED ESTIMATE

The MIMU orientation is commonly estimated using sensor fusion algorithms which exploit the complementary characteristics of the integrated sensors to obtain optimal error compensation. Extensive work has been conducted in the recent years to estimate the orientation of MIMUs attached to human body segments. Kalman filter based algorithms are the most prevalent solution but other interesting approaches such as complementary filters, particle filters have been also proposed. An interesting critical review is provided in [6]. Recent literature suggests that none of the state of the art algorithms for sensor fusion consistently prevails under different applications [7]. It is worth noting that because gyroscopes and accelerometers are internally referenced sensors, each MIMU computes the orientation of the GCS with respect to its local coordinate system (LCS) (commonly aligned with the edges of the unit case). Alteration of the sensor calibration parameters as well as distortion of the local magnetic field vector can result in different MIMUs sensing different GCSs. This circumstance is extremely critical when joint kinematics is sought since an initial orientation reset cannot be sufficient to ensure inter-MIMUs consistency once the orientation is varied [8].

The MIMU linear displacement can be estimated by double integrating the acceleration components once the gravity vector is removed. However, the latter operation is highly critical for three main reasons: (1) errors in the orientation estimate, cause an apparent gravity contribution which is doubly integrated causing position errors, (2) a drift, commonly present when integrating the accelerometer and gyroscope signals, introduces an error in the displacement estimations nonlinearly related to the integration time, (3) initial conditions (position and velocity) need to be provided. Beyond the solution of adding an externally reference aiding (e.g. GPS), other countermeasures for limiting the detrimental effects of the drift are either to exploit any instant of time where the velocity is known (preferably zero) to restrict the integration interval of time (e.g. zero velocity update), or the use of advanced filtering techniques for integration drift compensation [9]. As previously mentioned, only the relative position of the MIMU with respect to itself in a reference instant of time can be obtained. This implies that the relative position between two MIMUs can be obtained only if further information is provided (e.g. inter-distance).

Currently, the majority of MEMS sensors manufacturers declare, in ideal conditions (homogeneous magnetic environment, perfectly calibrated sensors, stabilised sensor fusion

algorithm) an overall static orientation accuracy under 1 deg and ≈ 2-3 deg for the dynamic orientation accuracy (rms). Nevertheless, recent studies have demonstrated that the orientation accuracy depends on several factors: (1) sensor noise characteristics, (2) the sensor fusion algorithms implemented, (3) the axis about which the rotation occurs (attitude/heading errors), (4) the type of movement analyzed (angular velocity, angular range of motion, duration, presence of stationary phases), (5) presence of ferromagnetic disturbances [7, 10]. These factors also explain the different results reported in the literature (attitude average errors from 1 to 5.5 deg, heading average errors from 1 to 21 deg.). These errors can further increase when relative orientation is estimated [8, 10]. In the light of the above considerations, prior to start experimental acquisitions, spot-checks aimed at assessing the orientation errors associated with the specific motor task analyzed are strongly recommended. This is particularly urgent when joint kinematics description is carried out. A simple and quick spot-check consists in aligning two or more units on a rigid flat plate, simulate the movement to be recorded and then compute the expected errors as the relative angles between pairs of MIMUs [8]. To improve the accuracy of the MIMU based position and orientation estimates, the first self-evident solution is to use sensors with better performance characteristics. To a certain extent, this is assured by the continuous technological advancements associated to the design of low cost MEMS sensors. Further research is required to devise methods for the automatic filter parameters tuning and the inclusion of additional complementary sensors (i.e vision-based, distance sensors, etc).

MIMU BASED HUMAN GAIT KINEMATICS

Probably the main advantage offered by the MIMUs, with respect to optoelectronic stereo-photogrammetry (*de facto* standard) is the capability to provide a continuous description of the subject motor performance in his/her specific daily life (at home/work, in outdoor playing field, etc). The level of accuracy and repeatability reached so far is fully adequate for those applications requiring a realistic and effective computer graphic representation of human motion (visual feedback generation, entertainment). Conversely, when movement analysis is used as a clinical tool, the level of reliability and validity of the estimated quantities needs to be much higher since it should allow to catch subtle modifications of the motor strategies and/or deviation from normality [11].

The extensive use of magneto-inertial sensing for high resolution kinematics estimates has been limited by several factors. First, the measurement devices were too cumbersome for

being continuously worn during daily life (size, weight, wires issues). Secondly, their performance was not sufficiently accurate for specific applications. Lastly, the protocols for human movement reconstruction were lacking of adequate validation in different pathological populations and "built environments". Whereas the size problem is almost solved and the sensor performances are expected to greatly improve in the near future, the development of effective protocols has been lagging behind.

Magneto-inertial sensing technology has the potential in the coming years to measure human movement with a level of accuracy and repeatability comparable to optoelectronic stereo-photogrammetry with the advantage of being applicable during daily life and for prolonged observation period. The new technological capabilities, along with appropriate methodologies, can enable to perform pervasive and ubiquitous movement data collection.

1.2. Thesis rationale and objectives

The objective of the research conducted and reported in this PhD thesis regards the development, application and testing in clinical contexts of MIMU based methods for assessing gait spatio-temporal parameters across a number of different pathological gait patterns.

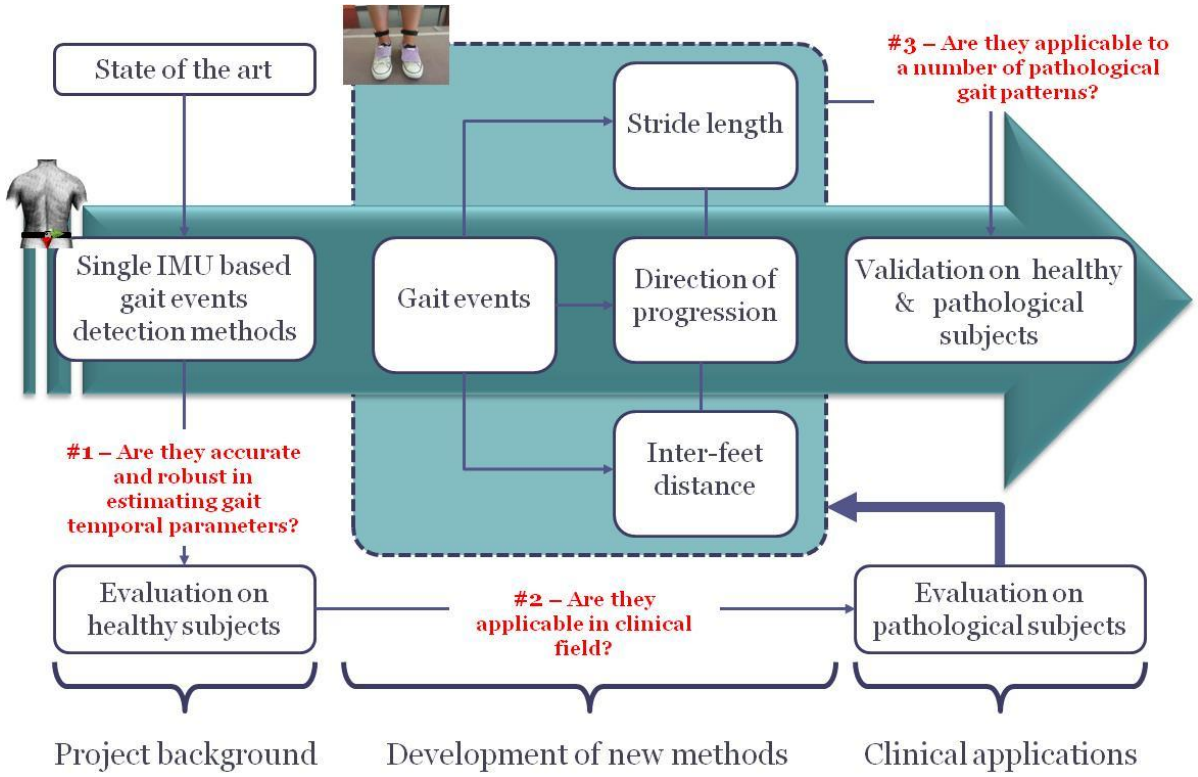
In figure 1.2 an overview of the research project is reported. The three main research questions to which this work try to answer are shown in red.

The first part of the project mainly regards an analysis of the methods for gait temporal parameters estimation based on a single unit attached to the trunk. The reason for studying the performance of single MIMU based methods first in healthy and then in pathological subjects comes from the wish of using the most unobtrusive instrumental setup.

The second part of the thesis focuses on the development of new algorithms for gait temporal and spatial parameters estimation using a bilateral MIMU based approach.

In fact, the results of the first part of the project suggest adopting an alternative MIMU configuration based on two units attached to the lower limbs. Additional parameters (i.e. direction of progression (DoP), inter-feet distance (IFD) never previously studied in the literature using MIMUs have been also introduced and validated.

FIGURE 1.2 OVERVIEW OF THE THESIS PROJECT



All the algorithms proposed are currently used in the framework of the V-TIME European project in order to assess the gait performances in 300 subjects (Parkinson's disease, Mild Cognitive Impairment, Elderly fallers) which were acquired in the last three years in four consecutive gait assessment sessions while repeating different walking tasks (normal walking, fast walking, dual task walking, obstacle negotiation walking).

1.3. Outline of the thesis

The thesis is organized as follows.

Chapter 1 (current chapter) introduces the topic of this thesis through the presentation of characteristics of human gait, both in normal and pathological subjects. Motor aspects of gait disorders with a focus on selected neurological disorders are mentioned along with the technology commonly employed in clinical gait analysis. The rational and motivations of the research work, as well as the methodology applied, are presented together with the objectives and outline of the thesis.

Chapter 2 presents the state of the art in the estimation of gait spatio-temporal parameters using wearable inertial sensors. Methods based on a) a single MIMU mounted on the trunk and b) multiple MIMUs, bilaterally attached to the lower limbs, are treated separately. The application of such methods to the gait of healthy subjects (normal gait) and that of subjects with motor related pathologies (abnormal gait) are presented along with the relevant implementation issues.

Chapter 3 presents a comparative evaluation of the performance of different methods for estimating gait temporal parameters using a single MIMU unit attached to the trunk in normal gait. The analysis is conducted in terms of accuracy, sensitivity and robustness of each of the tested methods with respect to a gold standard.

Chapter 4 extends the study presented in Chapter 3 to the gait of different groups of pathological subjects and to a group of healthy elderly. Again, the analysis is conducted in terms of accuracy, sensitivity and specificity of different methods based on a single MIMU attached to the trunk in estimating gait temporal parameters with respect to a gold standard. A comparison between the results obtained for different methods and the different subjects groups is also included.

Chapter 5 proposes new methods for estimating gait spatio-temporal parameters using shank worn MIMUs on different pathological subjects groups. Results of the technical validation of the proposed algorithms at various walking speeds against a gold standard are reported.

Chapter 6 proposes new methods for estimating the DoP changes using shank worn MIMUs on different pathological gait conditions in both straight and curvilinear path. Results of the technical validation of the proposed algorithms at different walking speed and along different path against a gold standard are reported.

Chapter 7 proposes a new hardware solution and relevant methodology for estimating IFD. A MIMU and an infra-red range sensor (IRR) were assembled together. Results of the technical validation of the proposed solution while performing various motor tasks, including walking at various speeds and step widths, against a gold standard are reported.

Chapter 8 presents an example of application of the developed algorithms for the determination of gait spatio-temporal parameters in motor rehabilitation after stroke. The

resulting values of the gait parameters were used to verify if the qualitative criteria used to set-up the tested motor rehabilitation tool effectively reduced gait asymmetry of a group of hemiparetic subjects.

Chapter 9 discusses the achievements of the research performed during the PhD program and an outlook for future research.

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Chapter 2

Gait spatio-temporal parameters estimation in normal and pathological gait: State of the art [*]

2.1. Overview

The assessment of spatio-temporal parameters is an essential component of clinical evaluations of gait. The determination of both temporal and spatial parameters requires the preliminary detection of the initial and final foot contacts (IC and FC), usually referred as gait events (GE). Among the technologies that could be used to detect the GEs, inertial sensing have been increasingly employed thanks to the development of miniaturized sensing technology, which progressively improved their wearability, reduced their cost and power consumption. The use of MIMUs allows to extend the assessment of both temporal and spatial gait parameters during the daily life.

The MIMU based approaches for the estimation of gait spatio-temporal parameters have been generally proposed using a single MIMU, often attached to the trunk, or a MIMU mounted on each lower limb. Features characterizing trunk accelerations and shank (or foot) sagittal angular velocity have been found in correspondence of GE timings, and were therefore used to detect them using signal-based analysis or machine learning methods. Once the gait cycle is segmented and gait temporal parameters estimated, spatial parameters can be obtained using one of the following approaches: human gait model, direct integration and machine learning. The application of such approaches to normal gait has been fairly well

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D. Trojaniello: ***Gait analysis by means of inertial sensors - Clinical applications*** presented during the XV SIAMOC-XXIII ESMAC joint conference 2014, Rome. Workshop: "Movement analysis with inertial sensors"

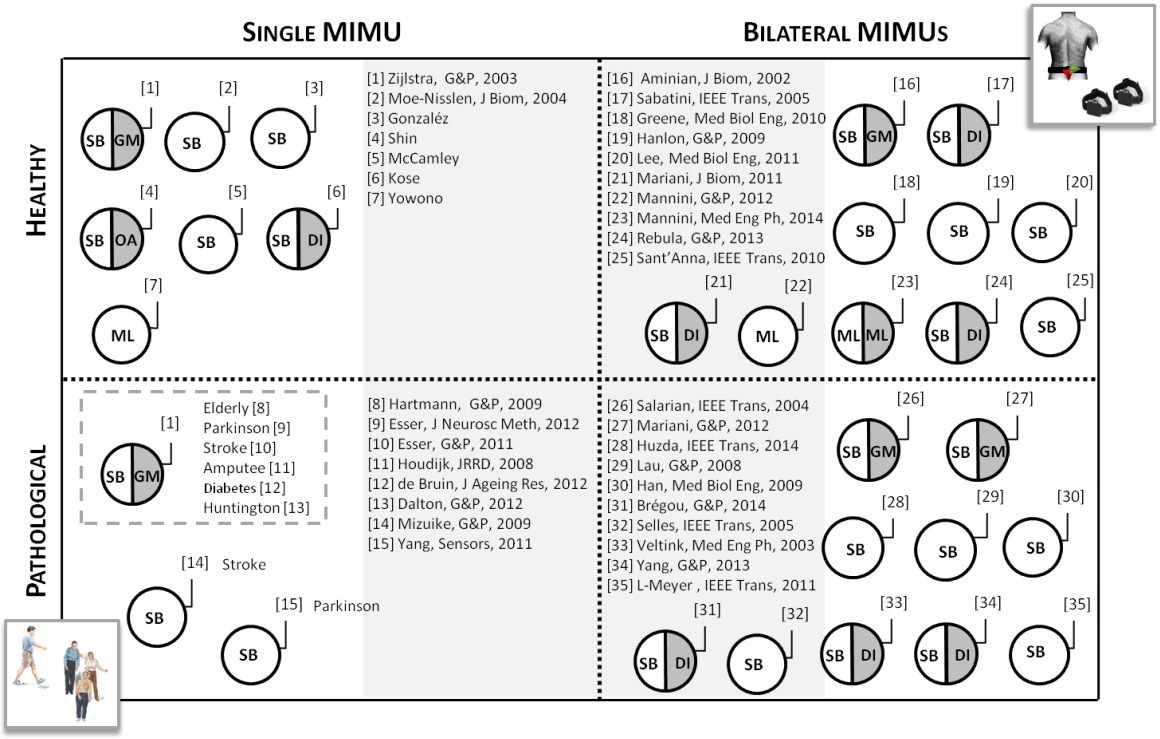
D. Trojaniello: ***Gait analysis by means of by means of wearable inertial sensors*** presented during the XX ISEK conference 2014, Rome. Workshop:"Movement analysis with wearable inertial sensors: stepping into clinics and sports"

explored and encouraging results have been obtained when trunk-mounted or lower-limb-mounted MIMUs are used. However, the use of these approaches, mostly validated for indoor straight walking, has to be validated in less controlled gait conditions (outdoors, uneven terrain, etc). Moreover, when applied to pathological gait, approaches based on a single MIMU showed lower accuracy, while methods based on the use of a MIMU mounted distally on each lower limb have shown promising results. However, considering the variability of signal patterns obtained from the recordings of the gait of subjects with different pathologies, additional efforts are needed for an effective use in clinical contexts.

The state of the art in gait spatio-temporal parameters estimation using wearable MIMUs is described in this chapter. In particular, techniques that have been employed in the literature for estimating such parameters are discussed. The single MIMU based and the bilateral MIMUs based approaches are presented separately. Both approaches are discussed focusing on the studies on healthy gait and on pathological gait. In figure 2.1 an overview of the existing gait spatio-temporal parameters estimation methods is reported.

FIGURE 2.2 OVERVIEW OF THE EXISTING GAIT SPATIO-TEMPORAL PARAMETERS ESTIMATION METHODS.

White circles represent gait temporal parameters estimation methods (SB: signal-based analysis, ML: machine learning); grey circles represent gait spatial parameters estimation methods (DI: direct integration, GM: human gait model, ML: machine learning, OA: other approaches).



2.2. Gait spatio-temporal parameters using wearable inertial sensors

The estimation of gait spatio-temporal parameters requires the identification of the foot initial and final contacts of the gait cycle, generally referred to as GEs. Features of acceleration and angular velocity signal patterns have been found to be in correspondence with GEs and are generally exploited for their detection. However, both amplitude and frequency content of the raw signals highly vary depending on the MIMU location on the body, thus orienting towards different solutions. As a result, authors proposed various MIMU based methods for estimating gait temporal parameters [1–9] or spatio-temporal parameters [10–13]. Only some of them have been validated against a gold standard. The number and the location of the MIMUs on the human body differed widely across studies. While a few methods using a single sensor placed on the lower trunk have been proposed for healthy subjects [14–20], with a limited application to pathologic gait [21–26], a larger number of methods have been proposed using MIMUs attached to the lower limbs, on the feet or shoes [11, 12, 27], on the shanks [7–9, 13, 28, 29], thighs [3], or both [5, 6, 10, 30]. The location of the MIMU on the human body plays a primary role in the robustness and accuracy of the detection of the GEs. As a general rule, the closer the sensor is to the point of impact (the foot) the higher are the chances of correctly detecting the GEs. A common solution proposed in the literature is positioning the MIMU at the waist level so that ground impacts of both feet could still be detected, while minimally conditioning the subject's movement. A consequence of such solution is the increased difficulty in identifying a robust and accurate method for the detection of GEs and, consequently, estimating gait temporal parameters. Instead, when a bilateral sensor approach is preferred, placing the MIMUs on the shanks may offer some advantages over the feet (or shoes). In fact, a MIMU can be attached more rigidly to the shank than to the foot which undergoes to large deformation, moreover the signals were found to be less variable between subjects for shank-mounted MIMUs signals with respect to signals from foot-mounted MIMUs signal.

Methods for GEs identification are usually based on the use of fixed or adaptive thresholds and peak identification in both the time and/or frequency domain (signal-based analysis). Standard methods suffer from a high inter-subject variability. Alternatively, machine learning methods (i.e. hidden Markov models) based on a stochastic approach have been recently proven to be robust to inter-subject variability [31]. However, the performance of such methods depends on the completeness and homogeneity of the training data set used to

build the models. A systematic review of the existing solutions for offline and online GEs identification in terms of experimental protocol adopted (number, type, locations, etc.) and techniques can be found in [32].

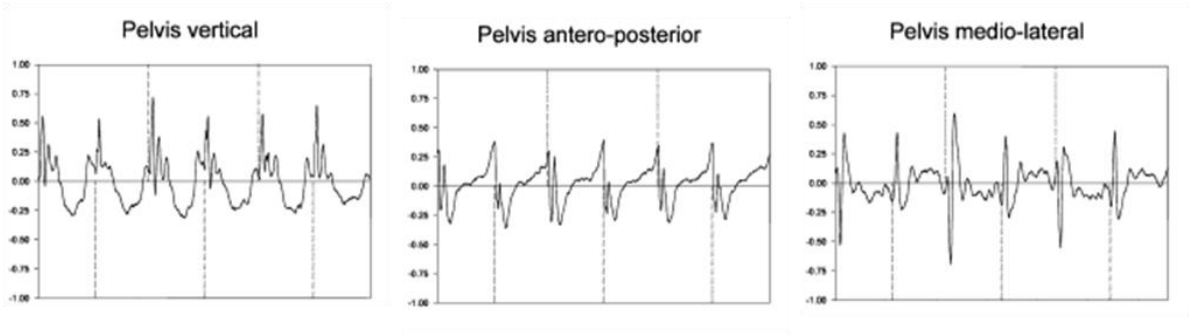
Spatial parameters have been obtained using MIMUs via one of the following approaches: (1) human gait models, (2) machine learning methods, (3) direct integration [33]. While the use of predefined human gait models (e.g. inverted pendulum), devised from physiological gait, can only be partially applied to pathological gait patterns, machine learning methods, based on abstraction models, are sensitive to inter-subject variability and often require some level of individualisation. The direct integration approach consists of obtaining the linear displacements by double integrating the MIMU linear gravity-compensated acceleration components in the global reference frame. However, due to some drawbacks such as the presence of drift in acceleration signals, the need of determination of the MIMU orientation with respect to the global reference frame and the necessity of estimating initial velocity for integrating the signals, the estimate of gait spatial parameters would be extremely poor unless some expedients are implemented. The cyclical nature of gait is typically used to reduce the detrimental effects of the drift by restricting the interval of integration time to a single gait cycle [34]. However, it requires the identification within the cycle of an instant of known velocity to be used as initial velocity in the integration of the acceleration. Zero velocity update (ZUPT) is generally used to this purpose in correspondence of the foot flat phase when the sensor is attached to the foot [35], while different strategies such as using the inverted pendulum model to estimate the initial sensor velocity are applied when the sensor is fixed to the shank [33]. Different strategies should be adopted when the sensor is attached to the trunk [19]. In addition, some de-drifting functions have been proposed [11, 12, 19, 27]. The above mentioned expedients rely heavily on the quality of GEs estimate. In fact, errors in determining the gait cycle and the instants of minimum velocity, as well as the chosen de-drifting function could compromise the estimate of gait spatial parameters.

The methods for the estimation of the spatio-temporal parameters in normal gait have nowadays reached acceptable levels of accuracy. Conversely, in severe pathological gait conditions, the methods validity is jeopardized by the following factors: (1) the signals features can greatly deviate from those observed in physiological gait, (2) the signals patterns show a lower intra- and inter-subjects repeatability, (3) different gait impairments show different waveforms.

2.3. Single MIMU based approaches

Several authors have described lower trunk acceleration patterns, including the identification of IC and FC. In particular, studies have shown that during walking a consistent pattern of trunk antero-posterior (AP) and vertical (V) accelerations occurs in correspondence of spatio-temporal parameters in healthy subjects. Medio-lateral (ML) acceleration has rarely been analyzed with the purpose of distinguishing between right and left cycles [14, 38]. Evans and colleagues [36] recorded acceleration signals in three dimensions at the sacrum using a small and light device and were able to manually identify right and left ICs. Auvinet and others [37] were likewise able to identify GEs related features within the gait cycle from V acceleration signals recorded at the L3-L4 level for 282 healthy subjects. Menz and others [38] described the pelvis basic acceleration patterns in the three directions (AP, ML and V) on 30 subjects walking at different speeds and on different surfaces (Fig.2.2). The authors reported the occurrence of IC at the positive peak of AP acceleration. Mansfield and Lyons [39] investigated the use of trunk mounted accelerometer for the detection of heel contact events during FES assisted walking. To this purpose, they explored the correspondence between the negative–positive change in lower trunk AP acceleration and IC and found a delay of 150 ms across different walking speeds (but different between subjects and simulated hemiplegic gait) over 4 subjects.

FIGURE 2.2 PELVIS ACCELERATIONS ALONG THE THREE AXIS AND RELEVANT GES (ADAPTED FROM [38])



Various authors focused their efforts in proposing methods aiming at automatically detecting the GEs from the acceleration signals of a single unit mounted at the waist level. Some limited their goal to the estimate of GEs and consequent gait temporal parameters [16, 18, 20]; others added the estimate of the mean step length [14] and some focused on the estimate of the step length [17, 19]. The most famous of the mentioned methods [14] was also applied to the gait of various populations: healthy adults [40, 41], healthy children [42], healthy

elderly [43] and pathological populations, such as amputees [23], various neurological patients [22], Parkinson's disease [21]. Other studies observed changes in trunk acceleration patterns and, eventually, correspondence between that patterns and gait events, in elderly and pathological populations [44–46].

2.3. Bilateral MIMUs based approaches

When the MIMU is attached to a lower limb segment, the GEs detection and the determination of gait cycle phases is often based on the analysis of the sagittal angular velocity features [6, 9, 10, 13, 28, 31, 47–49] or, less frequently, of the acceleration features [7, 8, 50], applying approaches such as empirically determined thresholds [11, 13, 51], frequency analysis [10] and machine learning algorithms [31]. Generally, the estimation algorithms detect invariant signal features, such as the sharp peaks occurring when the foot hits the ground [11]. In particular, when a gyroscope is attached to the shank, the GEs have distinctive signal features of shank angular velocity appearing as rather sharp negative peaks. Although the amplitude of these peaks vary according to various parameters such as subjects' velocity or weight they can always be localized in normal gait patterns [10]. In fact, as reported by Salarian et al [13], the swing phase of a gait cycle is characterized by a positive shank angular velocity reaching its highest values around midswing. Prior to swing phase, a negative angular velocity peak can be observed which is associated with TC. At the end of the swing period, the IC area is characterized by a several negative angular velocity peaks. The first negative peak in this area is associated with the IC.

FIGURE 2.3 ACCELERATION AND ANGULAR RATE OF THE SHANK AND RELEVANT GES (ADAPTED FROM [32])

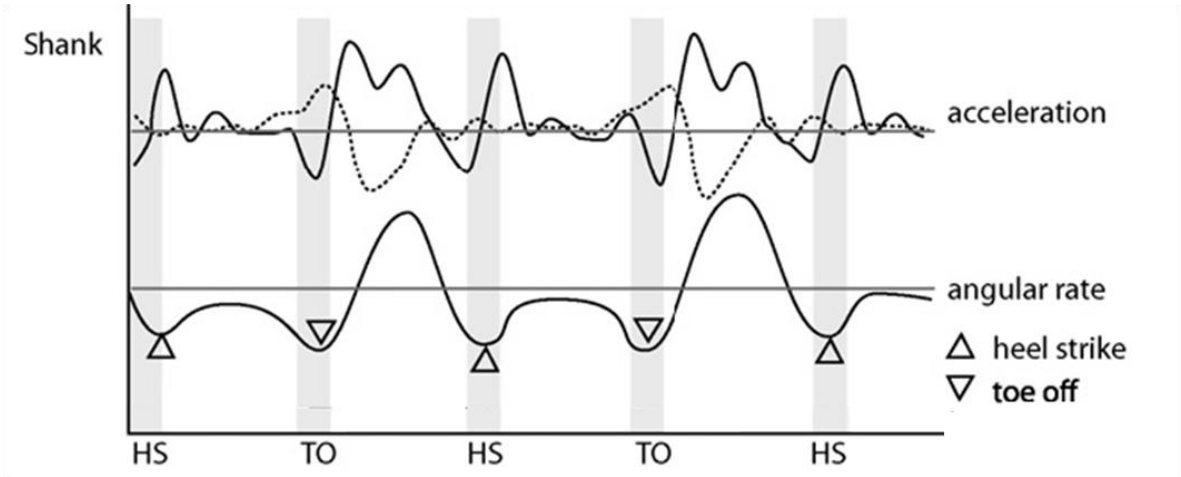
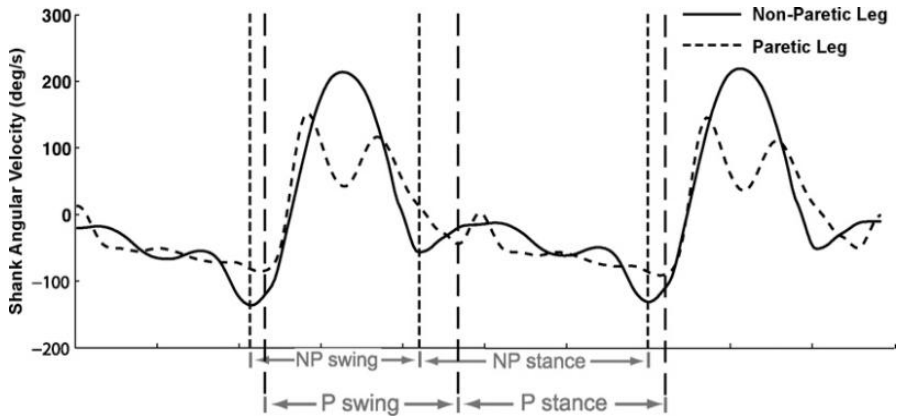
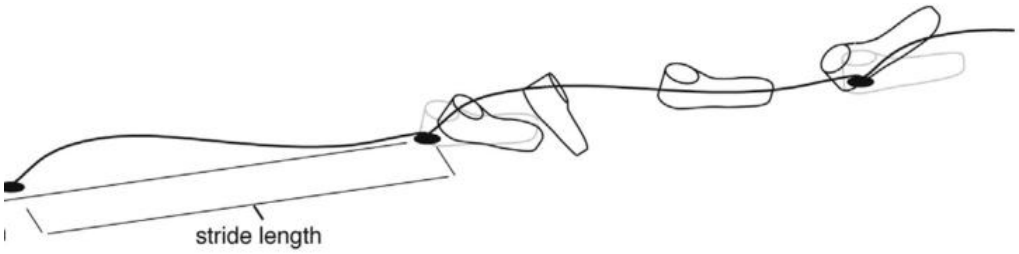


FIGURE 2.4 SHANK ANGULAR VELOCITY IN POST-STROKE SUBJECT [52]



Alternatively, some studies tried to estimate GEs and relevant gait temporal parameters using the acceleration features, i.e. the sharp peak of the AP and V acceleration in correspondence of the foot initial contact (IC) or the zero-crossing of the AP acceleration when the foot leaves the ground. In addition, machine learning techniques based on HMM showed interesting results [31]. In figure 2.3 an example of the accelerations and angular rate patterns during healthy gait is reported. When the gait of individuals affected by some pathology is recorded, the relevant signal patterns could be very different. In a recent study, Yang et al. [52] reported that their method for the determination of the gait cycle phases failed when the deviations of the angular velocity patterns from those typical of normal gait are not negligible (Fig. 2.4). Such deviations are often due to impairments and consequent compensatory strategies and result in signal alterations with respect to the normal gait signal pattern. Once the GEs are identified, methods for the determination of spatial parameters (i.e. stride length) have also been proposed in some studies [10–13, 47]. The majority of the studies proposed approaches based on direct integration methods, with few exceptions which mainly regards the application of machine learning approaches and human gait based models [13, 33, 53]. The most recent studies in this context are now directing in the estimation of the 3D foot trajectories [12, 54] (Fig. 2.5).

FIGURE 2.5 3D FOOT TRAJECTORY USING MIMUS [54]



Most of the studies mentioned above validated the proposed gait spatio-temporal parameters estimation methods on healthy subjects [11, 29, 49]. Some studies applied the proposed method to the gait of elderly, spinal cord injuried [4, 5], parkinsonian [13, 55–57], amputee [58] or patient with prostheses [30, 59]. Recently, Rueterbories et al [32] reviewed wearable sensor based methods of GEs detection for ambulatory rehabilitation uses applied to stroke patients, such as the functional electrical stimulation applied to stroke patients. They reported that, even if a number of methods have been proposed for GEs detection only few have been validated on stroke patients [3, 27].

2.4. Conclusions

In this chapter, a description of the state of the art of the methodologies proposed in the literature for the estimation of gait spatio-temporal parameters has been reported. Among the various MIMU locations proposed in the literature, two main approaches have been investigated: single MIMU based and bilateral MIMUs based. Both approaches have been described highlighting the principal features of the signals patterns. Only a limited number of studies proposing a single MIMU method included the validation of the method, mostly when applied to healthy subjects. On the contrary, the bilateral MIMUs based approach has been proposed for both healthy and pathological gait; in this case, a number of pathologies have been tested, but no studies have been found exploring the possibilities of applying the same method to different pathological gait conditions. Therefore, the following conclusions can be stated:

a. for the single MIMU approach, a comparative assessment of the performances of the existing methods on both healthy and pathological populations is still missing;
b. for the bilateral MIMUs approach, the possibility of applying the same method to different pathological gait conditions should be better explored.

The next chapters attempt to fill these gaps.

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Chapter 3

Accuracy, sensitivity and robustness of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk [*]

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D. Trojaniello, A. Cereatti, U. Della Croce, ***Accuracy, sensitivity and robustness of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk***. Gait Posture 2014, 40:487–92

Abstract

In the last decade, various methods for the estimation of gait events and temporal parameters from the acceleration signals of a single inertial measurement unit (IMU) mounted at waist level have been proposed. Despite the growing interest for such methodologies, a thorough comparative analysis of methods with regards to number of extra and missed events, accuracy and robustness to IMU location is still missing in the literature. The aim of this work was to fill this gap. Five methods have been tested on single IMU data acquired from fourteen healthy subjects walking while being recorded by a stereo-photogrammetric system and two force platforms. The sensitivity in detecting initial and final contacts varied between 81% and 100% across methods, whereas the positive predictive values ranged between 94% and 100%. For all tested methods, stride and step time estimates were obtained; three of the selected methods also allowed estimation of stance, swing and double support time. Results showed that the accuracy in estimating step and stride durations was acceptable for all methods. Conversely, a statistical difference was found in the error in estimating stance, swing and double support time, due to the larger errors in the final contact determination. Except for one method, the IMU positioning on the lower trunk did not represent a critical factor for the estimation of gait temporal parameters. Results obtained in this study may not be applicable to pathologic gait.

3.1. Introduction

Initial and final foot contacts (IC and FC), referred to as gait events (GE), are used for the estimation of temporal gait parameters. They determine the gait phases thus allowing for the interpretation of joint kinematics and muscle activity patterns. Thanks to the miniaturized sensing technology, inertial measurement units (IMU) have been increasingly employed to detect the GEs. An advantage of using the IMUs is the possibility of evaluating spatial and temporal gait parameters while monitoring daily life activities [1-4]. In this context, the instrumental setup should be as unobtrusive and wieldy as possible, leading towards the use of a single wearable unit. The IMU location on the human body influences the robustness and accuracy of the GEs identification. As a general rule, the closer the IMU is to the point of impact, the higher are the chances of correctly detecting the GEs [5]. The most intuitive solution would be to place the IMU on the foot, but if a bilateral determination of GEs is sought, two synchronized IMUs would be needed.

A common solution proposed in the literature to minimally alter the subject's gait is to position a single IMU at waist level to detect the impact of both feet [6]. A disadvantage of this solution is the increased difficulty in implementing a robust and accurate method for determining gait temporal parameters.

Both ICs and FCs were found to be associated to specific features of the lower trunk accelerations along the antero-posterior (AP), medio-lateral (ML) and vertical (V) directions, recorded during gait [6-10]. These observations have led several authors to propose methods for GEs and/or temporal gait parameters estimation from the acceleration signals of a single IMU mounted at waist level [11-13]. In particular, some authors detected ICs to estimate the mean step length [14] or estimated step duration to determine step length without detecting ICs [15]; others focused on the estimation of temporal and spatial parameters after detecting both ICs and FCs [16].

The method proposed by [14] was later applied to the gait of healthy adults [17,18], healthy children [19], healthy elderly [20] and pathological populations, such as amputees [21], neurological patients [22], or Parkinson patients [23]. In most cases, only mean values of gait parameters were analyzed and caution in interpreting gait parameters was often recommended [21].

Despite the clinical interest for such methodologies, there is no information in the literature on comparative analysis of: a) the number of missed GEs relative to the number of actual GEs (sensitivity) and of correctly detected GEs relative to the total amount of detected GEs (positive predictive values, PPV); b) the accuracy of the gait temporal parameters estimation, and c) their robustness to changes in the IMU positioning.

In this work, the performance of five methods for detecting GEs and determining gait temporal parameters from the signals of a single IMU attached at waist level [11,12,14-16] was evaluated in terms of: a) sensitivity and PPV and b) accuracy and robustness of the determination of temporal gait parameters. A method [14] was selected based on its popularity [17-23], while the remaining four represent the most recent published methods for the estimation of temporal parameters from a single IMU. The five methods have been applied to data acquired from an IMU attached to healthy subjects walking while recorded by a stereo-photogrammetric (SP) system and two force platforms (FP). The data from FPs and the SP system were used for reference.

3.2. Materials and Methods

3.2.1. Tested methods

The methods evaluated are summarized below. A schematic description of the methods is reported in Table 3.1; additional details can be found in the literature [11,12,14-16].

Z-method [14,24]. The study aimed at determining gait temporal parameters and mean step length using a 3-axis accelerometer positioned over the second sacral vertebra (S2). The ICs were identified as the timings of the peaks of the low-pass filtered AP acceleration (20 Hz) preceding the positive-to-negative transitions of the AP acceleration filtered at 2 Hz. The method was later improved by the authors [24] by aligning the IMU to the V direction during an upright posture.

G-method [11]. The study proposed a real-time GEs detection method. The IMU was fixed on the third lumbar vertebra (L3). The IC was searched in a region of interest defined by the positive values of the filtered AP acceleration. In this time interval, local maxima of the raw AP acceleration were searched. The timing of one of the maxima was identified as the IC. To select the correct local maximum, several empirical rules were applied. Once the IC was identified, the timing of the first local minimum occurring after the IC was identified as the FC timing.

S-method [15]. A 3-axis accelerometer was attached to the waist in the back (W). The values of the acceleration norm falling within a sliding window of fixed length (N) were summed (sliding window summation - SWS). The difference of the resulting SWS values and those obtained N samples earlier was then computed to remove gravity. The resulting pattern was a smooth curve crossing periodically the zero value. The instances of negative-to-positive transitions were then used as markers for determining the step duration. FC timings were not estimated.

M-method [12]. IC timings were identified as the times of the minima of the signal obtained after applying a Gaussian continuous wavelet transformation to the V acceleration recorded with a single IMU over the lower lumbar spine (L5). The resulting signal was then differentiated and FC timings were identified as the instances of its maxima.

K-method [16]. The method required the IMU to be positioned on the subject's belt on the right side of the body, since it was developed for monitoring physical activity. GEs were searched within regions of interest identified from the signal reconstructed with the first three levels of detail of a stationary wavelet decomposition of the V acceleration. Since the number of regions of interest identified in a trial could be higher than the number of gait cycles, only those featuring the highest peaks of the V acceleration (i.e. containing the instrumented side IC) were kept. First, the ipsilateral IC and contralateral FC were determined from the V acceleration in the region of interest, then the ipsilateral FC was identified from the AP acceleration; finally the contralateral IC was identified from the ML acceleration.

TABLE 3.1 Description of the tested gait event detection methods

	sensor type	**sampling rate [Hz]**	**sensor position**	**subjects #**	**shoes**	**estimated GEs**	**gold standard**	**missed/ extra GEs**	**estimated parameters**
Z-method [14]	3-axis acc	100	S2	15	yes	IC	FPs	no	GEs; mean step length
G-method [11]	IMU	100	L3	6	yes	IC; FC	FPs	no	real time GEs
S-method [15]	3-axis acc	50	waist	1	n.a.	IC	n.a.	n.a.	step length
M-method [12]	IMU	100	L5	18	n.a.	IC; FC	instrumented mat	no	GEs
K-method [16]	IMU	100	right side waist	9	n.a.	IC; FC	SP system	n.a.	step length

3.2.2. Data collection protocol

Subjects

Fourteen healthy volunteers (eight females, six males; age: 31.8±5.2 y.o.; height: 1.71±0.09 m; mass: 64.1±15.6 kg; walking speed: 1.2±0.3 m/s) were recruited.

Measurement protocol

A single IMU (Opal^{TM}, APDM; weight 22 g, size 48.5×36.5×13.5 mm^3) featuring a 3-axis accelerometer (±6g range) and 3-axis gyroscope and sampling at 128 Hz, was used. For each method, the suggested IMU locations were identified by a physical therapist and the IMU was attached using a semi-elastic band. The IMU performance was tested according to the guidelines proposed by Picerno et al. [25].

For each IMU location, subjects were asked to first maintain an upright posture for ten seconds and then walk barefoot at their self-selected comfortable speed along a walkway featuring two FPs (AMTI, 1000 Hz) located in the calibrated volume of a SP system (six cameras, VICON T20, 128 frames/s). The trajectories of three markers placed on each foot (toe, heel and lateral malleolus) were also recorded. The GEs were obtained by thresholding at 10 N the V ground reaction force [26] (or by applying the method proposed by Alton et al. [27] for those ICs occurring outside the FPs) and used as reference for all methods.

For each subject, three trials including a full right and a full left gait cycle were recorded for each IMU location.

3.2.3. Data analysis

For each trial and method, IC timing, stride and step duration estimations were obtained. Since FC timing estimations were provided only by the G-, M- and K- methods, stance, swing and double support time estimations were computed only for the above mentioned methods.

3.2.3.1. Sensitivity and positive predictive values

The number of GEs detected by each method was counted. Any falsely detected GE was labeled as extra event, while a true undetected GE was labeled as missed event. The sensitivity of each method in detecting GEs (i.e. the number of GEs correctly detected divided by the number of actual GEs) was determined. The PPV (i.e. the number of correctly detected GEs divided by the total amount of detected GEs) was also determined. Sensitivity and PPV together provide an evaluation of the performance of the tested method [28].

3.2.3.2. Accuracy of the temporal parameters estimation

For each method, the differences between the estimations of the gait temporal parameter *p* and the relevant reference value, averaged over the three trials, were calculated. Left and right side values of the above mentioned differences were also averaged for all methods except for the K-method, due to the asymmetric location of the IMU. Left and right parameters determined with the K-method were thus obtained by averaging half of the values used for the other methods. The resulting average was considered as the error (*E*) of the tested method in estimating the gait parameter *p* for a subject.

For every parameter *p*, as estimated by any of the methods, the percent error (*E%*) was also determined:

$$E\% = \frac{|p - p_t|}{|p_t|} \times 100,$$

where p_t is the true value of the parameter p. The $E\%$ values computed for all trials and all subjects were averaged.

3.2.3.3. Statistical analysis

Due to the presence of missing events found for some of the methods, the following was done to complete the dataset to be submitted to the statistical analysis [29]:

- when a GE was missing (a "*item non response*" case) and the relevant temporal parameters could not be determined, the missing values were replaced by the average of the remaining determinations of those parameters;
- when all GEs were missing (a "*unit non response*" case), the relevant temporal parameters were given the worst values found in the other subjects;
- extra events were not considered in the analysis.

For each temporal parameter and each method, mean and standard deviation of the E values were calculated. A normality test (Shapiro-Wilk test) was also performed.

A Friedman test for non-normal distribution was used to compare the E values obtained to verify if there were statistical differences among them. A Wilcoxon signed-rank test was then performed to assess differences between methods. A Bonferroni Holm's correction for multiple comparisons was applied. The Wilcoxon test was also performed to reveal differences between the E values obtained for the left and right side when the K-method was applied.

3.2.3.4. Robustness to IMU positioning

All methods were applied to signals from each IMU location (except for the K-method due to the asymmetric IMU location). This allowed assessing the robustness of the methods with respect to the IMU location. The $E\%$ obtained by using a method m applied to signals from the IMU in each location was determined. The $E\%$ values computed for all subjects were averaged.

3.3. Results

The trials acquired on the fourteen subjects produced 168 ICs and 84 FCs.

Sensitivity and positive predictive values

Missing ICs resulted in the Z- and the G- methods. Extra ICs were found for the G- and K- methods. The sensitivity in detecting ICs was less than 100% only for the Z-method (97%) and the G-method (82%), while the PPV was equal to 95% for the G-method and 94% for the K-method.Only the G-method showed missing FCs (sensitivity 81%), while both G- and K- methods had some extra events (PPV = 97% and 94%, respectively).

Accuracy of the temporal parameters estimation

The mean and standard deviation of *E* values for stride and step time (for all methods) and for stance, swing and double support time (for the G-, M- and K- methods) are reported in Table 3.2. The *E%* values for all methods are reported in Table 3.3.

TABLE 3.2 Mean and standard deviation (std) of the error (E) in estimating stride and step time (all five methods) and stance, swing and double support time (G-, M- and K-method)

(s)	**stride time**		**step time**		**stance time**		**swing time**		**double support time**	
	mean	std	mean	std	mean	std	mean	std	mean	Std
Z-method [14]	-0.006	0.028	0.004	0.025	-	-	-	-	-	-
G-method [11]	-0.018	0.020	-0.006	0.012	-0.069	0.018	0.063	0.024	-0.071	0.017
S-method [15]	0.001	0.011	0.005	0.005	-	-	-	-	-	-
M-method [12]	-0.011	0.008	-0.006	0.005	0.022	0.015	-0.033	0.016	0.028	0.015
K-method_R [16]	-0.013	0.012	-0.019	0.036	-0.008	0.019	-0.005	0.016	-0.010	0.028
K-method_L [16]	-0.010	0.014	0.006	0.042	-0.028	0.045	0.019	0.053	-0.014	0.032

Quantities are in seconds.

TABLE 3.3 Mean E% values for stride, step, stance and swing time estimations for each of the tested methods.

	stride time	**step time**	**stance time**	**swing time**
Z-method [14]	4%	8%	-	-
G-method [11]	2%	4%	10%	14%
S-method [15]	2%	4%	-	-
M-method [12]	2%	2%	4%	9%
K-method_R [16]	2%	5%	3%	4%
K-method_L [16]	2%	6%	6%	10%

Statistical analysis

Since data were not normally distributed, non-parametric statistics were chosen to present the temporal parameters errors (Fig. 3.1).

The Friedman test showed that only *E* values for stance, swing and double support time were significantly different among methods ($p<0.05$). Stance, swing and double support time errors were significantly different between each pair of methods (G-, M- and K- methods) ($p<0.017$). The Wilcoxon test revealed no significant differences between left and right side when the K-method was applied.

Robustness to IMU positioning

The *E%* values in stride and step time estimations computed for three methods (Z-, S- and M- methods) applied to the signals gathered from four IMU locations (S2, L3, L5 and W) are reported in Table 3.4. No results regarding the G-method are reported due to the high number of missed events resulting from the repositioning of the IMU.

TABLE 3.4 Mean E% values for stride and step time estimations computed for the Z-, S- and M- methods applied to the signals gathered from four IMU locations (S2, L3, L5 and W).
Values regarding the IMU location originally proposed are reported in bold.

		stride time	step time	stance time	swing time
Z-method [14]	*S2*	**4%**	**8%**	-	-
	L3	3%	5%	-	-
	L5	3%	9%	-	-
	W	2%	7%	-	-
S-method [15]	*S2*	2%	4%	-	-
	L3	2%	4%	-	-
	L5	2%	3%	-	-
	W	**2%**	**4%**	-	-
M-method [12]	*S2*	2%	2%	5%	7%
	L3	2%	2%	4%	7%
	L5	**2%**	**2%**	**4%**	**9%**
	W	3%	2%	4%	8%

3.4. Discussion

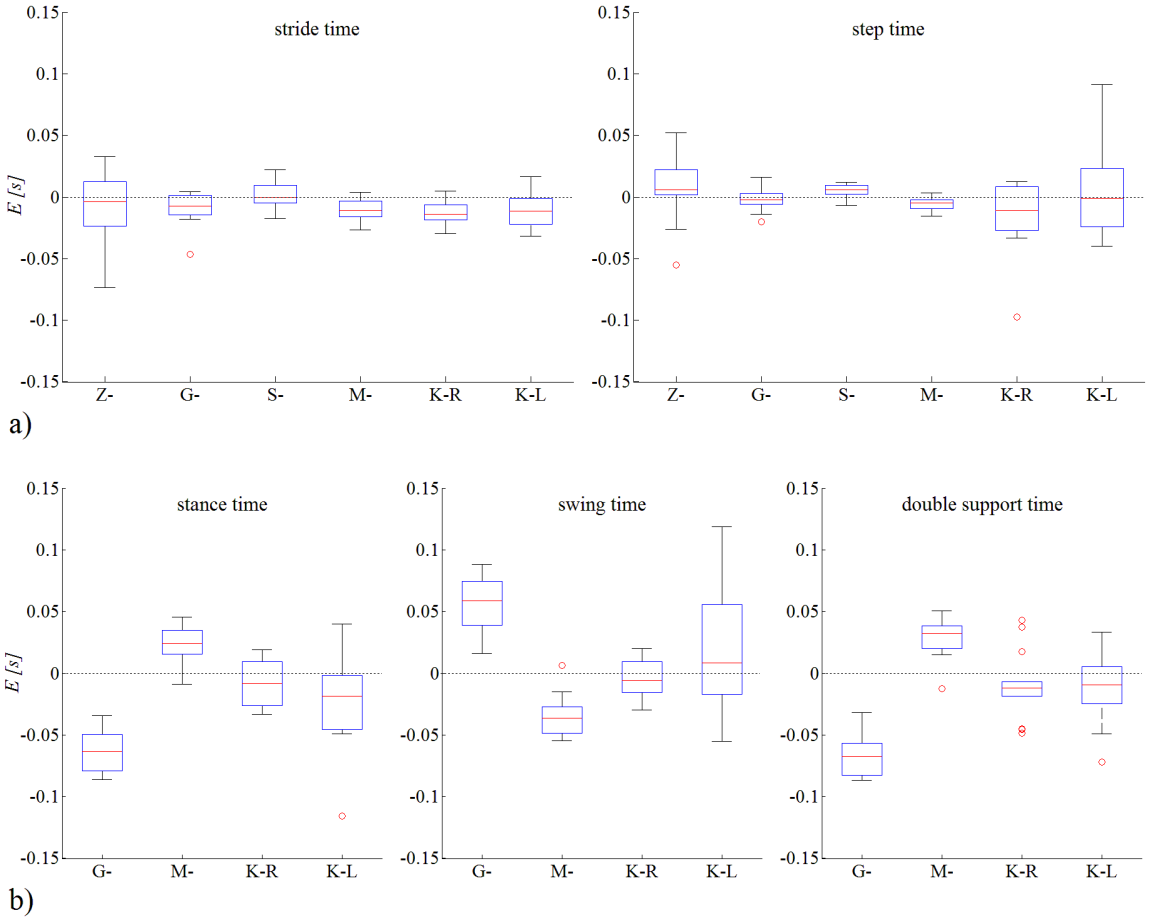
To our knowledge this is the first study evaluating accuracy, sensitivity and robustness with respect to the IMU positioning, of methods estimating gait temporal parameters from acceleration data obtained from a single IMU. McCamley et al. [12] performed a partial comparative evaluation of their method with two previously published methods [11,14],

however, sensitivity and robustness were not investigated. The selected methods were developed with different goals. Some of them estimate step and stride time to determine spatial parameters such as the step length (Z-, S- and K- methods), in one case without detecting any specific GE (S-method). Some methods include the determination of additional temporal parameters: stance, swing and double support time, therefore requiring the determination of both ICs and FCs (M-, G- and K- methods). Only two methods (Z- and G-methods) associate acceleration signal features to physical characteristics of gait to identify GEs. The *E%* values for stance and swing time across the four IMU locations could be computed only for the M-method.

In a previous study [30] we found that the Z- and G- methods are affected by IMU inclination changes. The Z-method failed frequently without correcting the inclination of the IMU (as recommended by the authors in a later study [24]); however, even after correcting for the IMU inclination, some missed events still remained. The G-method relies on the identification of regions of interest determined by zero crossings and therefore, small changes in the signal pattern could result in a failure of their identification, compromising the GE determination. Similarly, the K-method requires the identification of regions of interest in which all ICs and FCs are searched. In some cases, the identification of extra regions of interest produced GEs erroneously identified (extra events). The results of this study demonstrated that the accuracy in estimating step and stride duration was for all methods acceptable for clinical use (Table 3.2). In fact, no statistically significant difference was found for stride and step duration estimation errors as determined by the five methods. This result corroborates the idea that gait cycle duration could be accurately determined from the recording of a single IMU. Conversely, a statistical difference was found in the errors associated to stance, swing and double support time estimations ($p<0.017$), which are generally larger than those found for stride and step time estimations. In particular, the G-method suffered of the largest errors in all three parameters (Fig. 3.1b); the K-method showed a high asymmetry in their estimation and the M-method overestimated stance and double support time and underestimated swing time. This is caused by the inaccuracy with which all methods determine FCs, due to the fact that FCs occur during a smoother movement than that observed at ICs. As a consequence, more caution is necessary when interpreting estimations of the duration of stance, swing and double support. The robustness to the IMU positioning of three of the methods (Z-, S- and M- methods) was evaluated as the variability.

FIGURE 3.3 FIVE NUMBER STATISTICS FOR ALL GAIT TEMPORAL PARAMETERS AND EACH TESTED METHOD.

Minimum, first quartile (q1), median, third quartile (q3) and maximum values of: (a) stride time and step time estimation errors (E) as obtained from each of the tested methods; (b) stance, swing and double support time estimation errors (E) as obtained from each of the tested methods. Errors larger than q1+1.5(q3+q1) or smaller than q1−1.5(q3−q1) are considered outliers and represented with circles. Methods are listed in the x-axis of the plots and represented by the relevant initial. For the K-method, right and left parameter estimation errors are identified by "R" and "L", respectively.



of parameter errors when positioning the IMU in four different locations along the lower trunk. The S- and M- methods showed the highest robustness for both stride and step duration. The Z-method showed the lowest robustness (mean *E%* values ranging from 5% to 9% for step time and from 2% to 4% for stride time) most probably caused by the fact that the Z-method searches for specific peaks in the AP acceleration signal, while the other methods look for a unique periodic time marker in the relevant acceleration signal (negative to positive transition time of the acceleration norm for the S-method and the V acceleration minimum time for the M-method). Ultimately, the point of application of the IMU on the

lower trunk does not have to be identified with extreme care to provide reliable results, except for the Z-method.

There are several aspects in this study that need to be highlighted:

a) the main purpose of the study was to evaluate the performance of the tested methods in estimating gait temporal parameters. Errors in detecting GEs timing were not discussed since their evaluation was beyond the scope of the study;

b) the tested methods were evaluated with a sensor different in size and mass from those used in the original studies with possible consequences on signal characteristics;

c) for each subject, the methods were evaluated using different gait trial repetitions since the IMU used was not small enough to allow the concurrent positioning of four IMUs over the lower trunk landmarks. However, given the high reproducibility characterizing gait in healthy subjects [31], the latter experimental constraint was not expected to jeopardize the findings of the study;

d) gait data were acquired on subjects walking barefoot. Two of the tested methods (Z- and G- methods) were originally applied to recordings from the gait of shoed subjects. This may have resulted in a slight variation in the signal patterns and consequently higher errors in the results. In fact, previous studies [32] reported a difference between accelerometer signals recorded from the lower trunk of subjects walking barefoot and subjects walking with shoes. However, we chose to apply all methods to barefoot gait to facilitate a comparison among them, while conforming to the condition most commonly used in clinical evaluations;

e) only results from able bodied walkers were reported. Relevant interpretation should not be applied to pathologic gait. However, the results of this study represent a normative data reference for future studies addressing the validity of the analyzed methods when applied to groups of subjects with specific gait abnormalities.

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Chapter 4

Comparison of different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk: application to pathological gait [*]

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D. Trojaniello, A. Ravaschio, J.M. Hausdorff, A. Cereatti: ***Comparative assessment of different methods for the estimation of gait temporal parameters using a single inertial sensor: application to elderly, hemiparetic, parkinsonian and choreic gait***

Abstract

The estimation of gait temporal parameters with inertial measurement units (IMU) is a research topic of interest in clinical gait analysis. Several methods, based on the use of a single IMU mounted at waist level, have been proposed for the estimate of these parameters showing satisfactory performance when applied to the gait of healthy subjects. However, the above mentioned methods were developed and validated on healthy subjects and their applicability in pathological gait conditions was not systematically explored. We tested the three best performing methods found in a previous comparative study on data acquired from ten older adults, ten hemiparetic, ten Parkinson's disease and ten Huntington's disease subjects. An instrumented gait mat was used as gold standard. When pathological populations were analyzed, missed or extra events were found for all methods and a global decrease of their performance was observed to different extents depending on the specific group analyzed. The results revealed that none of the tested methods outperformed the others in terms of accuracy of the gait parameters determination for all the populations except the Parkinson's disease subjects group for which one of the methods performed better than others. The hemiparetic subjects group was the most critical group to analyze (stride duration errors between 4-5 % and step duration errors between 8-13 % of the actual values across methods). Only one method provides estimates of the stance and swing durations which however should be interpreted with caution in pathological populations (stance duration errors between 6-14 %, swing duration errors between 10-32 % of the actual values across populations).

4.1. Introduction

The assessment of the temporal and spatial parameters of gait is commonly considered of primary importance in clinical gait analysis since it contributes to the quantitative characterization of many common gait abnormalities. The determination of these parameters requires the detection of the initial and final foot contacts (IC and FC), usually referred to as gait events (GEs). Inertial measurement units (IMUs), including miniature gyroscopes and accelerometers, have been increasingly employed to this purpose thanks to their high wearability, reduced cost and low power consumption. The use of IMU technology is particular promising for the evaluation of gait parameters while monitoring daily life activities [1–3]. In the latter context, the instrumental setup should be even less invasive and

cumbersome than in the laboratory setting, directing researchers and developers towards the use of a single IMU. To minimally alter the subject's gait, a single IMU is often attached at the waist level so that the impact of both feet could be detected [4]. A downside of this solution is the difficulty to implement a robust and accurate method for identifying GEs, since in general, the farther from the ground the IMU location, the more difficult the parameters determination is.

In normal gait, some features of the lower trunk acceleration patterns (e.g., peaks, zero crossings) were consistently associated with the occurrences of ICs and FCs [4–8]. These observations have led several authors to propose methods for the detection of GEs and/or the estimate of temporal gait parameters from the acceleration signals of a single IMU mounted at the waist level [9–15]. In a previous study [16], we evaluated the performance of five selected methods employing a single IMU [17,10–13] for detecting GEs and estimating gait temporal parameters on a group of healthy young subjects. The comparison was carried out in terms of sensitivity and positive predicted values in detecting GEs, accuracy in estimating gait temporal parameters, and robustness with respect to the IMU positioning. The results reported in [16] showed an acceptable accuracy, sensitivity and robustness of all the evaluated methods in determining those gait temporal parameters based on the identification of ICs (e.g., stride duration), while a lower accuracy in determining the temporal parameters which also require the FCs identification (e.g., stance duration) was found.

The above mentioned methods were developed and validated on healthy young or elderly subjects and their applicability in pathological gait conditions was not systematically explored. The only exception is the method proposed by [9] which was later applied to pathological groups, such as amputees [18], various neurological patients [19], or patients with Parkinson's disease [20]. In most cases, only average values of the gait parameters were analyzed and caution in interpreting gait parameters was often recommended [18,19]. It seems that these methods cannot simply be extended to the analysis of pathological gaits.

Indeed, in some gait pathologies, deviations of the acceleration patterns (e.g., smaller amplitudes, higher variability) from those typically observed in normal gait are not negligible [21,22]. Such deviations are often due to impairments and consequent compensatory strategies. For example, hemiparetic gait is often characterized by an increased lateral displacement of the foot during swing in the paretic limb, consistently with limb vaulting to further assist limb clearance [23]. Other gait abnormalities, such as choreiform gait, also known as "drunken gait", are characterized by staggering from side to

side, with lateral swaying, and stride-by-stride lateral deviations from forward direction during walking [24], while parkinsonian gait is generally characterized by small shuffling steps and a stooped posture [25].

The gait abnormalities described above reflect in changes of the trunk acceleration waveforms which can potentially affect the performances of the single IMU based methods, thus limiting their applicability in the clinical setting. The aim of this work was to propose a comparative analysis of selected single IMU based methods for estimating gait temporal parameters in different pathological gait conditions. To this purpose, based on the findings reported in [16], the three best performing previously tested methods [9,11,12] were applied to the gait data of ten patients with hemiparesis, ten patients with Parkinson's disease, ten patients with Huntington's disease, and ten healthy elderly.

For each method, we evaluated the number of missed and extra GEs, along with the total number of GEs as detected by an instrumented gait mat, used here as a gold standard. The accuracy, associated with the GEs and temporal gait parameters determination, was evaluated against reference data provided by the instrumented mat. Comparative evaluations across methods within populations (Which is best performing algorithm for a given population?) and within methods for the different populations (Does a specific algorithm perform better for a given population?) were also performed.

4.2. Materials and Methods

4.2.1 Tested methods

Schematic descriptions of the Z-method [9], S-method [11] and M-method [12] are reported in Table 4.1; additional details can be found in the literature.

4.2.2. Data collection protocol

Instrumentation

A single IMU (OpalTM, APDM) featuring a 3-axis accelerometer and 3-axis gyroscope (unit weight 22 g, unit size 48.5×36.5×13.5 mm) was positioned over the subject's lumbar spine, between L4 and S2, using a semi-elastic waist belt. For the selected methods, the robustness to the IMU positioning along the lower trunk was found not to be a critical factor [16]. Sampling frequency was set at 128 Hz and accelerometer range at ±6 g. A spot check of the MIMU performance was performed according to the guidelines proposed by [26].

TABLE 4.1 Description of the tested gait event detection methods

	sensor type	sampling rate [Hz]	sensor position	estimated GEs	evaluated signals	alghoritm features	estimated parameters
Z-method [9]	3-axis acc	100	S2	IC	antero-posterior acceleration	zero crossing, peak detection	GEs detection; mean step length estimate
S-method [11]	3-axis acc	50	waist	IC	acceleration norm	sliding window summation, zero crossing	step length estimate
M-method [12]	IMU	100	L5	IC; FC	vertical acceleration	Gaussian CWT, minima and maxima	GEs detection

(*) The acceleration signals were filtered before processed (high pass filter, cut-off frequency 1 Hz [30]).

An instrumented gait pressure mat (GAITRiteTM Electronic Walkway, CIR System Inc) acquiring at 120 Hz (spatial resolution accuracy: ±12.7 mm; time accuracy: ±1 sample) was used to acquire reference data. The instrumented mat returned all GEs and temporal parameters analyzed. The IMU and the instrumented mat were synchronized (±1 sample).

Subjects

Ten hemiparetic subjects (HE) (two females, eight males; mean (sd) age: 58.6 (12.1) y.o., height: 1.72 (0.06) m, mass: 82.5 (15.9) kg), ten subjects with Parkinson's disease (PD) (five females, five males; mean (sd) age: 73.8 (5.7) y.o., height: 1.66 (0.10) m, mass: 67.7 (9.3) kg), ten subjects with Huntington's disease (HD) (five females, five males; mean (sd) age: 50.3 (13.3) y.o., height: 1.63 (0.05) m, mass: 60.6 (12.2) kg), and ten healthy elderly (EL) (six females, four males; mean (sd) age: 69.7 (5.8) y.o., height: 1.62 (0.08) m, mass: 63.6 (5.7) kg) were enrolled from the out-patient Movement Disorders Clinic of the University of Genoa. Disease severity was determined by means of the Functional Ambulatory Category (FAC) [27] for the HE subjects (3.3±1.5), the Unified Huntington's Disease Rating Scale (UHDRS) [28] for the HD subjects (62.7±19.1) and the Unified Parkinson's Disease Rating Scale (UPDRS) [29] for the PD subjects (34.9±16.9). The Declaration of Helsinki was respected, all subjects provided informed written consent, and local ethic committee approval was obtained.

Acquisition protocol

Subjects were asked to walk back and forth for about one minute along a 12-meter walkway with the instrumented mat placed two meters from the starting line where they

stood with their feet together for a few seconds after the beginning of the IMU acquisition. Subjects walked at self-selected, comfortable speed, wearing their own shoes. Walking aids such as canes or tripods were allowed if used in daily life. A single trial including several gait cycles was recorded for each subject.

4.2.3 Data analysis

All the methods analyzed provided an estimate of the stride and step durations. In particular, the Z-method and M-method define the gait cycle from the IC timing, conversely, the S-method identifies the zero-crossing instants of the acceleration norm (these instants occur in the proximity of the IC). Since only M-method provides FC timing estimates, stance and swing duration were estimated only for this method.

4.2.3.1. Number of missed and extra GEs

The number of actual GEs (*act*-GE) were provided by the gold standard ($N_{act\text{-}GE}$). They could either be detected (*det*-GE) or missed (*mis*-GE) by each of the methods ($N_{det\text{-}GE}$, $N_{mis\text{-}GE}$). The GEs estimated (*est*-GE) by each method ($N_{est\text{-}GE}$) could be either detected or extra GEs (*ext*-GE) ($N_{ext\text{-}GE}$). The following relationships exist:

$$\begin{aligned} &0 \le N_{det\text{-}GE} \le N_{act\text{-}GE}; \\ &0 \le N_{mis\text{-}GE} \le N_{act\text{-}GE}; \\ &N_{est\text{-}GE} = N_{det\text{-}GE} + N_{ext\text{-}GE}; \end{aligned} \quad (1)$$

When neither mis-GEs nor ext-GE are present, the estimated GEs coincide with the act-GEs.

4.2.3.2. Accuracy of the temporal parameters estimates

For each method, the differences between the IC timing, stride and step duration estimates (plus FC timing, stance and swing duration for M-method) and the relevant gold standard values were calculated. In the EL, HD and PD subjects left and right sides were not differentiated, conversely for the HE subjects, the results relative to the affected and non-affected sides were considered separately. For each subject and each tested method, the errors (*e*) of the estimated GEs and gait temporal parameters were computed as the averages of the above mentioned differences over the recorded gait cycles. Their group mean (μ), standard deviation (*sd*), mean absolute error (*mae*) and the relevant percent error (*mae%*) were then computed.

4.2.3.3. Comparative evaluations across methods within populations

To verify if differences among methods were present, the following statistical tests were performed (affected and non-affected side for the HE group were dealt with separately).

A Wilcoxon signed-rank test was used to compare the *mae* values of the IC timings obtained with Z-method and M-method. Differences were considered significant if the p-value was less than 0.05. A Friedman test for non-normal distribution was used to compare the *mae* values obtained for the stride and step duration estimates across all methods for each subject group. A post-hoc analysis (Wilcoxon signed-rank test) was then performed. A Bonferroni Holm's correction for multiple comparisons was also applied.

4.2.3.4. Comparative evaluations within methods for the different populations

To verify if errors obtained for each of the pathological groups were larger than those obtained for the EL group, for each method a Wilcoxon rank sum test was performed on the *mae* values found for the GEs and the gait temporal parameters. A Wilcoxon signed rank test was also performed to reveal differences between the mae values obtained for the affected and unaffected side in the HE subjects. Differences were considered significant if the p-value was less than 0.05.

4.3. Results

Over 2,253 gait cycles were obtained with the instrumented mat and used for the comparative analysis. The total number of gait cycles analyzed for each subject group along with the descriptive statistics (μ and *sd*) values of the temporal parameters (gait velocity, stride time, step time, stance time, swing time) as determined by the instrumented mat are reported in Table 4.2.

TABLE 4.2 Number of gait cycles and mean (sd) of gait velocities, stride time, step time, stance time and swing time for all groups (healthy elderly – EL, hemiparetic – HE, Parkinson's disease – PD and Huntington's disease – HD).

Group	gait cycles	gait velocity [m/s]	Stride time [s]	Step time [s]	Stance time [s]	Swing time [s]
EL	574	1.17 (*0.16*)	1.05 *(0.10)*	0.53 *(0.05)*	0.68 *(0.07)*	0.38 *(0.03)*
HE *	576	0.61 (*0.24*)	1.35 *(0.24)*	0.67 *(0.12)*	0.94 *(0.17)*	0.41 *(0.10)*
PD	532	0.85 (*0.14*)	1.14 *(0.09)*	0.57 *(0.05)*	0.76 *(0.07)*	0.38 *(0.03)*
HD	567	1.08 (*0.30*)	1.11 *(0.14)*	0.56 *(0.07)*	0.71 *(0.10)*	0.40 *(0.05)*

(*) Six hemiparetic subjects used a walking aid during the data acquisition sessions

Number of missed and extra GEs

In Table 4.3 the number of mis-GEs and ext-GEs along with their percentage with respect to *act*-GEs and *est*-GEs for each subjects group and each method has been reported.

TABLE 4.3 Missed and extra GEs for all methods and their percentage (light gray: 1-3%; medium gray: 4-8%; dark gray: >9%) with respect to the number of actual and estimated GEs obtained for all groups (healthy elderly - EL, hemiparetic - HE, Parkinson's disease - PD and Huntington's disease - HD).

Method/GE		mis-GE	% of act-GE	ext-GE	% of est-GE
Z-method/IC	EL	0	0.0%	0	0.0%
	HE	37	6.4%	5	0.9%
	PD	0	0.0%	1	0.2%
	HD	5	0.9%	5	0.9%
S-method/IC	EL	0	0.0%	0	0.0%
	HE	3	0.5%	250	30.4%
	PD	2	0.4%	36	6.4%
	HD	1	0.2%	50	8.1%
M-method/IC	EL	0	0.0%	0	0.0%
	HE	27	4.7%	13	2.3%
	PD	6	1.1%	0	0.0%
	HD	4	0.7%	3	0.5%
M-method/FC	EL	0	0.0%	0	0.0%
	HE	0	0.0%	73	11.2%
	PD	0	0.0%	0	0.0%
	HD	1	0.2%	5	0.9%

Accuracy of the temporal parameters estimates

Descriptive statistics (μ and *sd*) of *e* and *mae* for IC timings, stride duration and step duration (for all methods) and FC timings, stance and swing time (for M-method) for all the subjects groups are reported in Table 4.4. The *mae*% values for stride and step durations are also reported for all the methods while *mae*% values for stance and swing durations are reported only for M-method. In figure 4.1 a five number summary statistics was used to represent the *mae* values in estimating stride and step durations for each subjects group and each method.

Comparative evaluations across methods within populations

No significant differences were found in the *mae* values obtained for all the gait parameters between the tested methods for all the subject groups ($p>0.017$) except for the

PD group for which (a) IC timing errors for the Z-method were smaller than the M-methods; (b) stride time errors for the M-method were smaller than the S-method; and (c) step time errors for the Z-method were smaller than the S-method.

Comparative evaluations within methods for the different populations

For the Z-method, the IC timing errors, the stride time and step time errors for the HD group resulted significantly larger than those obtained for the EL group.

For the S-method, the stride time and step time errors for the HE (both affected and non affected side) and PD groups resulted significantly larger than those obtained for the EL group.

For the M-method, the IC timing errors, the stride time and step time errors for all the pathological groups (HE, PD and HD) were significantly larger than those obtained for the EL group. In addition, both stance and swing duration errors were significantly larger for the pathological groups.

4.4. Discussion

In the healthy elderly group, no missed or extra events were found for any of the tested methods, confirming previous results in healthy young adults [60]. It should be noticed that in the present study, the acceleration signals were filtered before processed using the Z-method (high pass filter, cut-off frequency 1 Hz [61]). This simple solution is extremely helpful when using the Z-method since it prevents from extra events detection associated to erroneous zero-crossing values due to the signal offset. In healthy elderly, no significant differences were found for IC timings estimate errors across methods. All methods showed a good accuracy level when estimating the stride duration (mae% values < 2%) and an acceptable accuracy level for the step duration (mae% values < 4%). Slightly larger errors were observed for the swing duration estimates provided by the M-method (mae% values < 5%). Conversely, when pathological populations were analyzed, missed or extra events were found and a global decrease of performance was observed to different extents depending on the specific group analyzed. The results revealed that the hemiparetic subjects group is the most critical group to analyze. In particular, the hemiparetic subjects group showed a moderate number of missed ICs when the Z- and M- methods were applied (respectively 6% and 5% of the act-ICs), and a high number of extra ICs when the S- and M methods was applied (30% and 11% of the est-ICs).

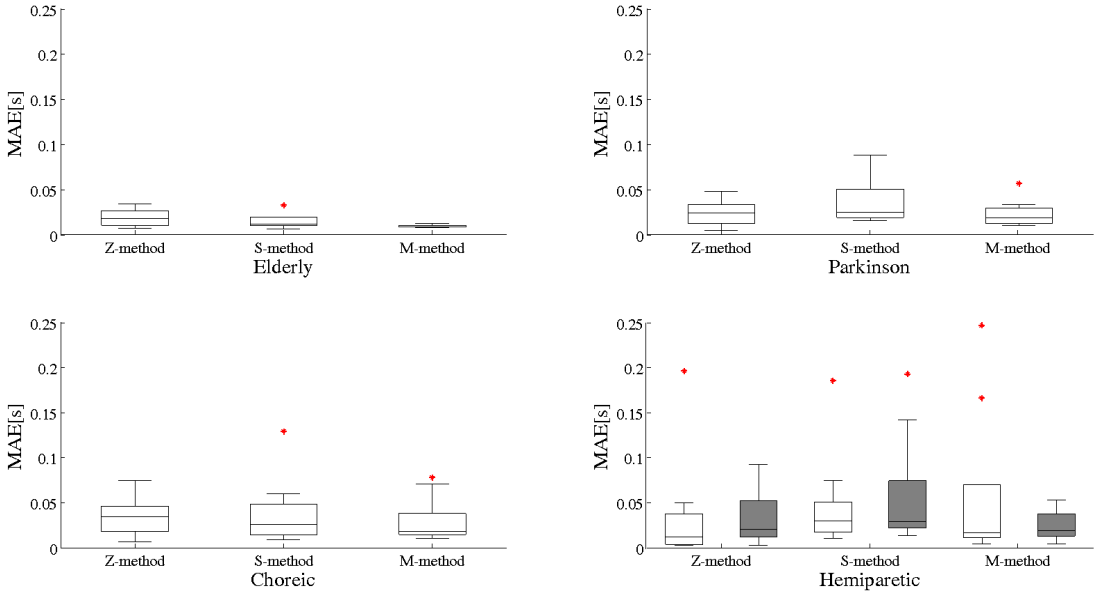
TABLE 4.4 Mean (μ) and standard deviation (*sd*) of the error and mean absolute error (MAE) in estimating IC timing, stride and step duration with all the methods (Z-Method, S-Method, M-Method) and FC timing, stance and swing duration with M-Method for all groups (healthy elderly - EL, hemiparetic - HE, Parkinson's disease - PD and Huntington's disease - HD). The percent mean absolute error MAE% values for stride, step, stance and swing duration estimates are also reported (light gray: 1-3%; medium gray: 4-8%; dark gray: >9%). Affected (bold) and non affected side estimate errors obtained for the H group are reported separately. Quantities are in milliseconds.

Method		IC		stride time			step time			FC		stance time			swing time		
		μ (sd)	MAE	μ (sd)	MAE	MAE%	μ (sd)	MAE	MAE%	μ (sd)	MAE	μ (sd)	MAE	MAE%	μ (sd)	MAE	MAE%
Z-method	EL	-7 *(30)*	21	0 *(33)*	20	2%	0 *(36)*	23	4%	-	-	-	-	-	-	-	-
	HE	-11 *(47)*	33	1 *(50)*	22	2%	29 *(138)*	59	9%	-	-	-	-	-	-	-	-
		-84 *(177)*	**100**	**2 *(121)***	**52**	**4%**	**-29 *(135)***	**57**	**8%**	-	-	-	-	-	-	-	-
	PD	-7 *(33)*	25	0 *(38)*	24	2%	0 *(38)*	25	4%	-	-	-	-	-	-	-	-
	HD	-40 *(60)*	47	1 *(68)*	37	3%	0 *(74)*	46	8%	-	-	-	-	-	-	-	-
S-method	EL	137 *(51)*	137	0 *(23)*	14	1%	0 *(25)*	17	3%	-	-	-	-	-	-	-	-
	HE	157 *(86)*	162	-4 *(100)*	42	3%	21 *(121)*	80	12%	-	-	-	-	-	-	-	-
		131 *(114)*	**155**	**-1 *(140)***	**73**	**5%**	**-26 *(139)***	**84**	**12%**	-	-	-	-	-	-	-	-
	PD	183 *(65)*	186	1 *(69)*	36	3%	1 *(83)*	49	9%	-	-	-	-	-	-	-	-
	HD	138 *(75)*	146	0 *(80)*	37	3%	1 *(109)*	57	10%	-	-	-	-	-	-	-	-
M-method	EL	42 *(23)*	43	0 *(13)*	10	1%	0 *(16)*	13	2%	36 *(29)*	42	-6 *(29)*	21	3%	7 *(28)*	20	5%
	HE	72 *(62)*	81	4 *(78)*	26	2%	66 *(170)*	89	13%	-4 *(78)*	58	-75 *(103)*	94	10%	79 *(99)*	94	23%
		-5 *(177)*	**112**	**1 *(185)***	**69**	**5%**	**-62 *(175)***	**90**	**13%**	**-32 *(107)***	**68**	**-27 *(189)***	**133**	**14%**	**28 *(190)***	**132**	**32%**
	PD	65 *(68)*	75	1 *(69)*	24	2%	0 *(91)*	34	6%	34 *(33)*	40	-31 *(70)*	47	6%	32 *(68)*	46	12%
	HD	57 *(62)*	68	0 *(73)*	29	3%	-2 *(66)*	31	5%	50 *(40)*	56	-10 *(68)*	39	6%	10 *(68)*	38	10%

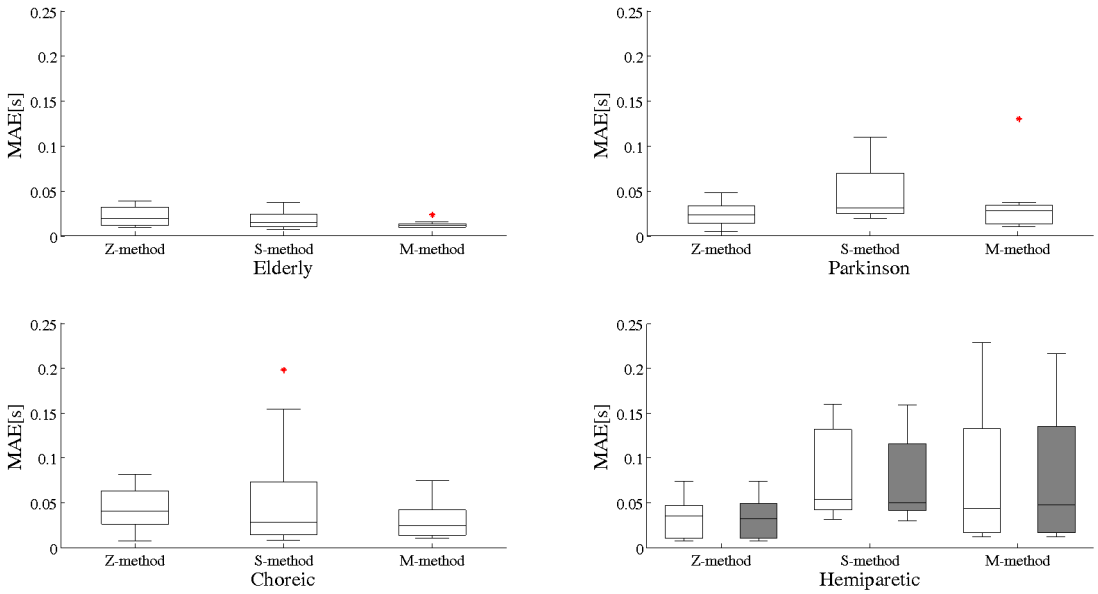
FIGURE 4.1 FIVE NUMBER STATISTICS FOR ALL GAIT TEMPORAL PARAMETERS AND EACH TESTED METHOD.

Minimum, first quartile (q1), median, third quartile (q3) and maximum values of: (a) stride time estimate mean absolute errors (MAE) as obtained from each of the tested methods for each subjects group (Elderly, Parkinson, Choreic, Hemiparetic); (b) step time estimate mean absolute errors (MAE) as obtained from each of the tested methods for each subjects group (Elderly, Parkinson, Choreic, Hemiparetic). Errors larger than q1+1.5(q3+q1) or smaller than q1−1.5(q3−q1) are considered outliers and represented with stars. Methods are listed in the x-axis of the plots and represented by the relevant initial. Affected (gray box) and non affected side estimate errors obtained for the hemiparetic group are reported separately.

(a)



(b)



The M-method also returned a high number of extra FCs (13% of the det-FCs). Conversely, all methods perform very well in terms of ICs detection when applied to the Parkinson's disease and Huntington's disease subjects groups with the only exception of the S-method which found a moderate number of extra ICs (respectively 6% and 8% of the Est-ICs). The presence of the significantly high number of missed and extra events in the hemiparetic subjects can be explained by trunk acceleration patterns that are much more irregular compared to normal gait also due to the use of walking aids and by the lowest gait speed which causes a signal attenuation (mean gait speed of 0.6 m/s). On the contrary, Parkinson's disease subjects group showed the most similar performances for all the tested methods with respect to the healthy elderly group. It is worth to notice that the presence of missed or extra GEs could greatly affect the validity of the gait temporal parameters estimates. In fact, since the gait cycle and each sub-phase (i.e. step, stance and swing durations) are identified starting from the IC and FC timings, if any missed or extra event is present in the data, the gait parameters estimation will be incorrect (i.e., longer or shorter stride/step/stance/swing time or higher or smaller number of gait cycles). This would potentially weaken the clinical applicability. Furthermore, the presence of extra or missed events can be especially critical when functional electrical stimulation is adopted for a proper and timely dispensing of the electrical stimuli during walking, for example [25, 39].

None of the tested methods outperformed the others in terms of accuracy of the gait parameters determination for all the populations except the Parkinson's disease subjects group. A general decrease of the methods accuracy was observed when they were applied to pathological groups with respect to healthy elderly. The accuracy analysis confirmed that the hemiparetic subjects group was the most critical one for all methods and the largest errors were found for the affected side (mae% between 4% and 5% for the stride time and between 8% and 13 % for the step time). The errors were even larger for the estimates of the stance and swing durations provided by the M-method (mae% between 10% and 32%).

For the Parkinson's disease subjects group, the Z-method performed relatively better than the other methods, reporting absolute errors comparable with those obtained in the healthy elderly group. No clear trends emerged for the Huntington's disease subjects group. The errors, affecting the estimates of the stance and swing durations provided by the M-method, were found to be significantly larger in the pathological groups with respect to the healthy elderly group.

In summary, on the basis of the results of this study, the following remarks can be drawn:

1) The analysis of the gait of hemiparetic subjects using a single inertial unit worn on the lower back can be critical both in terms of missed/extra gait events and temporal parameters accuracy irrespective of the method employed.

2) The Z-method, including a preliminary filtering of the acceleration signals, should be preferred when analyzing Parkinson's disease population.

3) The estimate of the stride duration is more reliable and valid than the step duration.

4) The estimates of the stance and swing durations in pathological population are not be reliable.

It is important to note that the results reported in the present study are referred to a straight level walking. During daily life when the subject varies the direction of progression and keeps stopping and starting, the methods performance are expected to decrease.

In conclusion, when highly impaired gait is analyzed (e.g. hemiparetic subjects), methods employing two inertial units on each leg should be preferred, at least for those gait parameters related to the accurate detection of both the ICs and FCs (e.g. stance time). In this regard, it has been recently shown [62] on similar pathological populations, that by exploiting some lower limb invariant kinematic characteristics, both missed and extra events can be avoided and that the errors can be reduced to 1% for the stride duration, 2-3 % for the step and stance durations and 6-7% for the swing.

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Chapter 5

Estimation of step-by-step spatio-temporal parameters of normal and pathological gait using shank-mounted magneto-inertial sensors: application to elderly, hemiparetic, parkinsonian and choreic gait [*]

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Abstract

Background. The step-by-step determination of the spatio-temporal parameters of gait is clinically relevant since it provides an estimation of the variability of specific gait patterns associated with frequent geriatric syndromes. In recent years, several methods, based on the use of magneto-inertial units (MIMUs), have been developed for the step-by-step estimation of the gait temporal parameters. However, most of them were applied to the gait of healthy subjects and/or of a single pathologic population. Moreover, spatial parameters in pathologic populations have been rarely estimated step-by-step using MIMUs. The validity of clinically suitable MIMU-based methods for the estimation of spatio-temporal parameters is therefore still an open issue. The aim of this study was to propose and validate a method for the determination of both temporal and spatial parameters that could be applied to normal and heavily compromised gait patterns.

Methods. Two MIMUs were attached above each subject's ankles. An instrumented gait mat was used as gold standard. Gait data were acquired from ten hemiparetic subjects, ten choreic subjects, ten subjects with Parkinson's disease and ten healthy older adults walking at two different gait speeds. The method detects gait events (GEs) taking advantage of the cyclic nature of gait and exploiting some lower limb invariant kinematic characteristics. A combination of a MIMU axes realignment along the direction of progression and of an optimally filtered direct and reverse integration is used to determine the stride length.

Results. Over the 4,514 gait cycles analyzed, neither missed nor extra GEs were generated. The errors in identifying both initial and final contact at comfortable speed ranged between 0 and 11 ms for the different groups analyzed. The stride length was estimated for all subjects with less than 3% error.

Conclusions. The proposed method is apparently extremely robust since gait speed did not substantially affect its performance and both missed and extra GEs were avoided. The spatio-temporal parameters estimates showed smaller errors than those reported in previous studies and a similar level of precision and accuracy for both healthy and pathologic gait patterns. The combination of robustness, precision and accuracy makes the proposed method suitable for routine clinical use.

5.1. Introduction

Walking allows humans to move forward by alternatively and repetitively swinging their left and right lower limbs. The gait pattern can be segmented into cycles that are typically divided into different phases in relation to the position of each foot with respect to the ground and of one foot with respect to the other (e.g. stance, swing and double support phases). The duration of the gait cycle phases is estimated by identifying the initial (IC) and final foot contacts (FC) timings, usually referred to as gait events (GE). The duration of the gait cycle is typically estimated by determining the time interval between two consecutive ICs of the same foot. The distance, along the direction of progression, traversed during a gait cycle, is referred to as stride length. Both stride length and duration can be seen as the sum of two consecutive steps, i.e. the distance traversed or the time interval between an IC and the following one of the contralateral limb [1].

From a lower limb kinematics perspective, human walking requires that: a) the two lower limbs alternate their swing phase while the opposite foot is in contact with the ground; b) at some point in stance there is at least one foot point fixed with respect to the ground (i.e. no sliding), c) swing begins with a roto-translation of the shank and ends with foot impact with the ground. The above-mentioned requirements apply to both healthy and pathologic gait and therefore can be exploited to detect GEs and spatio-temporal parameters.

A step-by-step determination of the spatio-temporal parameters is of great clinical relevance [2-5]. Often, the variability of different aspects can provide information that is independent of the average values. Variability of gait parameters has been associated with frequent geriatric syndromes such as falls, dementia and frailty [6]. In addition, gait variability has been associated with fall risk and disease progression in patients with Parkinson's disease [7,8]. Variability is also larger in patients with other movement disorders, like Huntington's disease and in post-stroke patients. Because variability reflects the step-to-step consistency of the gait, it has been used to describe the quality of the gait pattern and dynamic stability.

Various sensing technologies have been proposed to estimate step-by-step gait temporal and spatial parameters. Force platforms, instrumented mats, and footswitches are examples of devices sensing the contact of the foot with the ground. Motion analysis systems and magnetic and inertial measurement units (MIMU) as well as combinations of MIMUs and

other wearable technologies (i.e. pressure sensors [9]) have also been used to estimate GE timings from body segment motion [10,11]. To some degree, force platforms and instrumented mats suffer from the same limitations. They require extensive laboratory space, force subjects to walk in a specific environment and are relatively costly. Their main advantage is the possibility of estimating spatial gait parameters in addition to temporal parameters. Foot switches are portable and relatively inexpensive but may require extensive subject set up and can provide temporal parameters only. Motion capture systems capabilities go beyond the estimation of the gait spatio-temporal parameters, since they are devised for 3D point kinematics measurements. These systems are pricier than the above mentioned alternatives and generally can only capture a small number of consecutive steps.

The use of the MIMUs has been increasingly explored in the recent years thanks to the development of miniaturized sensing technology and the consequent improved wearability. However, MIMU-based recordings require appropriate processing to estimate gait parameters for clinical applications [12].

A number of authors have proposed methods applied to MIMU measurements for estimating gait temporal parameters [13-23] or spatio-temporal parameters [24-32]. A single sensor placed on the lower trunk has been proposed for healthy subjects [33-37] and pathologic gait [38-42]. A larger number of methods have been proposed using MIMUs attached to the lower limbs: on the feet or shoes [19,23,25,26], on the shanks [13-16,27], thighs [21], or both shanks and thighs [18,24]. In general, the farther from the contact point the MIMU is placed, the more difficult the GEs identification is. However, placing the MIMUs on the shanks may offer some advantages over the feet (or shoes). In fact, the shank is a more rigid segment and may allow for a firmer attachment of the MIMU [13]. Moreover, the recorded signals were found to be less variable across homogeneous subjects populations when MIMUs are mounted on the shank than when mounted on the foot [43].

When the MIMU is attached to a lower limb segment, the GEs detection and the determination of gait cycle phases is often based on the analysis of the sagittal angular velocity features [13,14,23,26,27] or, less frequently, of the acceleration features [15,17,19,20], applying approaches such as empirically determined thresholds [13,26,27], frequency analysis [24] and machine learning algorithms [23].

Methods for the determination of stride length from MIMU signals have also been proposed either using abstraction models, human gait models or signal integration [44]. Methods based on abstraction models perform poorly since the accuracy of the spatial parameters estimation depends on the completeness of training data; difficulties in controlling the performance across subjects have been also reported. The use of predefined human gait models requires subject specific anthropometric measurements. Since such models are based on the observation of physiological gait, accuracy issues in applying them to pathological gait patterns have been reported [44]. The signal integration methods consist of obtaining linear displacements by double integrating the MIMU gravity-compensated linear acceleration in the global reference frame [31,37]. However, due to the presence of drift in acceleration signals [45], the inaccuracy related to the estimation of the MIMU orientation [46] and the value of the constant of integration of the relevant signals (initial condition) [47], the estimate of gait spatial parameters is extremely poor unless some countermeasures are implemented. The cyclical nature of gait is typically used to reduce the detrimental effects of the drift by restricting the interval of integration time to the duration of a single gait cycle [47]. This requires the identification within the cycle of an instant of known velocity to be used as the initial value in the integration of the acceleration. The zero velocity update (ZUPT) is generally applied for this purpose to foot mounted MIMUs at the instant of flat foot [26,28,48]; when the MIMU is mounted on the shank, an inverted pendulum model is often used to estimate the initial integration value [30]. In addition, some de-drifting functions have been proposed [25,26,28]. The above mentioned expedients rely heavily on the quality of GE estimates. In fact, errors in determining the gait cycle and the instants of minimum velocity, as well as the chosen de-drifting function could compromise the estimate of gait spatial parameters.

Most of the studies mentioned above validated the proposed GE detection methods on healthy subjects [13,14,16,19,23,26]. The validity of MIMU based methods for the estimation of gait spatio-temporal parameters in clinical applications is still an open issue. Some studies applied the proposed method to the gait of elderly [24,28], spinal cord injuried [17], Parkinsonian [15,27,32], amputee [22] or patient's with prostheses [49]. Spatial parameters in pathologic gait have been estimated mostly as average values and only in a few studies on a step-by-step basis [24,26-29,32,50]. Only a few of the above mentioned studies have been validated against a gold standard. In a recent study, Yang et al. [24]

reported that methods for the determination of the gait cycle phases failed when the deviations of the angular velocity patterns from those typical of normal gait are not negligible. Such deviations are often due to impairments and consequent compensatory strategies. For example, hemiparetic gait is often characterized by an increased lateral displacement of the foot during swing in the paretic limb, consistently with limb vaulting to further assist limb clearance [5]. Other gait abnormalities, such as choreiform gait, also known as "drunken gait", are characterized by staggering from side to side, with lateral swaying, and stride-by-stride lateral deviations from forward direction during walking [51], while Parkinsonian gait is generally characterized by small shuffling steps and a general slowness of movement [3]. Each of the abnormal gait patterns reported above affects the MIMU signal patterns. Therefore a highly reliable method for the step-by-step estimation of spatio-temporal parameters should be validated for both healthy and heavily impaired gait.

The aim of this study was to propose and validate a method, based on the use of two MIMUs attached above the malleoli, for the determination of both temporal and spatial parameters that could reliably be applied to both healthy and heavily compromised gait. The above mentioned invariant characteristics of the lower limb kinematics characterizing human walking were exploited in developing the algorithm for the detection of the GEs instances, with the aim of enhancing its robustness across a variety of walking patterns by limiting the risk of experiencing extra and missed GEs. The GEs are detected by first identifying time intervals in which they cannot occur due to the intrinsic kinematic constraints, and then searching for GEs in the remaining portions of the gait cycle. The spatial parameters are determined by applying a modified version of a method originally developed for a waist-mounted MIMU [37]. Spatial and temporal parameters estimates were validated against those obtained using an instrumented mat.

5.2. Materials and Methods

5.2.1. Data collection protocol

Instrumentation

Two MIMUs (Opal, APDM) featuring a tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer (unit weight 22 g, unit size 48.5 mm × 36.5 mm × 13.5 mm) were

used. Sampling frequency was set at 128 Hz and accelerometer range at ±6 g. MIMUs were attached to the subject ankles (about 20 mm above the malleolus) with X, Y and Z axes pointing downward, forward and to the right, respectively (Fig. 5.1). The physical quantities (proper accelerations, angular velocities and magnetic field vector) are measured with respect to the axes of a local frame aligned to the edges of the unit housing. An estimate of the MIMU local coordinate system (LCS) orientation with respect to the global coordinate system (GCS) was provided by the APDM proprietary software. A spot check of the MIMU performance was performed according to the guidelines proposed by [46]. A gait pressure mat (GAITRite Electronic Walkway, CIR System Inc) acquiring at 120 Hz (spatial resolution accuracy: ±12.7 mm; temporal accuracy: ±1 sample) was used for validation purposes (Fig. 5.1). The instrumented mat returned all GEs, temporal and spatial parameters under analysis. The MIMUs and the instrumented mat were synchronized (±1 sample).

Subjects

Ten hemiparetic subjects (H), ten subjects with a choreic movement disorder (C), ten subjects with Parkinson's disease (P) and ten healthy elderly (E) were enrolled from the out-patient Movement Disorders Clinic of the University of Genoa. Disease severity was determined by means of the Functional Ambulatory Category (FAC) [52] for the H subjects,

FIGURE 5.1 SUBJECT WEARING TWO MIMUS ATTACHED ABOVE THE ANKLES AND WALKING ON THE INSTRUMENTED MAT.

the Unified Huntington's Disease Rating Scale (UHDRS) [53] for the C subjects and the Unified Parkinson's Disease Rating Scale (UPDRS) [54] for the P subjects. Demographic and clinical characteristics of the groups are summarized in Table 5.1. The Declaration of Helsinki was respected, all subjects provided informed written consent, and local ethic committee approval was obtained.

TABLE 5.1 Summary of demographic characteristics and the clinical scores of the groups participating in the study (healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C)

Subjects group	Gender	Age	Height	Weight	Clinical score
E	6 females 4 males	69.7 ± 5.8	161.8 ± 7.7	63.6 ± 5.7	-
H	2 females 8 males	58.6 ± 12.1	172.6 ± 5.8	82.5 ± 15.9	3.3 ± 1.5 [(a)]
P	5 females 5 males	73.8 ± 5.7	166.1 ± 9.7	67.7 ± 9.3	62.7 ± 19.1 [(b)]
C	5 females 5 males	50.3 ± 13.3	162.8 ± 5.1	60.6 ± 12.2	34.9 ± 16.9 [(c)]

The clinical scores reported are: (a) FAC; (b) UPDRS; (c) UHDRS.

Acquisition protocol

Subjects were asked to walk back and forth for about one minute along a 12-meter walkway with the instrumented mat placed two meters from the starting line where they stood with their feet together for a few seconds after the beginning of the MIMU acquisition. Subjects walked both at self-selected, comfortable speed (V1) and higher speed (V2). Subjects wore their own shoes and walking aids such as canes or tripods were allowed if used in daily life. Subjects could rest in between acquisitions if requested.

5.2.2. Gait temporal and spatial parameter estimation method

The algorithm implemented for detecting GEs required as first step the identification of time intervals in which no GE can occur (intervals of trusted swing - T_{SW}). Their identification is based on the angular velocity signals in the sagittal plane (ω_z) obtained from the gyroscopes. In fact, in both normal [26] and Parkinson's disease gait [27], the ω_z recorded from either the shank or the foot shows the largest values at mid-swing and a T_{SW} can be defined as the time interval with ω_z larger than a set threshold (20%) of its local maximum value M_p. If the ω_z crossed the threshold multiple times within a fraction of a second, as it occurs in some pathologic gait patterns, the T_{SW} was defined as the interval between the first and last threshold crossings including ML angular velocity local maxima (see Fig. 5.2a). The

following additional conditions also had to be satisfied: i. the minimum T_{SW} duration was set at 100 ms; ii. two consecutive T_{SW} of the same foot were separated by a minimum of 200 ms. Since the two lower limbs alternate their swing phase while the opposite foot is in contact with the ground, the T_{SW} of a lower limb can be used as interval of trusted stance (T_{ST}) of the other limb. Therefore, when coupled, the two T_{SW} allow for the identification of both T_{ST} and T_{SW} for each lower limb, reducing considerably the size of the time intervals in which ICs (T_{IC}) and FCs (T_{FC}) have to be searched, and consequently the risk of detecting extra GEs (see Fig. 5.2b for details). The IC was identified as the minimum value of the ML angular velocity [26,27] occurring in T_{IC} before the instant of maximum AP acceleration. The FC was identified as the instant of minimum AP acceleration in the T_{FC}, since it is expected to occur at the time of a sudden motion of the shank preceding the instant of the last maximum AP acceleration value in T_{FC} (Fig. 5.2b). Missed GEs could therefore occur only if T_{SW} were missed, which could happen only if the subject's feet progressed without swinging. Once the IC and FC were determined for each gait cycle, stride, step, swing and stance times were computed for both sides.

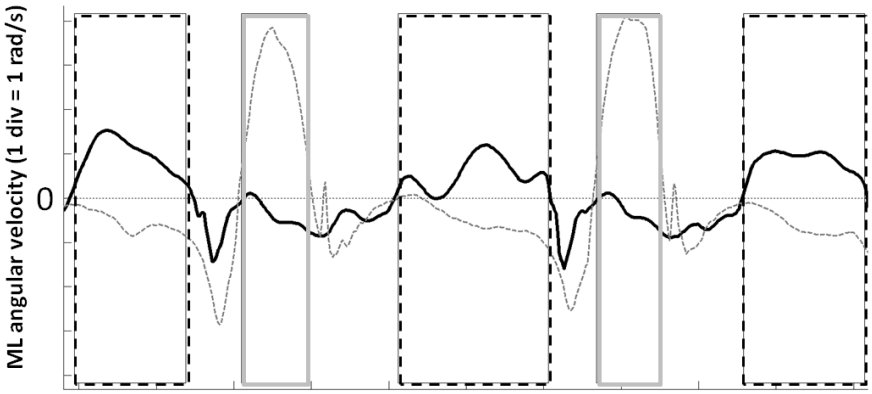
The stride length was estimated as the distance traversed by the MIMU between two consecutive ICs of the same foot. To estimate it, the proper acceleration signals were first expressed in the GCS, then gravity was removed. For each gait cycle analyzed, a specific motor task coordinate system (MTCS) was defined [55]; the vertical axis (V) was made to coincide with the gravity direction whereas the anterior-posterior (AP) axis was made to coincide with the direction of progression, which was determined as the direction of maximum average velocity obtained by integrating the horizontal acceleration components using the Optimally Filtered Direct and Reverse Integration (OFDRI) technique [56], while the ML axis was defined as the direction orthogonal to the AP axis. The latter MTCS has the advantage to do not be affected by errors in the heading estimates [46]. For each gait cycle, the AP acceleration component expressed in the MTCS was integrated using the OFDRI [37] from the 40% of the stance phase when at least a selected point of the foot (the calcaneous) can be considered fixed with respect to the ground [47]. The OFDRI technique requires the knowledge of the final value of the integral to set a cut off frequency for the high pass filter employed to reduce the effect of the drift in the accelerometer signals. The resulting cut-off frequency was then applied for filtering the acceleration signals in the MTCS, one gait cycle at a time. The initial integration value for the linear AP velocity of the MIMU was

determined as the product of ML angular velocity and the MIMU distance from the calcaneous. The velocity values found for the final instant of the gait cycle were used as initial velocity values for the integration of the following gait cycle. Finally, the stride length was obtained as the AP displacement resulting from a further simple integration of the AP velocity previously obtained. Both temporal and spatial parameters were estimated for left and right sides.

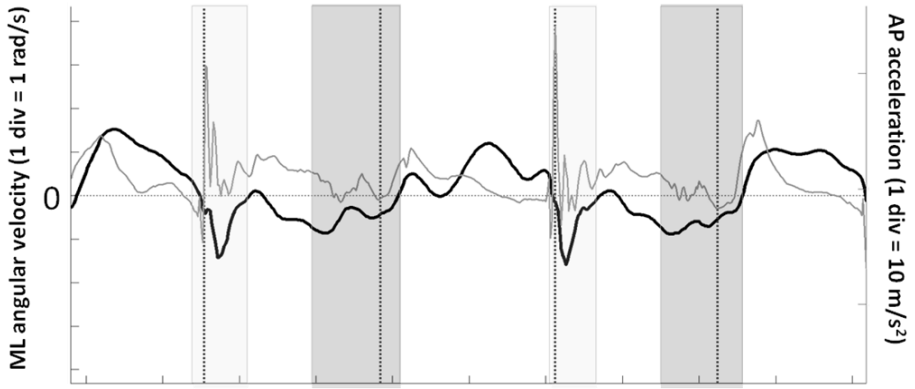
Figure 5.2 MIMU signals and gait events detection method.

(a) Angular velocities in the sagittal plane (ωz) for a hemiparetic subject are reported (black line: affected side). Rectangular frames represent trusted swing (dotted line) and trusted stance (solid line) intervals for the affected limb. (b) ML angular velocity (black line) and AP acceleration (gray line) for the affected side of a hemiparetic subject. Colored boxes represent time intervals for the IC (light gray) and FC (intense gray) search; dotted vertical lines represent the GEs timings.

(a)



(b)



A flowchart describing the algorithm used for estimating the spatio-temporal parameters of gait is reported at the end of the chapter in [Additional file 1].

5.2.3. Data analysis

5.2.5.1. Spatio-temporal parameters estimation errors

For each gait cycle, the difference between the estimated gait parameter (IC, FC, stride, step, stance, swing durations and stride length) and the reference value provided by the gold standard (instrumented mat) was determined and referred to as the error (*e*). Its absolute value and the relevant percent value were also computed.

For each subject, descriptive statistics for the error (mean and standard deviation values) and for the absolute and percent errors (mean values) were determined for both left and right sides. A Wilcoxon signed rank test was also performed to reveal differences between the absolute errors values obtained for the affected and unaffected side at both comfortable and higher speed in the H subjects. For each subject, left and right errors were then averaged. The resulting group averages were finally computed (*me, sde, mae, %mae*).

5.2.5.2. Comparison of errors between comfortable and higher walking speed

Given the limited sample size of the four groups, a five number summary statistics (i.e. the minimum, the maximum, the median, the first quartile and the third quartile) was used to represent the errors in estimating each gait parameter for each subject group and for both the comfortable and higher walking speed conditions. A Wilcoxon signed rank test was used to compare the subject's mean values of the absolute errors obtained for the two walking conditions to evaluate if there were statistical differences between them. Differences were considered significant if the p-value was less than 0.05.

5.2.5.3. Comparison of errors between healthy elderly and pathologic groups

A Wilcoxon rank sum test was performed between the subject mean values of the absolute errors obtained for the E group and those obtained for each of the pathologic groups. Differences were considered significant if the p-value was less than 0.05.

5.3. Results

Over 4,514 gait cycles were obtained with the instrumented mat and used for the comparative analysis. The total number of gait cycles analyzed for each subject group at the

two different gait speeds along with the mean (*me*) and standard deviation (*sde*) values of the analyzed spatio-temporal parameters (gait velocity, stride time, step time, stance time, swing time and stride length) for both walking speed conditions as determined by the instrumented mat are reported in Table 5.2.

TABLE 5.2 Number of gait cycles and mean (sd) of gait velocities, stride time, step time, stance time, swing time and stride length for all groups (healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C) at both comfortable (V1) and higher (V2) speed

Group	**Comfortable speed (V1)**							**Higher speed (V2)**						
	gait cycles	**gait velocity [m/s]**	**Stride time [s]**	**Step time [s]**	**Stance time [s]**	**Swing time [s]**	**Stride length [m]**	**gait cycles**	**gait velocity [m/s]**	**Stride time [s]**	**Step time [s]**	**Stance time [s]**	**Swing time [s]**	**Stride length [m]**
E	578	1.17 (*0.16*)	1.05 *(0.10)*	0.53 *(0.05)*	0.68 *(0.07)*	0.38 *(0.03)*	1.23 *(0.15)*	610	1.49 (*0.22*)	0.92 *(0.10)*	0.46 *(0.05)*	0.58 *(0.08)*	0.34 *(0.02)*	1.35 *(0.19)*
H	576	0.61 (*0.24*)	1.35 *(0.24)*	0.67 *(0.12)*	0.94 *(0.17)*	0.41 *(0.10)*	0. 81 *(0.30)*	516	0.79 (*0.30*)	1.22 *(0.21)*	0.60 *(0.10)*	0.83 *(0.17)*	0.39 *(0.07)*	0.86 *(0.30)*
P	532	0.85 (*0.14*)	1.14 *(0.09)*	0.57 *(0.05)*	0.76 *(0.07)*	0.38 *(0.03)*	0.97 *(0.15)*	560	1.02 (*0.14*)	1.04 *(0.10)*	0.52 *(0.05)*	0.68 *(0.07)*	0.36 *(0.04)*	1.06 *(0.15)*
C	567	1.08 (*0.30*)	1.11 *(0.14)*	0.56 *(0.07)*	0.71 *(0.10)*	0.40 *(0.05)*	1.16 *(0.21)*	575	1.28 (*0.26*)	1.00 *(0.11)*	0.50 *(0.05)*	0.64 *(0.08)*	0.36 *(0.03)*	1.27 *(0.23)*

5.3.1. Spatio-temporal parameters estimation errors

5.3.1.1. Gait events and temporal parameters

Neither missed nor extra GEs generated by the proposed method were observed. Therefore, all 4,514 gait cycles obtained with the instrumented mat were used for the analysis. The values of *me, sde, mae* and *%mae* of each group at both walking speeds, are presented in Table 5.3 for IC, FC, stride time, step time, stance time and swing time.

TABLE 5.3 Values for the group mean errors (*me*), mean standard deviation of the subject errors (*sde*), mean absolute errors (*mae*) and the percent of it (*%mae*) in estimating gait events (IC and FC) and temporal parameters (stride, step, stance and swing time) for the four groups (healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C)

p	Group	*me* (*sde*) [ms]		*mae* [ms]		*% mae*	
		V1	V2	V1	V2	V1	V2
IC	**E**	2 (10)	9 (10)	10	12	-	-
	H	0 (17)	3 (15)	17	15	-	-
	P	11 (11)	22 (9)	15	22	-	-
	C	7 (13)	7 (11)	12	13	-	-
FC	**E**	7 (15)	16 (9)	20	19	-	-
	H	11 (18)	13 (17)	21	21	-	-
	P	5 (18)	0 (15)	22	19	-	-
	C	2 (14)	6 (13)	18	16	-	-
Stride time	**E**	0 (14)	0 (13)	10	10	*1%*	*1%*
	H	0 (17)	0 (16)	13	12	*1%*	*1%*
	P	1 (15)	0 (13)	12	10	*1%*	*1%*
	C	0 (17)	0 (15)	13	12	*1%*	*1%*
Step time	**E**	0 (15)	0 (14)	12	12	*2%*	*3%*
	H	1 (26)	0 (22)	22	22	*3%*	*4%*
	P	0 (15)	0 (14)	12	11	*2%*	*2%*
	C	0 (18)	0 (16)	14	13	*3%*	*3%*
Stance time	**E**	10 (19)	25 (13)	22	28	*3%*	*5%*
	H	11 (11)	11 (22)	25	25	*3%*	*3%*
	P	15 (20)	21 (18)	26	27	*3%*	*4%*
	C	5 (18)	1 (17)	22	19	*3%*	*3%*
Swing time	**E**	9 (19)	25 (13)	22	27	*6%*	*8%*
	H	11 (23)	10 (22)	25	25	*6%*	*6%*
	P	16 (21)	21 (18)	24	27	*7%*	*8%*
	C	5 (19)	0 (17)	22	19	*6%*	*5%*

5.3.1.2. Gait spatial parameters

The *me*, *sde*, *mae*, *%mae* of the stride length are presented in Table 5.4 for each group and at both walking speeds. The agreement in estimating gait spatio-temporal parameters between the proposed MIMU based approach and the reference method is also reported using Bland-Altman plots [see Additional file 2 at the end of the chapter]. No statistically significant differences were found for all the gait parameters at both comfortable and higher speed between the subject mean values of the absolute errors obtained for the affected and unaffected side of H subjects.

TABLE 5.4 Values for the group mean error (*me*), mean standard deviation of the subject error (*sde*), mean absolute error (*mae*) and the percent of it (*%mae*) in estimating stride length for the four groups **(**healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C)

Group	***me* (*sde*) [mm]**		***mae* [mm]**		***% mae***	
	V1	**V2**	**V1**	**V2**	**V1**	**V2**
E	2 (19)	0 (19)	18	15	*1%*	*1%*
H	−6 (27)	−11 (22)	21	20	*3%*	*3%*
P	4 (21)	1 (19)	18	16	*2%*	*2%*
C	−8 (29)	−7 (31)	26	24	*2%*	*2%*

5.3.2. Comparison of errors between comfortable and higher speed

All *mae* values were not significantly different between walking speeds except for the *mae* of the IC of the P group. The stride time *mae* estimated for the C group was borderline statistically significant ($p = 0.05$). In figure 5.3, the five-number summary plots for the above mentioned parameters are reported.

5.3.3. Comparison of errors between healthy elderly and pathologic groups

None of the *mae* were significantly different between elderly and any of the pathologic groups except for the IC of the E and the P groups as well as that of the E and the H groups. The step time *mae* of the H group and the stride length *mae* of the C group were significantly different from those of the E group. In figure 5.4, the five-numbers plots for the above mentioned parameters are reported.

5.4. Discussion

In this study, we proposed a methodology based on the use of two magneto-inertial units attached above the ankles for the bilateral estimation of gait spatio-temporal parameters. The method exploits some invariant kinematic constraints characterizing both healthy and compromised gait to reduce the time intervals in which the initial and final contacts are sought. The method also includes an optimal integration technique to reduce the errors caused by the drift affecting the acceleration signals. In this study, we also validated the method on the gait of healthy (elderly) and pathological groups (hemiparetic, Parkinson's

disease, and choreic). No missed or extra GEs were detected for any of the groups. For the elderly, hemiparetic and choreic groups, the error in identifying IC at comfortable speed were the lowest errors ever reported in the literature. For the Parkinson's disease group, the average error was slightly higher than that found in one study [27] (11 ms vs. 8.7 ms), although the authors reported some false positive events.

Similarly, in detecting the FC timing, our method outperformed most of those found in the literature. For the elderly and Parkinson's disease groups, the errors were larger (2–3 ms) than those obtained by [27]. As far we know, no study in the literature showed lower errors than those found for the hemiparetic and choreic groups.

The stride and step time estimations exhibited, for all groups, higher accuracy than that found in any previously published method. Stance and swing time estimation errors were one order of magnitude larger than those found for the stride time. The error found for the stance time estimate of the elderly group was larger only than that found by [29] (about 9 ms), although they did not report standard deviation values. When the method was applied to the Parkinson's disease group, the error affecting the stance time estimate was larger only than that found in [27] (11 ms vs. 5.9 ms), but with a much lower standard deviation (11 ms vs. 29.6) at comfortable speed. No previous studies reporting stance time estimation errors in choreic and hemiplegic populations were found in the literature.

Swing time determination errors could be compared only to those obtained for healthy elderly subjects by [29], which were higher than those we found (16.5 vs. 9 ms) at comfortable speed.

For the elderly group, stride length estimation errors were negligible and comparable to those found in [49]. The errors found for all pathological groups were about one order of magnitude lower than those reported in [27,32].

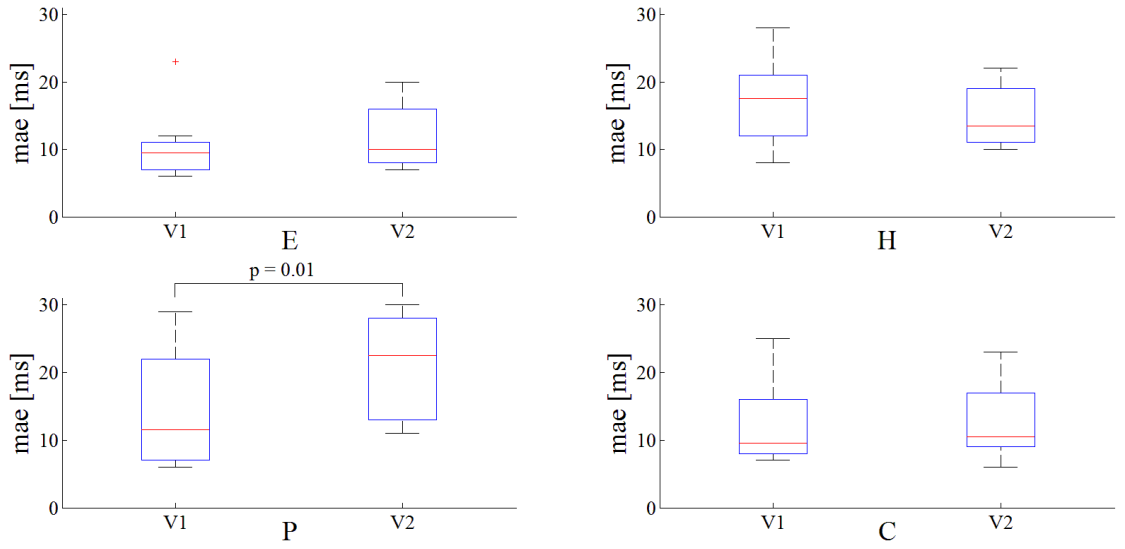
A thorough comparison of the performance of the different methods published so far could not be performed since most of the existing studies did not provide the mean absolute error which provides a better picture of the extent of estimation errors than the mean error.

As opposed to other methods [14], the present method is not influenced by walking speeds.

FIGURE 5.3 FIVE NUMBER STATISTICS (IC AND STRIDE TIME) FOR EACH PATHOLOGICAL GROUP.

Minimum, first quartile (q1), median, third quartile (q3) and maximum values of mean absolute errors (mae) relative to: (a) IC and (b) stride time for all groups (healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C) and for both comfortable (V1) and higher (V2) speed. Errors larger than q1 + 1.5(q3 + q1) or smaller than q1–1.5(q3–q1) are considered outliers (red marks (+))

(a)



(b)

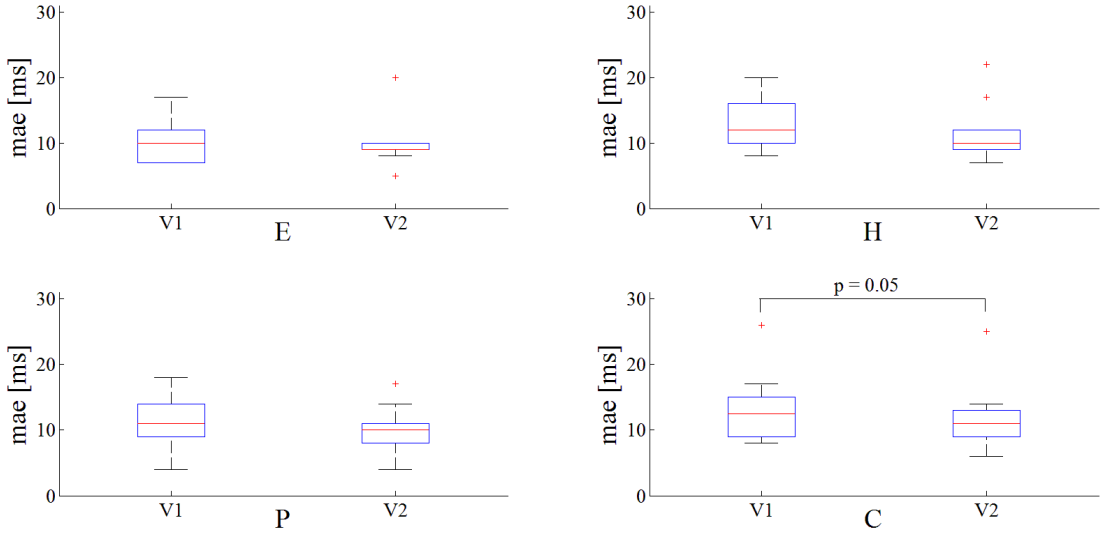
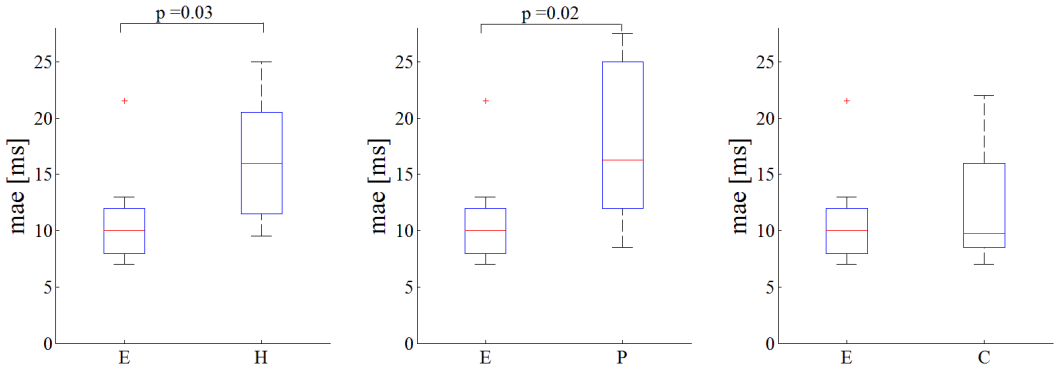


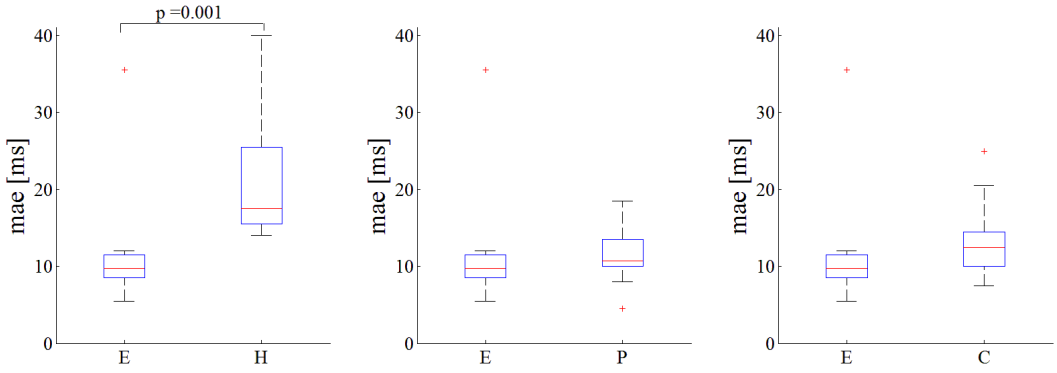
FIGURE 5.4 FIVE NUMBER STATISTICS (IC, STEP TIME AND STRIDE TIME). COMPARISON BETWEEN ELDERLY AND PATHOLOGICAL GROUPS.

Minimum, first quartile (q1), median, third quartile (q3) and maximum values of mean absolute errors (mae) relative to: (a) IC, (b) step time and (c) stride length for all groups (healthy elderly – E, hemiparetic – H, Parkinson's disease – P and choreic – C). Errors larger than q1 + 1.5(q3 + q1) or smaller than q1–1.5(q3–q1) are considered outliers and represented with red marks (+).

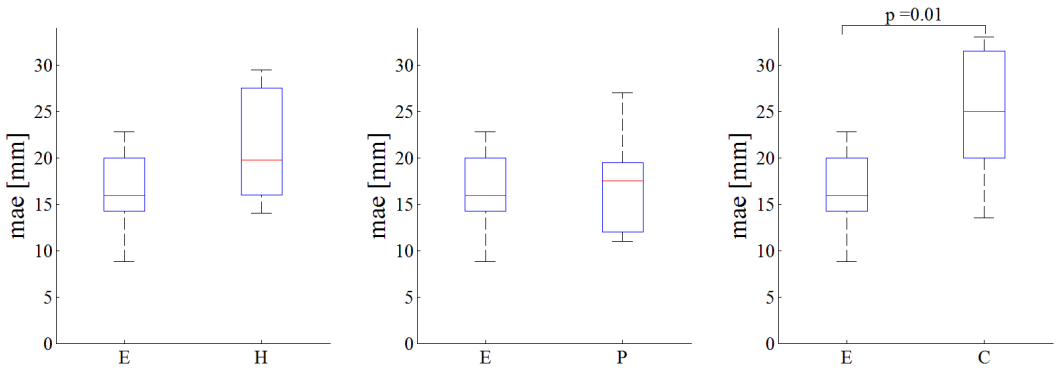
(a)



(b)



(c)



In conclusion, the proposed method appeared to be extremely robust since: a) it did not present neither missed nor extra GEs; b) gait speed did not substantially affect the performance of the method. Moreover, the gait spatio-temporal parameters estimates showed a similar level of precision and accuracy for both healthy and various pathologic gait patterns. The combination of robustness, precision and accuracy suggests that the proposed method is suitable for routine clinical use.

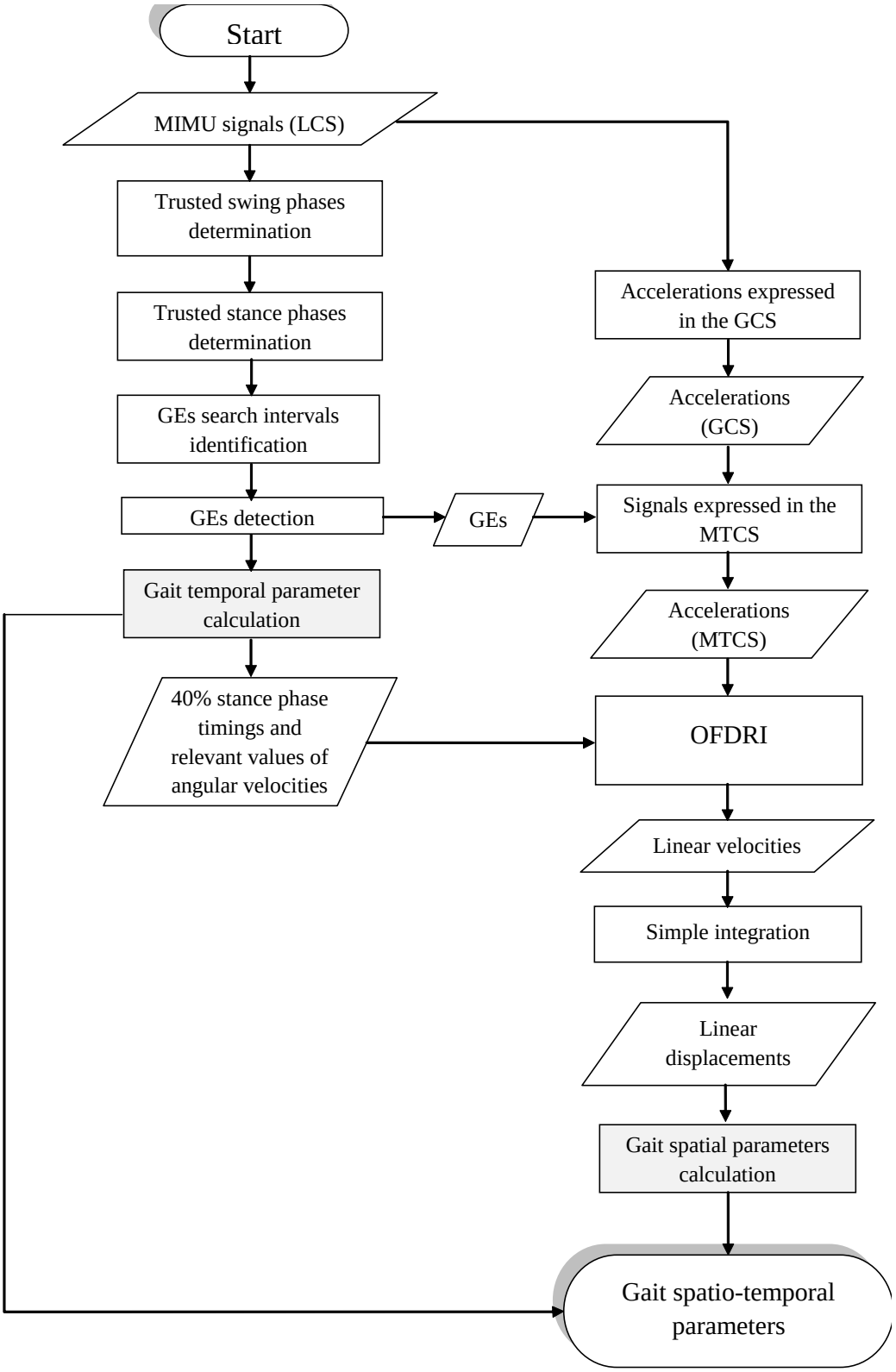
As expected, the stride length estimation error was larger for the C group, most probably due to the intrinsic difficulties associated with the determination of the direction of progression from the choreic gait patterns characterized by jerky lower limb movements.

Some aspects of the proposed method may be further improved. The proposed method performs well when applied to straight line walking, however the results cannot be extended to the analysis of gait including turns. The ZUPT was applied at 40% of the stance phase, which was shown to be the most appropriate instant when analyzing normal gait. However, there are not indications that the latter assumption is optimal for any the pathologic groups examined in this study.

Additional file 1 - Flowchart of the algorithm.

FIGURE 5.5A FLOWCHART OF THE ALGORITHM

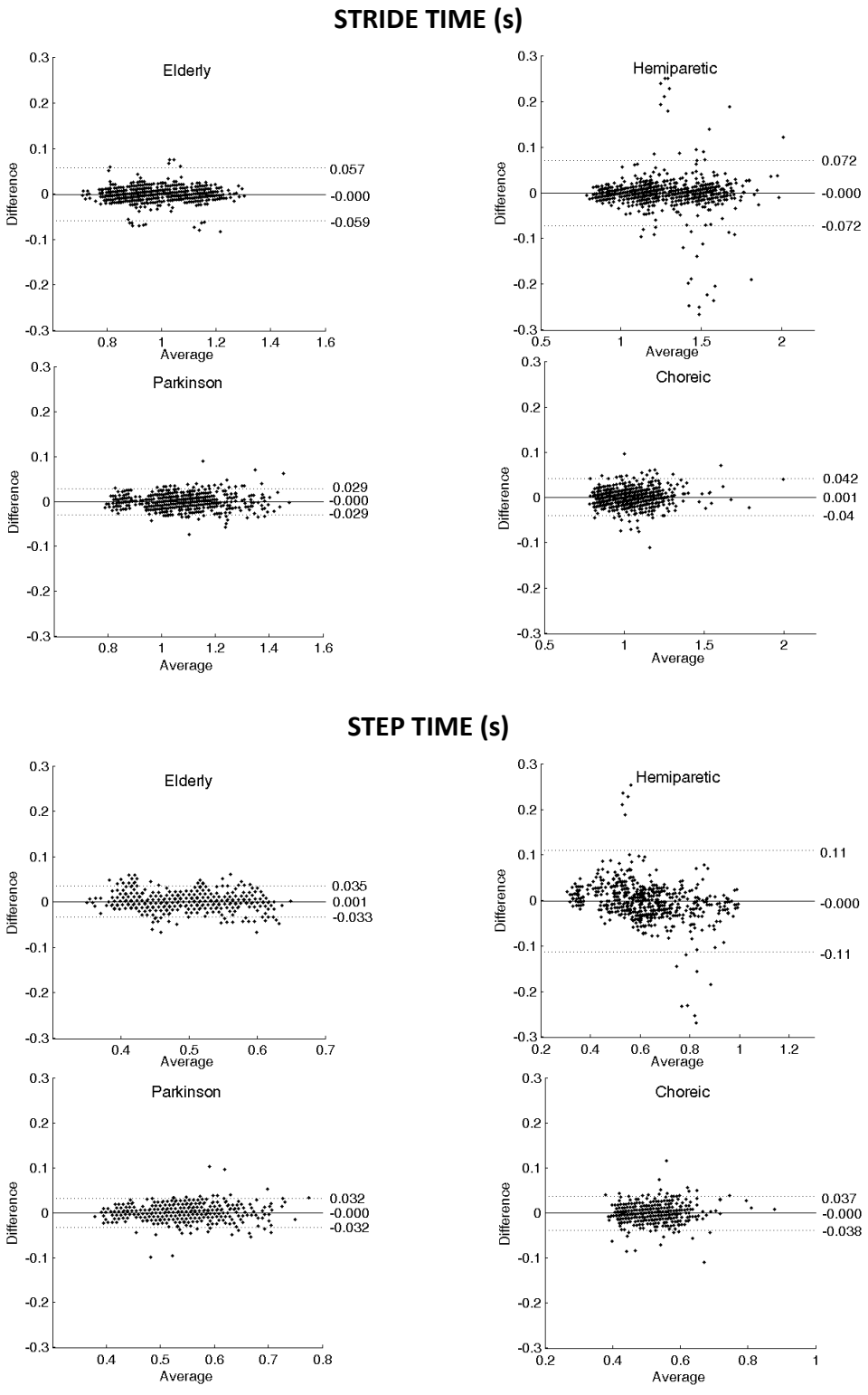
Flowchart detailing operations of the gait spatio-temporal parameters estimation algorithm.



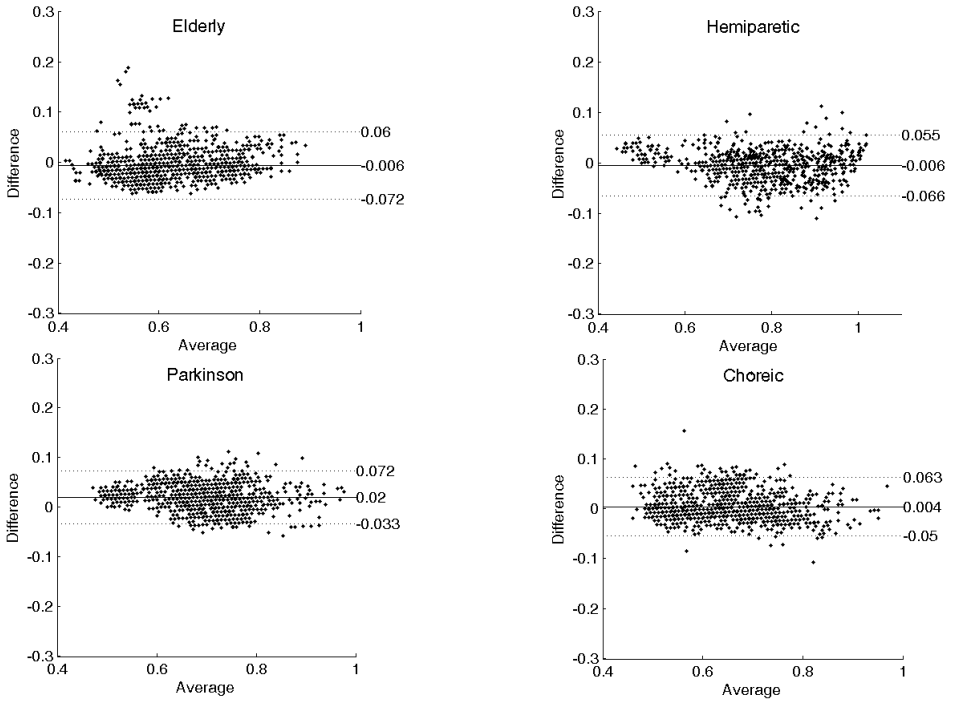
Additional file 2 - Bland-Altman plots

FIGURE 5.5B BLAND-ALTMAN PLOTS

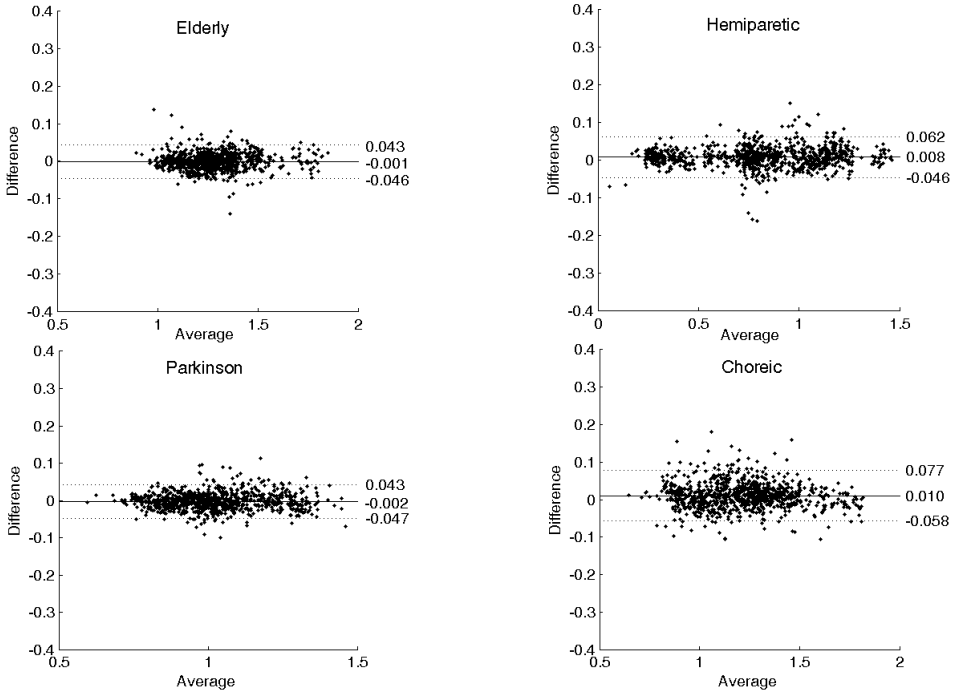
Bland-Altman plots illustrating the agreement between selected gait spatio-temporal parameters (stride time, step time, stance time, stride length) obtained using the proposed MIMU-based method and those derived from the reference method for each subjects group. Limits of agreement are specified as average difference (solid line) ±1.96 standard deviation of the difference (dotted line). Data from normal and fast walking conditions are merged for each subjects group.



STANCE TIME (s)



STRIDE LENGTH (m)



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Chapter 6

Assessment of gait direction changes during straight-ahead walking and turning in normal and pathological gait [*]

[*] Published in

D. Trojaniello, A. Cereatti, U. Della Croce: **Gait direction of progression estimate using shank worn MIMUs**, Proceedings 4th Conference Gruppo Nazionale di Bioingegneria (GNB), Pavia, Italy, June 2014

D. Trojaniello, A. Cereatti, A. Ravaschio, M. Bandettini, U. Della Croce: **Assessment of gait direction changes during straight-ahead walking in healthy elderly and Huntington Disease patients using a shank worn MIMU**, 36th Annual International Conference of the IEEE EMBC, Chicago, USA, August 2014, vol. pp.2508,2511, 26-30

Abstract

In this chapter the results of two experiments aiming at estimating DoP changes using MIMU based approaches are presented and discussed.

In the first experiment, five original methods for the estimate of the stride-by-stride DoP of gait from measurements of a MIMU placed over the malleolus and applied to the data of gait of both healthy and traumatic brain injured subjects are comparatively assessed. The methods were validated with the simultaneous measurements obtained with a stereo-photogrammetric system. The results showed that the MIMU-based DoP estimates were most satisfying in both straight and curved gait when one of the methods was used.

The second experiment aimed to propose and comparatively evaluate four methods (two of them were previously tested in the first experiment) for assessing stride-by-stride changes of direction of progression during straight walking. The four methods were evaluated by comparing their estimate of the gait changes of DoP with that obtained from an instrumented gait mat used as a gold standard. The methods were applied to the data obtained from the gait of both healthy subjects and patients with Huntington's disease, the latter characterized by a jerky swing phase. The results showed that the errors associated to the best estimates of the gait direction changes were about 10% of its range of variability for the healthy subjects and increased to about 30% for the patients, both walking at comfortable speed when the range of variability is the largest.

Additional testing on gait at various radius of curvature should be carried out to fully validate the MIMU-based proposed methods.

6.1. Introduction

Clinical gait analysis requires the objective assessment of gait spatial and temporal features which help clinicians characterizing pathological conditions as well as monitoring the progression of diseases or the influence of a treatment [1]. In general, gait spatial parameters such as stride length, step length, step width and foot angle are defined with respect to the direction of progression (DoP), i.e. the angle of the stride vector from one point of the foot at initial contact (IC) to the same point of the foot at the following IC. Moreover, current definitions of gait spatial parameters have been based on the premise that walking occurs along a straight line. However, as reported by [2], when the DoP is not constant during walking, these definitions do not

provide meaningful information and alternative ones should be used. Information about the DoP time evolution can be used to characterize the ability of the subject in maintaining a straight path (mean path lateral deviation), or in performing curved paths. In fact, physiological gait requires the capability of holding the programmed direction of progression. The control of the direction of progression is provided by the vestibular system in conjunction with inputs from the visual and somato-sensory systems. The ability of maintaining a pre-planned straight path is compromised in those subjects who suffer from vestibular deficits [10]. Deviations from straight gait can also be induced by blindfolding healthy subjects undergoing a galvanic stimulation [11]. Even gait disorders not involving vestibular dysfunctions, such as Huntington disease (HD), also known as "drunken gait", are characterized by staggering from side to side, with lateral swaying, and stride-by-stride lateral deviations from forward direction [12, 13]. The clinical tests generally adopted to assess the changes of direction during straight walking (GDC) such as the Babinski-Weil test routinely applied to subjects with vestibular deficits [14] or the tandem gait test used in the HD assessment [15], do not provide a stride-by-stride quantitative GDC estimates. Other tools such as clinical scales only provide scores of abnormal deviations during tandem gait (Unified Huntington's Disease Rating Scale, UHDRS [16]) or moderate to marked deviations along a straight path (Tinetti balance assessment scale - gait section [17]). In addition, difficulties in turning during gait are often encountered in movement disorders such as Parkinson disease, and could often result in an increased fall risk [4]. An accurate and objective GDC estimate would therefore be useful in clinical contexts.

In instrumented clinical gait analysis, a quantity that could be used to properly estimate the GDC is the direction of progression (DoP). Its stride-by-stride changes can assess the ability of a subject of maintaining a straight path or turning. Recently, Miranda et al [14] proposed a simple method for quantifying the GDC during the Babinski-Weill test in healthy subjects. However, they provided only an evaluation of the overall GDC (from the start to the end of the path). Other studies used stereo-photogrammetry or floor markers to evaluate deviations from a straight path [18,19].

Several methods based on magnetic and inertial measurement units (MIMUs) for the estimate of gait temporal and spatial parameters as well as turning parameters [5,6] have been proposed. The latter ones are mostly based on the study of angular velocity signals recorded on the trunk and do not allow for a proper estimation of the DoP along straight paths.

Therefore, the aim of this preliminary study was to:

1) to propose and compare different methods for estimating GDC along straight and curved paths using a single MIMU attached to the ankle for a wide range of natural gait speeds. To this purpose the comparison was performed on two groups of subjects whose gait is characterized by different speed. The measurements obtained from a stereo-photogrammetric (SP) system were used as a gold standard. The main hypothesis of the study was that the DoP during gait corresponds to the maximum variation of the velocity vector along the three MIMU axes (x,y,z) within a gait stride for both healthy and reduced speed pathologic gait.

2) to propose and evaluate four methods for estimating the GDC while walking along a straight path using a single MIMU attached above the ankle. The methods were applied to the gait of healthy elderly subjects and subjects with HD. In this experiment, simultaneous measurements from an instrumented gait mat were used as a gold standard.

6.2. Materials and Methods

Instrumentation

One MIMU (Opal^{TM}, APDM, Inc, APDM, Inc) was attached to the subject's shank about 20 mm above the lateral malleolus. The performance of the MIMU (spot check) was tested according to the guidelines proposed by [20]. The MIMU measures accelerations, angular velocities and local magnetic field with respect to the axes of a local frame (LF) aligned to the edges of the unit housing. An estimate of the LF orientation with respect to the global frame (GF) was provided by an on-board Kalman filter.

6.2.1. Data collection protocol

First experiment

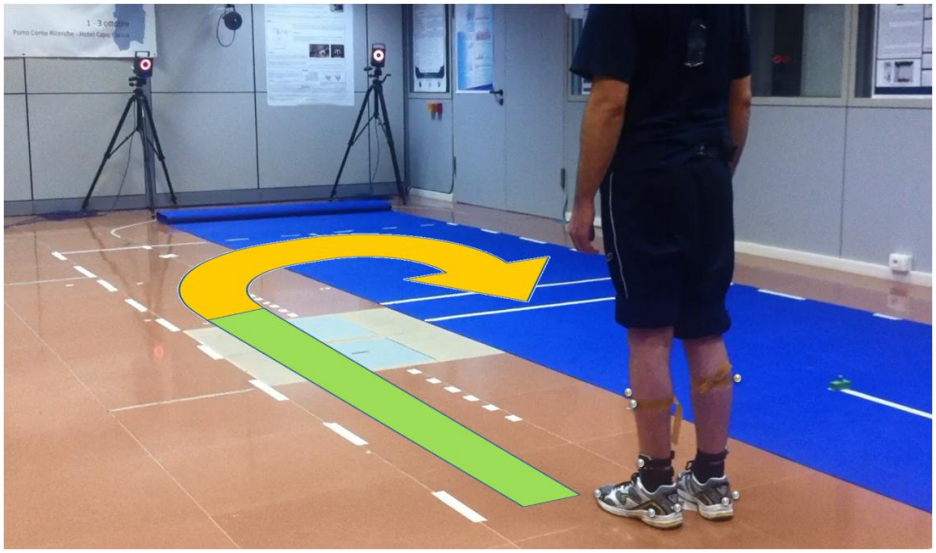
Gold standard. A six-camera SP system (Vicon T20) was used to acquire reference data (calibrated volume: 8×4×1.8 m^3). Signals were sampled at 128 Hz. Three retro-reflective markers were placed on each foot (toe, heel and malleolus) and an additional one was placed on the MIMU. The MIMU and the SP system were synchronized.

Subjects. The study included five healthy subjects (H) (2 females, 3 males; mean (SD) age: 30.2 (4.8) y.o., height: 1.78 (0.08) m, mass: 75.2 (13.3) kg, gait speed: 1.18 (0.16) m/s) and five subjects with reduced gait speed (traumatic brain injury - TBI) subjects (5 males, mean (SD) age: 55.4 (21.3) y.o., height: 1.69 (0.04) m, mass: 70.2 (5.2) kg, gait speed: 0.84

(0.20) m/s) enrolled from the out-patient Neurologic Clinic of Sassari, Italy. The inclusion criteria were patients who (1) had sustained a TBI and (2) were able to walk independently over a distance of 20 m, including subjects who needed gait aids.

Acquisition protocol. Subjects were asked to walk for about a minute at a self-selected, comfortable speed along a pre-designed loop made of two U-turns (Fig. 6.1) inside the SP system calibrated volume. At the beginning of each acquisition, subjects stood with parallel feet for a few seconds after the beginning of the MIMU acquisition. Three trials were recorded for each subject. Subjects wore their shoes and walking aids (canes or tripods) were allowed if used in daily life.

FIGURE 6.1 PORTION OF THE PRE-DESIGNED PATH (EXPERIMENT 1)



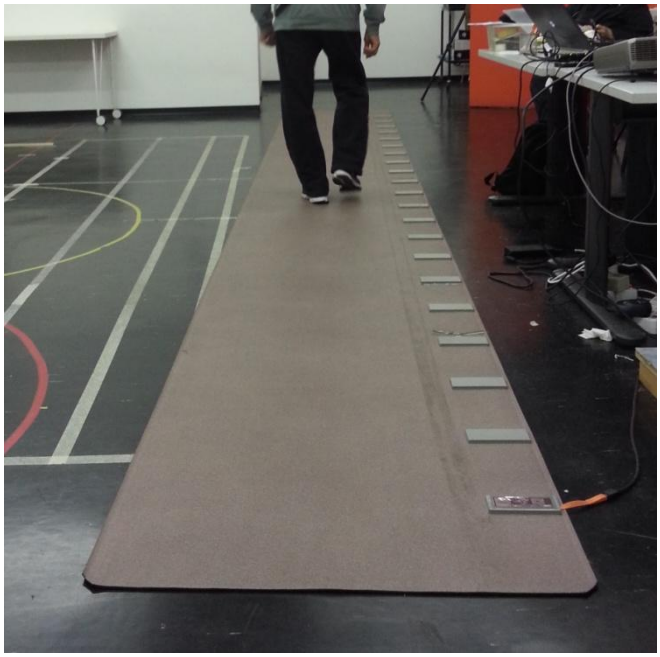
Second experiment

Gold standard. An instrumented gait mat (GAITRite™ Electronic Walkway, CIR System, Inc) acquiring at 120 Hz (length: 9 m, spatial resolution accuracy: ±12.7 mm; temporal accuracy: ±1 sample) was used for validation purposes. The dedicated software (PKMAS, ProtoKinetics, LLC) returned all temporal and spatial gait parameters, including the DoP defined as the angle of the vector joining the heel footprint of two consecutive heel strikes of the same foot (degrees) with respect to the mat midline. Stride-by-stride DoP changes were used as GDC reference values. The MIMU and the instrumented mat were synchronized (±1 sample).

Subjects. The study included ten healthy elderly (E) subjects (six females, four males, mean ± *sd*; age: 68.7 ± *5.8* y.o., BMI: 24.3 ± *1.5*) and ten HD patients (three females, seven males, mean ± *sd*; age: 54.2 ± *11.9 y.o.*, BMI: 23.6 ± *4.3*) enrolled from the outpatient Movement Disorders Clinic of the University of Genoa. Disease severity was determined by means of the UHDRS. The inclusion criteria were patients who had (1) a confirmed diagnosis of HD and (2) the UHDRS score relative to the gait and tandem walking greater than or equal to 1.

Acquisition protocol. Subjects were asked to walk back and forth for about one minute along a 12-meter walkway with the instrumented gait mat placed two meters from the starting line where they stood with their feet together for a few seconds after the beginning of the MIMU acquisition (Fig. 6.2). Subjects walked wearing their shoes both at self-selected, comfortable speed (V1) and higher speed (V2) (i.e. maximum walking speed). In between acquisitions subjects could take a rest.

FIGURE 6.2 PORTION OF STRAIGHT PATH (EXPERIMENT 2)



6.2.2. Direction of Progression estimation

The MIMU raw signals, proper acceleration and angular velocity, were expressed in the GF using the quaternion provided by on-board Kalman filter. The gravity contribution was

then removed from the acceleration signals obtaining the acceleration ($^{G}a(t)$). Gait cycles were isolated using the algorithm proposed in [7].

By integrating $^{G}a(t)$ within the j^{th} gait cycle using 30% of the stance time as zero-update timing (ZUPT) [8], an estimate of the velocity variation $^{G}\hat{v}(t)_j$ from the cycle initial value $^{G}v(0)_j$ was obtained as in (1):

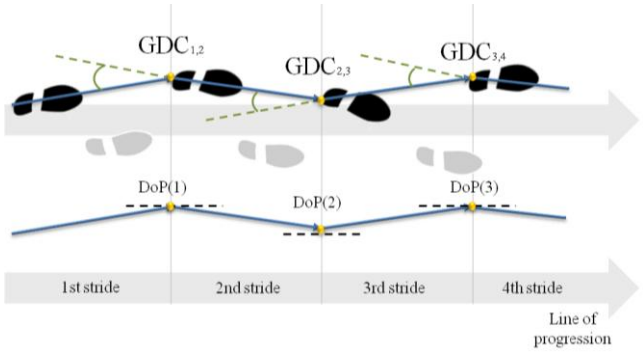
$$^{G}\hat{v}(t)_j = {}^{G}v(t)_j - {}^{G}v(0)_j = \int_{jZUPT_i}^{jZUPT_f} {}^{G}a(t)_j\,dt \qquad (1)$$

and the mean velocity variation for each gait cycle was then computed as in (2):

$$^{G}\bar{v}(j) = avg(^{G}\hat{v}(t)_j) \qquad (2)$$

during one phase of the gait cycle (see below). The $^{G}\bar{v}(j)$ is then projected on the horizontal plane and the angle between $^{G}\bar{v}(j)$ and $^{G}\bar{v}(j+1)$ is obtained and considered as the change of DoP (GDC) from one gait cycle to the following (Fig. 6.3).

FIGURE 6.3 CHANGES OF DOP DURING STRAIGHT WALKING (GDC).



In the phases of the gait cycle

First experiment: (i) all the gait cycle (*M1*); (ii) the swing phase (*M2*); (iii) the time interval in which the medio-lateral angular velocity reaches the 70% of its maximum (ω_{Zmax}) (*M3);* (iv) the time interval between the final contact (FC) and ω_{Zmax} (*M4*). The same approach was applied to the displacement $^{G}s(j)$ along the three directions obtained with a further simple integration of $^{G}v(t)_j$ (*M5*) and to the reference data (displacement of the marker placed on the MIMU along the three directions) (Tab. 6.1).

Second experiment: (i) the swing phase (*Method 1*); (ii) the entire gait cycle (*Method 2*). The GDC was also estimated (iii) as the angle between the mean unit vector of the angular velocity $^{G}\bar{\omega}(t)_j$ during the swing phase of two consecutive strides (*Method 3)* and (iv) by

computing the displacement ${}^{G}s(j)$ along the three directions obtained with a further integration of ${}^{G}v(t)_j$ throughout the gait cycle (*Method 4*). (Tab. 6.1).

TABLE 6.1 Overview of the methods proposed and tested in both the experiments

FIRST EXPERIMENT			SECOND EXPERIMENT		
Method	**Vector**	**Time interval**	**Method**	**Vector**	**Time interval**
M1	${}^{G}\bar{v}(j)$	Gait cycle	**Method 1**	${}^{G}\bar{v}(j)$	Swing phase
M2	${}^{G}\bar{v}(j)$	Swing phase	**Method 2**	${}^{G}\bar{v}(j)$	Gait cycle
M3	${}^{G}\bar{v}(j)$	>70% of ω_z max	**Method 3**	${}^{G}\bar{\omega}(j)$	Swing phase
M4	${}^{G}\bar{v}(j)$	FC to ω_z max	**Method 4**	${}^{G}s(j)$	Gait cycle
M5	${}^{G}s(j)$	Gait cycle			

A schematic view of the phases of the gait cycle taken into account in the proposed GDC estimation methods for both the experiments are reported in figure 6.4 and figure 6.5.

FIGURE 6.4 VELOCITY (DOTTED LINE) AND DISPLACEMENT (SOLID LINE) IN THE HORIZONTAL PLANE (X,Y) DURING ONE GAIT CYCLE. GAIT CYCLE PHASES USED FOR THE ESTIMATION OF GDC ARE SHOWN AS COLOURED AREA.

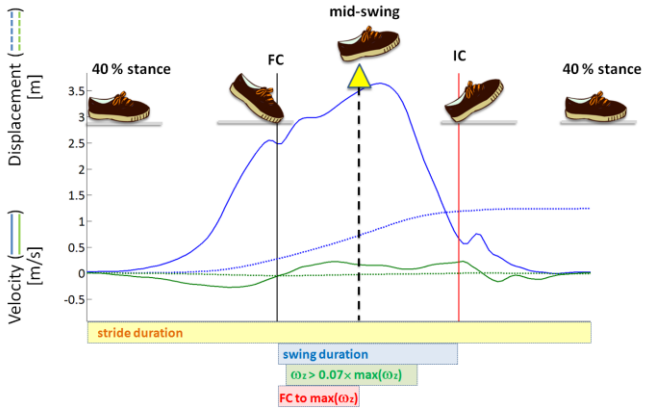
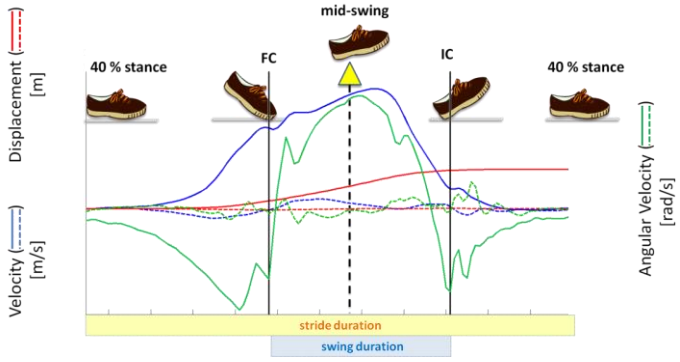


FIGURE 6.5 VELOCITY (BLUE LINE), ANGULAR VELOCITY (GREEN LINE) AND DISPLACEMENT (RED LINE) IN THE HORIZONTAL PLANE (SOLID, DOTTED) DURING ONE GAIT CYCLE.



6.3. Results

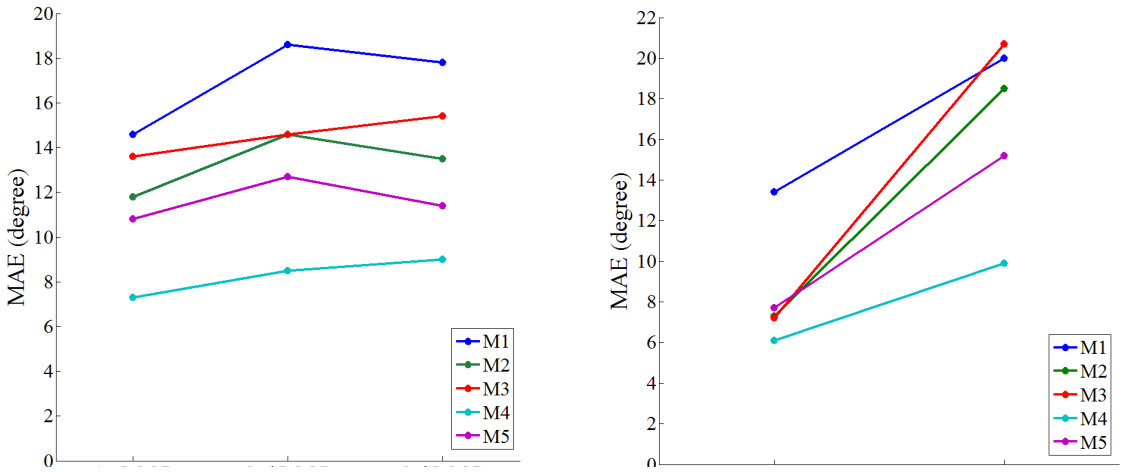
First experiment

The error estimated as the difference between the MIMU-based and the SP-based DoP estimates was determined for all methods *(M1-M5)*. In Table 6.2, DoP mean differences (μ), standard deviations (*sd*) and mean absolute error (*mae*) across repetitions and subjects for each MIMU based DoP estimation method for one complete loop are reported for both H and TBI subjects, for a total of 138 measurements (H subjects: 52; TBI subjects: 86). The *mae* values for the three loops (Loop 1, Loop 2, Loop 3, completed only by healthy subjects) are reported separately in figure 6.6a. In figure 6.6b *mae* values relative to DoP computed during straight and curved path for all three loops are reported separately.

TABLE 6.2 Differences in estimating DoP between five MIMU based methods and reference data for a complete loop

Groups	*[deg]*	*M1*	*M2*	*M3*	*M4*	*M5*
H	μ	13.3	10.0	11.8	4.8	9.2
	sd	11.2	10.3	11.9	7.9	9.5
	mae	14.6	11.8	13.6	7.3	10.8
TBI	μ	4.8	2.3	2.0	-0.1	1.3
	sd	8.3	7.0	8.0	5.3	6.1
	mae	9.3	7.0	7.2	5.8	7.2

FIGURE 6.6. (A) MEAN ABSOLUTE ERROR FOR SUBSEQUENT LOOPS (1ST LOOP, 2ND LOOP, 3RD LOOP) COMPLETED BY HEALTHY SUBJECTS ALONG THE PREDESIGNED GAIT PATH; (B) MAE RELATED TO THE DOP ESTIMATE DURING STRAIGHT AND CURVED PATH FOR THE THREE LOOPS COMPLETED BY HEALTHY SUBJECTS.



Second experiment

The mean and standard deviation values of the gait speeds V1 and V2 for both E and HD subjects are reported in figure 6.7. The mean and standard deviation values of the GDC ranges for both E and HD subjects and for both gait speeds are shown in figure 6.8.

FIGURE 6.7 MEAN AND STANDARD DEVIATION VALUES OF THE GAIT SPEED (FROM GOLD STANDARD) FOR BOTH THE E AND HD SUBJECTS GROUPS FOR EACH GAIT SPEED TRIAL (V1, V2).

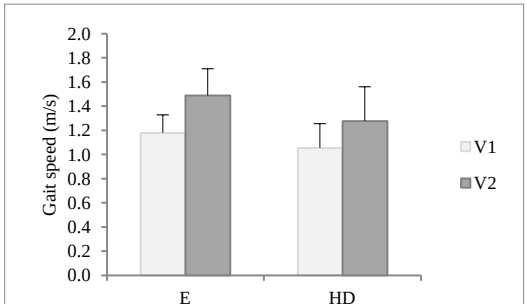
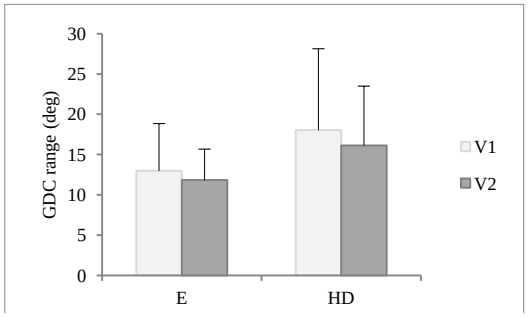


FIGURE 6.8 MEAN AND STANDARD DEVIATION VALUES OF THE GDC RANGES (FROM GOLD STANDARD) FOR BOTH THE E AND HD SUBJECTS GROUPS FOR EACH GAIT SPEED TRIAL (V1, V2).



An estimate of the GDC range, determined as the interval between minimum and maximum GDC as obtained from the instrumented gait mat, was computed for both E and HD groups. The error, defined as the difference between the MIMU-based and the instrumented gait mat GDC estimates, was determined for the tested methods. In figure 6.9 the mean value of the *mae* and its *sd* of all four MIMU-based GDC estimation methods computed over the gait tests of E and HD subjects are reported for both gait speeds. The same *mae* values, normalized with respect to the relevant GDC ranges, are reported in figure 6.10. Three gait tests were removed from the analysis due to technical issues.

FIGURE 6.9 AVERAGE VALUES AND STANDARD DEVIATION OVER THE E AND HD SUBJECTS OF THE MEAN ABSOLUTE ERROR (*MAE*) OF THE MIMU-BASED GDC ESTIMATES FOR BOTH COMFORTABLE (V1) AND FAST (V2) GAIT SPEEDS

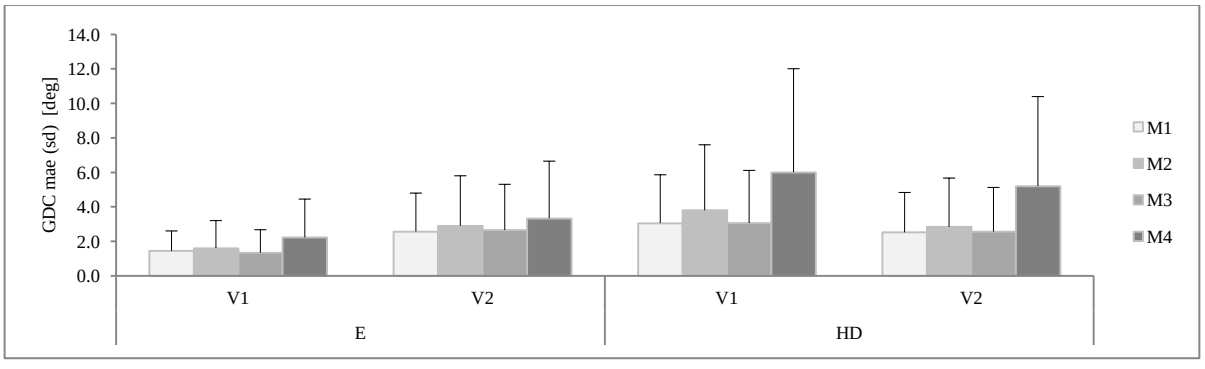
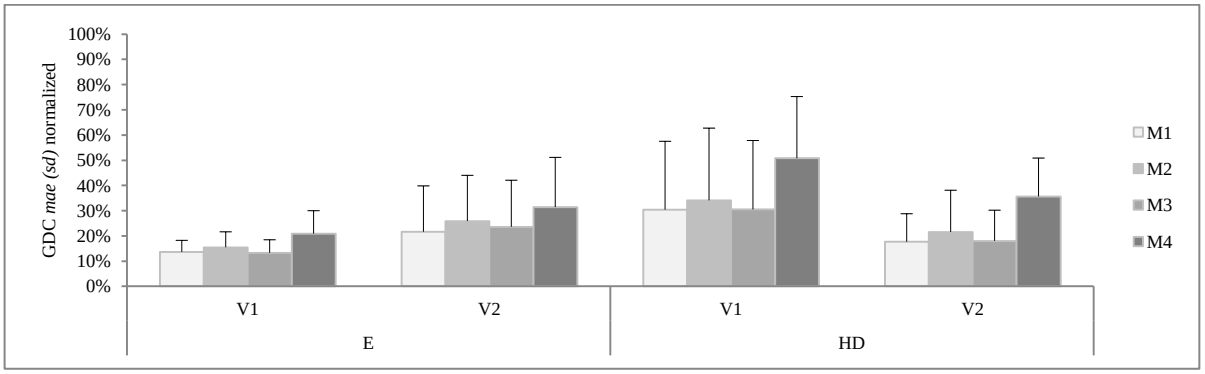


FIGURE 6.10 AVERAGE VALUES AND STANDARD DEVIATION OVER THE E AND HD SUBJECTS OF THE MEAN ABSOLUTE ERROR (*MAE*) OF THE MIMU-BASED GDC ESTIMATES FOR BOTH COMFORTABLE (V1) AND FAST (V2) GAIT SPEEDS NORMALIZED WITH RESPECT TO THE GDC RANGES.



6.4. Discussion

Wearable inertial sensors may potentially estimate changes in the direction of progression, among other key gait characteristics, when walking outdoors and for extended time opening new scenarios in the assessment of people's gait. In fact, the relationship between gait speed and direction could be a prognostic parameter to use for monitoring the rehabilitation outcome of patients. In these preliminary studies we proposed and compared different methods for a stride-by-stride estimation of GDC in both healthy and pathological subjects with different gait abnormalities using a shank-worn MIMU. We chose to evaluate the tested methods on groups characterized by extremely different gait features expecting to make the validation more robust than if performed on a group of healthy subjects as it is often the case in the literature on MIMU applications. Although the preliminary validation was carried out in the confined environment of a gait laboratory using in one case (first experiment) a path made of two wide U-turns followed by short straight sections and in the other case (second experiment) a straight path, the final goal is to use these methods for analyzing the mean path lateral gait deviation as well as turnings in real-world environments with variable speed. While a remarkable number of studies have proposed methods for the estimation of turning parameters from MIMU signals [5,6], to the authors' knowledge no studies have attempted to estimate GDC during "straight" gait using MIMUs. Schafer [9] proposed a method to be applied to MIMUs attached to the feet in order to determine the heading information from gait cycle patterns. However, they only tested the method on one healthy subject, without reporting errors in estimating the GDC.

In the first experiment, our results showed low *mae* values between data obtained with all the MIMU based methods and those obtained with SP systems (<15 deg). For both H and TBI subjects, the first method M1 performed poorly with respect to the other ones. This means that the use of the data recorded during the entire gait cycle duration does not improve the GDC estimate. The methods M2 and M3, which take into account smaller gait cycle subintervals for the GDC estimate, showed better results with respect to M1 for both H and TBI subjects; however, the performances for M2 and M3 are very similar. This means that GDC estimate does not improve by reducing the interval of integration to the midswing phase. Contrary, the fourth method M4, which takes into account only the part of the swing phase, until ω_{Zmax} is reached, showed the best results for both H and TBI subjects. This result shows that the GDC is mostly set between toe off and the time of max angular velocity of the lower limbs. Although M5 is the most intuitive method to determine the GDC, it performs worse than M4. In general, smaller mean differences and *mae* have been found for TBI subjects with respect to the H subjects. It's probably due to the different gait speed for the two groups of subjects: all the methods seem to perform better at slower gait speed. However, additional data on the same subjects group, walking at different gait speeds, have to be acquired and analyzed to confirm the statement. Differences between the *mae* related to the first loop and the following loops along the pre-designed path were found (Fig. 6.6a), probably due to the effect of the acceleration drift. Therefore, the use of advanced acceleration integration techniques is expected to improve the results. The smaller *mae* values obtained during the straight paths as opposed to those obtained in the U-turns (Fig. 6.6b) confirm the usability of the proposed methods when "straight" walks are under analysis.

In the second experiment, the best performing tested methods (*Method 1* and *Method 3*) showed *mae* values about one order of magnitude lower than the GDC range for the E subjects at comfortable speed, but even if they remain the best performing methods, their performance worsened remarkably when applied to the HD subjects at comfortable speed (*mae* of about 30% of GCD range). This might be due to the higher variability of the swing patterns typical of the HD subjects at lower speeds, consistently with the findings of other studies carried out on both healthy subjects and patients suffering of vestibular deficits [22]. As expected, lower errors in estimating GCD were found in the gait of the E group for both

speeds. However, the performance of all methods (with the exception of *Method 4*), when applied to the two groups higher gait speed was very similar.

Method 1 and *Method 3* can better estimate the GCD since they only take into consideration the portion of the gait cycle that determines for the most part the direction of progression. Methods including the stance phase are more prone to instrumental errors such as the drift typical of MIMU measurements. Moreover, the "drunken gait" characteristic of HD subjects includes lateral swaying during stance, especially at lower speeds, that can increase the variability of the direction of both angular and linear velocity in stance.

Additional analysis on HD subjects aimed at investigating the influence of gait speed on the GCD estimates accuracy and at assessing the methods performance during different experimental conditions such as the tandem gait test (slowly walking in a straight line, touching the heel of one foot to the toes of the other), would be desirable.

Additional information regarding the gait progression (i.e. turning angle computed with a pelvis mounted MIMU), more complex pre-designed gait paths (i.e. turning on both sides) and longer acquisitions will be analyzed to further validate and improve the methods performance. A second ankle mounted MIMU would be expected to provide additional information only when a highly asymmetric gait is under analysis.

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Chapter 7

Towards the integration of wearable inertial sensing with other sensing technologies: the case of the estimate of the inter-feet distance during the execution of motor tasks, a preliminary study [*]

[*] Published in (*in press*)
D. Trojaniello, A. Cereatti, A.K. Bourke, K. Aminian, U. Della Croce, **A wearable system for the measurement of the inter-foot distance during gait**, 20th IMEKO TC4 International Symposium Benevento, Italy, September 2014, ACTA IMEKO pp. 765-769 (in press)

Abstract

Inter-foot distance (IFD) is an important indicator of gait stability. The IFD evaluation in outdoor conditions is still an open issue. The aim of this work was to develop and evaluate a wearable system integrating an infrared range sensor (IRR) and an inertial measurement unit (IMU), for the IFD estimation during mid-stance and mid-swing. First, the IRR sensor output was characterized and calibrated. Second, precision and accuracy were assessed in static conditions using a target object. Third, data were acquired on a subject during various lower limb movements and compared to a gold standard to evaluate the IRR-IMU dynamic performance. Mean error during the IRR accuracy tests revealed a mean error of 2.7 mm. During walking the error was about 5 mm (up to 10 mm for gait with wide steps). In conclusion, the tests performed seems to support the feasibility of the IRR-IMU use for the estimation of the IFD during specific gait phases.

7.1. Introduction

Inter-foot distance (IFD) is defined as the projection along the medio-lateral direction of the distance between corresponding points of the feet. During gait, it is informative of the feet motion coordination and relative position, gait symmetry and the base of support. It is considered an indicator of the stability of gait throughout the gait cycle [1]. Its value at heel strike coincides with the step width (SW). SW ranges from 50 to 170 mm in normal subjects and increases up to 200 mm in subjects with limited balance [2,3]. It is used in clinical gait analysis to evaluate the stability of gait and risk of falls. In fact, its variability has been associated to the risk of falling in older adults [4,5] and it has been identified as a more meaningful descriptor of locomotion control than step length and step time variability [6]. SW is commonly measured in laboratory settings with instrumented treadmills and instrumented gait mats [6,7]. Conversely, to measure the entire IFD pattern during the gait cycle (including SW), conventional marker based motion capture systems [1] or LIDAR laser range sensors [8] have been proposed. However, IFD or SW measurements obtained in laboratory settings may not represent the subject specific gait characteristics in real life. Few studies proposed the measurement of IFD using wearable technologies such as ultrasounds (US) and infrared light (IR), often by integrating the measurement units into the shoes [9-12]. In both cases, transmitter(s) and receiver(s) are attached to different shoes. US

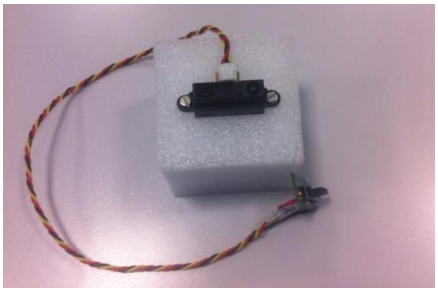
based systems were not validated and were found to be bulky and obtrusive [9,10]. IR based systems proposed in the literature included a micro camera and a panel with LEDs and were integrated with inertial measurement units (IMUs) [11,12]. In the latter study, the authors used the IR based measurements to correct the inter-shoes position error to properly estimate the 3D trajectories of the two feet [12]. Although the technology employed provided promising results, the sensor unit size was relatively large with consequences on walking patterns [12]. Infrared range sensors (IRR) integrated with IMUs may represent a valid alternative to the above-mentioned technologies. IRR sensors employ the single point optical triangulation principle for measuring the distance from a target object and are competitive in terms of response time, resolution, beam width, power consumption and size. Unfortunately, IRR sensors are characterized by a non linear output [13] (more precise at smaller distances from the target object), and cannot measure distances smaller than 20-40 mm. However, since SW reference values range between 70 and 90 mm [14,15], such limitation does not affect their potential use in gait analysis applications.

The aim of this preliminary work was to evaluate the feasibility and applicability of the use of IRR sensor technology for the IFD estimation in the two time instances of the gait cycle in which the IFD is minimum (in mid-stance and mid-swing). To this purpose an IRR sensor was integrated to IMUs placed on the subject shoes, laying the foundations for the estimation of the entire IFD pattern within the gait cycle and therefore of the SW. The IRR sensor output was characterized and its accuracy and precision evaluated in static conditions. Data acquired during human lower limbs movements, including gait, were compared to a gold standard to evaluate the accuracy of the IRR-IMU system in dynamic conditions.

7.2. Materials and Methods

An IRR sensor (mod. GP2Y0A41SK0F, Sharp Corp, Japan) with a measuring range of 40 to 300 mm and a short measuring cycle (16.5 ms) was used. The IRR sensor works with IR radiation (λ = 870nm ± 70 nm) and returns a voltage as the target object reflects back the beam transmitted by the transceiver [13]. The output analog voltage is dependent on the transceiver-target distance. The IRR sensor was connected through an analog expansion board (Shimmer^{TM} AnEx board, Shimmer sensing, Ireland) (Fig.7.1) to a pre-calibrated IMU (Shimmer^{TM} 2r) featuring a three-axial accelerometer and a three-axial gyroscope.

FIGURE 7.1 THE IR RANGE SENSOR WIRED CONNECTED TO THE ANALOG EXPANSION BOARD



The analog output voltage of the IRR and the IMU signals are measured simultaneously. Recorded data (sampling frequency: 204.8 Hz) were transmitted via Bluetooth™ to a nearby computer and then analyzed.

7.2.1. IR sensor characterization

To estimate and characterize the noise affecting the IRR sensor output, several tests with the IRR sensor placed at various distances from a white target object were performed. For each distance, the distribution of about 2000 consecutive samples was evaluated. Descriptive statistics (mean, mode, median, standard deviation) was computed for each distance to characterize the samples distribution.

7.2.1.1. IR sensor calibration

According to the IRR sensor datasheet [13], a solid white box was used as target object during the calibration [16]. IRR data were collected within the full sensor measurement range and used to determine the calibration function.

7.2.1.2. Accuracy and precision

The target object used for calibrating the IRR sensor was also used to test the accuracy of the IRR sensor estimates at nine different distances. Error, absolute error and percentage error values were computed for each distance and then averaged. The measurement precision was expressed as the 95% confidence interval of the measured samples distribution.

7.2.2. Human movement acquisition session

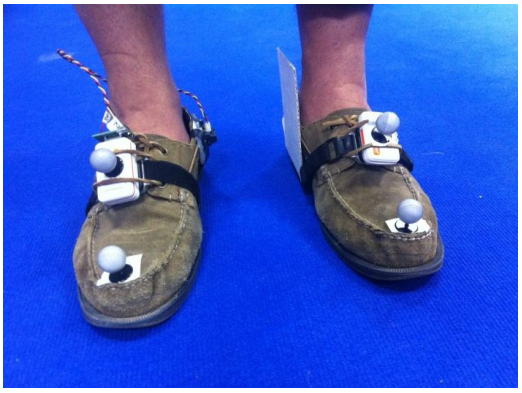
7.2.2.1. Experimental setup

Data from a healthy subject (male, 49 y.o., height: 1.87 m) were acquired. A single IMU

was attached on the dorsal region of each foot. The IRR sensor was positioned on the right shoe and connected to the IMU placed on the same shoe whereas a target object (a white flat cardboard of 100 mm x 120 mm) was firmly attached to the left shoe. Both the IRR sensor and the target object were placed just below the medial malleolus (Fig. 7.2).

The trajectories of three retro-reflective markers placed on each foot (toe, heel and over the IMU) were recorded with a five-camera stereo-photogrammetric (SP) system (Vicon T20, 128 frames/s, λ = 870nm) and used as reference data. Two additional markers were attached to the IRR sensor case and in the middle of the target object to calibrate their position with respect to the feet markers [17] and were then removed.

FIGURE 7.2 IR RANGE SENSOR ON THE RIGHT FOOT, WHITE CARDBOARD FACING IT ON THE LEFT FOOT, IMUS ON THE DORSAL ASPECT OF THE FEET AND TOE AND IMU MARKERS



7.2.2.2. Analysis of the interferences with the SP system

Static tests were performed with the subject standing in the upright posture with the feet parallel at a distance of about 150 mm inside the SP calibration volume. Before acquiring data, levels of strobe intensity and visibility thresholds of the cameras were set to limit interferences with the IRR sensor. Tests were performed first disabling the cameras (test1), then enabling the cameras (test2). For both tests, the distribution of 4000 samples acquired by the IRR sensor was examined. To characterize the samples distribution, descriptive statistics (mean, mode, median, standard deviation) was computed.

7.2.2.3. Movement data acquisition

The following acquisitions were performed:

1) subject standing with parallel feet at shoulder width (*ST*);
2) subject standing while swinging the left leg (target object leg) back and forth, while the

right leg (IRR sensor leg) was on the ground (*SWl*);

3) subject standing while swinging the right leg (IRR sensor leg) back and forth, while the left leg (target object leg) was on the ground (*SWr*);
4) slow gait with narrow steps (*sGn*);
5) comfortable speed gait with narrow steps (*cGn*);
6) slow gait with wide steps (*sGw*).

Data were acquired for about 30 seconds in all conditions.

7.2.2.4. Inter-feet distance estimation

In the *ST* condition the IFD values were obtained by simply averaging the readings obtained from the IRR sensor.

When a lower limb swings while the other stands (*SWl* and *SWr*), the minimum IFD was supposed to occur at the timing of maximum absolute values of the IMU angular velocity signals along the medio-lateral direction of the swinging limb. Therefore, only the IRR readings occurring at those timings were used to estimate IFD values.

In walking (*sGn*, *cGn* and *sGw*) left and right legs swing repetitively alternating their swing phase while the opposite leg is in contact with the ground. Therefore, one limb swings in front of the other twice in the gait cycle (i.e. middle swing and middle stance) and at those times the distance between feet (i.e. the euclidean distance between the medial malleoli) is minimum. Hence, we hypothesized that, in each gait cycle, the minimum values of the IRR sensor readings in proximity of the mid-swing and mid-stance could reliably estimate the IFD values. Time intervals of trusted swing and trusted stance were identified from the IMU angular velocity signals for each foot [18]. Trusted swing was identified by isolating the time interval during which the gyroscope signal along the medio-lateral direction exceeded the 60% of its cycle maximum value. The trusted swing interval of a lower limb was made to coincide with a trusted stance time interval of the opposite lower limb. The minimum distance within those intervals as detected by the IRR sensor was assumed as the measurement of the IFD value.

7.2.2.5. Data analysis

The IFD values were computed with both IRR-IMU system and the SP system which was used as gold standard. Errors, absolute errors and percentage errors of the IFD values estimates were computed for each swing/step and then averaged for each test (mean absolute errors, MAE and mean percentage absolute errors, MAE%).

7.3. Results

7.3.1. IR sensor characterization

7.3.1.1. IR sensor calibration

Analog to Digital Converter (ADC) and IRR sensor voltage (V) outputs for the tested static distances were normally distributed and therefore their mean values and standard deviation were associated to the actual distances (Table 7.1). The resulting calibration curve is a quasi-inverse function of the distance (D) (Eq.1):

$$D = 125.59\ V^{-1.117} \quad (1)$$

$$R^2 = 0.9989 \quad (2)$$

TABLE 7.1 Calibration look up table (actual distances, values of 12 bit Analog to Digital Converter (ADC) and associated voltages)

actual distance [mm]	ADC value mean (*sd*)	voltage mean (*sd*) [V]
40	3659 (4)	2.681 (0.003)
50	3063 (5)	2.244 (0.004)
60	2659 (7)	1.948 (0.005)
70	2334 (5)	1.710 (0.004)
80	2075 (5)	1.520 (0.004)
90	1874 (7)	1.373 (0.005)
100	1685 (5)	1.234 (0.004)
120	1452 (5)	1.064 (0.004)
140	1264 (9)	0.926 (0.006)
160	1108 (5)	0.812 (0.003)
180	969 (7)	0.710 (0.005)
200	888 (5)	0.651 (0.003)
250	728 (5)	0.533 (0.003)
300	621 (6)	0.455 (0.004)

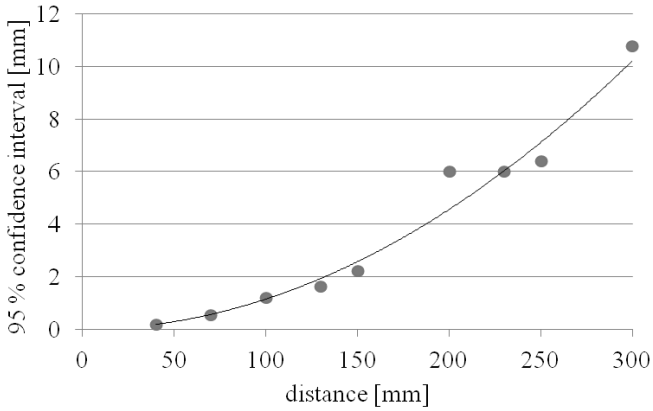
7.3.1.2. Accuracy and precision

The nine imposed and measured distances are reported in Table 7.2. Accuracy of the measurement was expressed in terms of error, absolute error and percentage error, while the precision of the measurement was computed as the 95% confidence interval (Fig. 7.3). Mean error (±*sd*), mean absolute error and mean absolute percentage error over the nine measurements were respectively 2.7 mm (±4.8 mm), 4.3 mm and 2%.

TABLE 7.2 Accuracy and precision of the IR sensor measured distance compared to actual values (error, absolute error, percentage error and 95% of confidence interval)

actual distance [mm]	measured distance [mm]	error [mm]	absolute error [mm]	% error	95% confidence interval [mm]
40	40.4	0.4	0.4	1%	0.2
70	67.9	-2.1	2.1	-3%	0.6
100	97.9	-2.1	2.1	-2%	1.2
130	127.0	-3.0	3.0	-2%	1.6
150	150.7	0.7	0.7	0%	2.2
200	205.8	5.8	5.8	3%	6.0
230	238.4	8.4	8.4	4%	6.0
250	257.5	7.5	7.5	3%	6.4
300	308.5	8.5	8.5	3%	10.8

FIGURE 7.3 VALUES OF 95% CONFIDENCE INTERVAL OF THE MEASURED SAMPLES DISTRIBUTION REPORTED FOR THE NINE MEASURED DISTANCE FOR THE IR SENSOR OUTPUT VALUES CHARACTERIZATION.



7.3.2. Human movement acquisition session

7.3.2.1. Analysis of the interferences with the SP system

Differences between the measured distance samples distributions with and without SP cameras interference were negligible.

7.3.2.2. Inter-feet distance estimation

Twelve IFD values (two times for each swing cycle) were evaluated for the *SWl* and *SWr* conditions. Two gait cycles were evaluated for the *sGn*, *cGn* and *sGw* conditions and two IFD values were computed for each gait cycle. The mean error (±*sd*), the MAE and MAE% for all tests, are reported in Table 7.3.

TABLE 7.3 Mean (sd), mean absolute error (MAE) and mean percentage absolute error (MAE%) of the IFD values for the five test conditions.

Test	error: mean (*sd*) [mm]	MAE [mm]	MAE %
ST	-5.5 (n.a.)	5.5	4%
SWl	0.5 (*4.6*)	2.7	5%
SWr	-2.3 (*2.4*)	2.7	5%
sGn	1.1 (*6.6*)	5.3	8%
cGn	3.1 (*6.6*)	5.8	8%
sGw	2.1 (*12.8*)	10.1	5%

7.4. Discussion

The results presented in this paper are a preliminary step for the development of a wearable IRR-IMU system for measuring gait parameters typically used in clinical applications. The bench tests allowed to characterize the IRR sensor. The IRR sensor was calibrated between 40 and 300 mm using a function closely related to the inverse of the output voltage (the IRR calibration range includes the expected operating range for IFD estimates during walking). Consequently, the sensor sensitivity was higher for lower distances. During the test with the target object accuracy errors up to 8.5 mm (3% of the actual distance), with an average of 2.7 mm, were observed.

Due to the non linear sensor sensitivity and a constant signal to noise ratio values, the measurements of higher distances (between 250 and 300 mm) suffered of lower precision (Fig. 7.3).

The tests performed after fine tuning the amount of IR light emitted by the SP cameras and their visibility thresholds showed that it was possible to avoid the effects of the SP system IR emissions on the IRR sensor readings.

The errors affecting the IRR sensor readings while the subject was standing were about 5 mm (i.e. 4% of the measured distance). The IRR sensor measurement error was lower during the leg swing trials since the absolute distance between the feet was lower. As expected, no differences were noticed between the errors generated when the target object was made to swing and when the IR sensor was made to move.

During walking, the error was again about 5 mm, but with IFD values lower than those recorded when the subject was standing. The reason why during gait the MAE doubles with respect to the leg swing trials could be related to the ankle motion and standing foot

deformation which are limited during the swing trials. Finally, as expected, when gait was performed with a wide base of support (large IFD values) the error reached 10 mm, which was however only 5% in terms of MAE%.

7.4. Conclusions

In conclusion, the preliminary tests performed appear to support that the IRR based measurements of the IFD during gait can be used for clinical evaluation with an approximate range of validity of 5-10 mm.

The determination of the IFD values associated with the recordings of the IMUs located on the feet (or ankles) can be exploited to compensate for sensor noise and drift and thus improving the determination of the 3D feet trajectories during gait. Moreover, the combination of inertial data and information regarding the IFD during midstance and midswing (twice in a gait cycle) might open new possibilities for the development of algorithms for the estimation of the entire IFD pattern during the gait cycle (therefore including the SW).

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Chapter 8

Use of wearable MIMUs for the fine-tuning of gait rehabilitation tools: an example[*]

[*] Published in
D. Trojaniello, A. Cereatti, G. D'Addio, M. Cesarelli, B. Lanzillo, U. Della Croce: **The role of quantitative assessment in setting-up a gait rehabilitation tool: an experience with the Regent Suit**, Proceedings 23th National Congress of SIAMOC, Pisa, Italy, September 2013

Abstract

The routine use of gait rehabilitation tools applied in clinics such as exoskeletons, suits, etc requires a set-up that operators have to customize based on patient physiological and anatomical characteristics. Often, operators set the quantitative parameters required by the rehabilitation tool counting on personal experience and sensory inputs. The aim of the study was to evaluate the role of the set-up, based on quantitative informations, of the Regent Suit (RS), a motor rehabilitation tool that can be used to reduce gait asymmetry. Gait temporal parameters of six hemiparetic subjects walking with and without the RS using MIMUs were estimated. Then the Asymmetry Index was computed for each gait parameter in both conditions in order to verify if the qualitative criteria used to set-up the RS reflected in an actual reduction of gait asymmetry. Results showed that for five subjects the qualitative evaluation of step duration asymmetry reflected in the corresponding quantitative estimate.

8.1. Introduction

Gait rehabilitation tools are gaining access to the clinical practice. Their routine use requires the operators to set them up taking into account the patient physiological and anatomical characteristics. Often, operators can only set the quantitative parameters required by the rehabilitation tool using qualitative methods based on experience and personal sensory inputs.

The Regent suit includes a number of elastic bands generating force fields influencing both upper and lower body movement, whose goal is to stabilize and make more symmetric the user's gait. It has been used as a gait rehabilitation tool showing positive results [1]. However, no quantitative information is available to the operators in setting up the suit. Gait asymmetry can be qualitatively evaluated by looking at the step duration and length differences between left and right, while it is often quantified by measuring asymmetries in stance and swing phase durations [2]. The aim of the study was to evaluate the potential role of a quantitative assessment in setting up the Regent suit (Fig. 8.1). To this purpose, we estimated the gait temporal parameters of six hemiparetic subjects walking with and without the suit using inertial technology with the aim of quantifying asymmetry changes introduced by the use of the suit and evaluating if the criteria used to set up the suit reflected in an actual reduction of gait asymmetry.

FIGURE 8.1 SUBJECT WEARING THE REGENT SUIT

8.2. Materials and Methods

8.2.1. Data collection protocol

Two physical therapists operating in the clinic hosting the study were asked to setup the Regent suit on six hemiparetic subjects as they would routinely. They selected the number of elastic bands and their tension level on both affected (aff) and non affected (n-aff) side based on their experience (Table 8.1). Inertial measurements were obtained from units (Opal, APDM) attached to the subject's ankles during walking at self selected speed (13-meter walkway) with and without the suit (no suit=NS, suit=S). To get acquainted to the use of the suit, subjects walked for five minutes before data acquisition. Three trials were acquired for both conditions. A total of about 25 full gait cycles per condition were acquired for each subject. A total of 25 full gait cycles per condition were acquired for each subject. Turning movements were excluded.

TABLE 8.1 Regent Suit main set-up parameters

Subject	no. of elastic bands			band tension aff vs naff	
	front	back	side	front	back
1	**2**	**2**	**2**	>	=
2	**2**	**2**	**2**	=	>
3	**2**	**2**	**2**	>	>
4	**2**	**2**	**2**	=	=
5	**2**	**2**	**0**	>	>
6	**2**	**2**	**0**	>	>

8.2.2. Data analysis

Data were processed using an algorithm previously validated for pathologic groups [3]. Step duration, stance and swing mean durations were determined for both sides. Step duration (stp), stance (st) and swing (sw) mean durations were determined for both sides. The mean values of gait temporal parameters were computed for all gait cycles and three trials for each subjects in both NS and S conditions.

The asymmetry index (AI) [%] was calculated as: $AI = \frac{p_{aff} - p_{naff}}{\frac{1}{2}(p_{aff} + p_{naff})} \times 100$

where p is any of the above-mentioned parameters [4]. In hemiparetic subjects, a positive AI should be expected for step and swing time [5].

8.3. Results

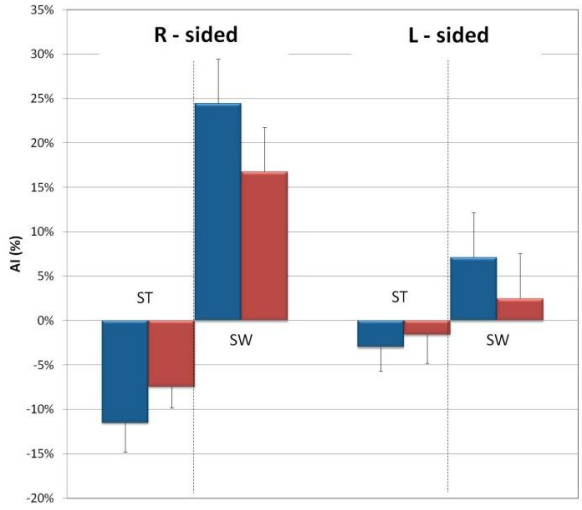
In Table 8.2 the AI of step, stance and swing time are reported for each subject and for the two walking conditions (NS, S).

TABLE 8.2 Asimmety Index of gait temporal parameters with (S) and without (NS) the Regent Suit

Subject	*Step time*		*Stance time*		*Swing time*	
	NS	S	NS	S	NS	S
1	**8**	**4**	**-11**	**-7**	**24**	**17**
2	**-3**	**-1**	**1**	**-5**	**0**	**7**
3	**4**	**3**	**3**	**4**	**-4**	**-6**
4	**7**	**6**	**1**	**1**	**-1**	**0**
5	**21**	**14**	**-3**	**-2**	**7**	**3**
6	**-2**	**-5**	**1**	**5**	**0**	**-8**

In figure 8.2 an example of the stance and swing time AI evaluated for two subjects (one right-affected, one left-affected) is reported. Results relative to the two conditions (NS = blue, S = red) are shown..

FIGURE 8.2 ASYMMETRY INDEX FOR TWO SUBJECTS (R-SIDED AND L-SIDED)



8.4. Discussion

Results showed that a reduction in the step time, stance time and swing time AI was found for subject 1. A higher stance and swing AI found in NS condition reflected an evident asymmetry that could be associated to an appropriate RS set-up, and then resulting in an AI reduction in the S condition. Subjects 2, 3 and 4 did not show a clear asymmetry as reflected by the AIs; no clear improvements were found using the RS. A higher step AI was found for subject 5, for whom a reduction of the step, stance and swing asymmetry were found in the S condition. No improvements were detected for subject 6 since a very low AI for all the temporal parameters was found in NS condition.

The qualitative evaluation of stp asymmetry reflected in the corresponding quantitative estimate, except for subject 6 for whom the stp AI slightly increased, probably due at the increased tension of both front and back elastic bands. However, st and sw AI showed that the use of the suit increased the st and sw asymmetry for subjects 2 and 6, while it did not have effects on subjects 3 and 4. A more inclusive set of quantitative data regarding the patient's gait (i.e. spatial gait parameters and EMG data from selected muscles) could improve the setting of the suit before the training.

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Chapter 9

Conclusion and Future Perspectives

9.1. General results and main contributions

The research presented in this thesis consists in the development, application and testing in clinical contexts of methods for assessing gait spatio-temporal parameters using wearable inertial sensors across a number of different pathological gait patterns. Pre-existent methods and their application in clinical contexts were analyzed and new methods for quantifying various gait parameters were proposed. The main results and contributions of this work are summarized in the following sections.

9.1.1. Performance evaluation of single IMU based methods

Normal gait

The evaluation of the performance of five methods for detecting GEs and determining gait temporal parameters from the signals of a single inertial unit attached at waist level was performed. The evaluation was done in terms of: a) sensitivity and PPV and b) accuracy and robustness of the determination of gait temporal parameters. The five methods have been applied to data acquired from healthy subjects. The results suggested that: a) the accuracy in estimating gait temporal parameters related to the correct identification of ICs was acceptable for all methods, while those gait parameters depending on the FCs detection were less accurate; b) some of the tested methods showed a poor sensitivity and PPV which could result in the erroneous identification of the number of gait cycles; c) the tested methods showed an acceptable robustness with respect to the different locations of the sensor along the trunk. The results obtained lead to the conclusion that methods based on a single unit attached to the trunk could be used to estimate a subset of gait temporal parameters (i.e. stride duration, step duration) when applied to healthy gait. No experiments in un-controlled conditions were performed.

Abnormal gait

A subset of the previously tested methods was applied to the gait of four different subjects groups (healthy elderly, Parkinson's disease, Huntington's disease, post stroke). Missed or extra events were found for all methods and a global decrease of their performance was observed to different extents depending on the pathological group analyzed. The results revealed that none of the tested methods outperformed the others in terms of accuracy of the gait parameters determination for all groups except the Parkinson's disease subjects group for which one of the methods performed better than the others. The hemiparetic subjects group was the most critical group to analyze. Only one method provided estimates of the stance and swing durations with errors over 30% of the actual values across populations. The results of this study suggested that caution should be used in the interpretation of gait parameters obtained from pathological populations when single sensor based methods are applied.

9.1.2. Development of methods for gait parameters estimation using shank mounted sensors

Based on the measurement of shank mounted MIMUs, a new method for the estimation of gait spatio-temporal parameters was proposed and validated in the laboratory setting. First, a novel method for estimating GEs during gait using two inertial sensors attached just above the ankles was proposed. The developed method consists of a preliminary identification of trusted swing and stance phases based on specific invariants of the human gait, so that the search time intervals for detecting IC and FC could be narrowed. IC and FC timings are then identified from characteristics of the gyroscope and accelerometer signals. Following the identification of GEs and consequent gait temporal parameters, methods for the estimation of gait spatial parameters such as stride length and direction of progression were proposed. A combination of a MIMU axes realignment along the vertical direction and the direction of progression and of an optimally filtered direct and reverse integration is used to determine the stride length along straight paths. The estimation of the direction of progression during gait was mostly based on the assumption that the direction of progression corresponds to the maximum variation of the velocity vector along the three directions during gait. The investigation of which time interval inside the gait cycle is the most appropriate for the estimation of the direction of progression represents a major challenge. The method was tested along straight and curved paths for a wide range of natural gait speeds.

Application to abnormal gait resulting from different pathologies

The proposed method for gait spatio-temporal parameters estimation was validated against data obtained from an instrumented gait mat (used as *gold standard*) on the gait data acquired from four different subjects groups (elderly, Parkinson's disease, Huntington's disease, post stroke), characterized by different abnormal gait patterns, walking at two different gait speeds (comfortable, fast). The method for the estimation of the direction of progression changes was validated on a group of traumatic brain injury subjects characterized by a slow walking speed and on a group of subjects with Huntington's disease characterized by staggering from side to side, with lateral swaying, and stride-by-stride lateral deviations from forward direction. The results of these studies lead to the conclusion that the proposed methods could be reliably applied to various abnormal gaits obtaining in some cases a comparable level of accuracy with respect to normal gait.

Application in rehabilitation

The developed gait spatio-temporal parameters estimation methods have been applied to evaluate the potential role of a quantitative assessment in setting-up a motor rehabilitation tool (the Regent suit). In particular, in this study, an evaluation of the asymmetry changes introduced by the use of the suit was performed.

9.1.3. Inter-feet distance estimation

A wearable system for the inter-foot distance estimation was proposed based on the combination of IRR sensor technology and inertial sensors. Data acquired during human lower limbs movements including gait (slow/fast/normal gait at narrow/wider steps), were compared to the reference data obtained using a stereo-photogrammetric system. The preliminary tests performed appear to support that the IRR based measurements of the inter-feet distance during gait can be used for clinical evaluation with an approximate range of validity of 5-10 mm (5-8% of the true value).

9.2. Future directions and related researches

Magneto-inertial sensing technology has the potential to measure human movement with a level of accuracy and repeatability comparable to optoelectronic stereo-photogrammetry with the advantage of being applicable during daily life and for prolonged observation period

(weeks/months). Commercially available 9-axis sensors are now enclosed in modules of few cubic millimeters. Besides, the possibility of manufacturing flexible and stretchable electronics (epidermal electronics, band-aid like devices) has been recently demonstrated. The new technological capabilities, along with appropriate methodologies, may enable performing pervasive and ubiquitous movement data collection. This would allow answering the question "how do we move when nobody looks at us?", which is one of the most challenging open questions in human movement science. However, at the state of the art and in conclusion of the presented research, the methods for the determination of the gait spatio-temporal parameters have been mainly validated in the confined environment of a gait laboratory during straight walking, and their performance in the real-world is still an open issue. In order to overcome these problems a look to the future works and future development of this work should be addressed both at the algorithm development and optimization and at the clinical application perspectives.

9.2.1. Algorithms development and optimization

Validation and optimization of the proposed algorithms on a larger sample of subjects

As pointed out in the thesis, the step-by-step determination of the spatio-temporal parameters of gait is clinically relevant since it provides an estimation of the variability of specific gait patterns associated with frequent geriatric syndromes. The validity of clinically suitable MIMU-based methods for the estimation of spatio-temporal parameters was proven in the present work on a number of different pathological gait patterns; however a complete and more extensive validation and optimization of the developed algorithms on the various gait pathologies represents the next step to confirm the clinical applicability of such methods. In the framework of the V-Time European project, a large dataset has been already acquired (300 subjects) of three populations (Parkinson's disease, MCI and elderly fallers) and data are now under analysis.

Analysis of gait parameters during various gait tasks

Walking in real-world consists in a number of tasks (i.e. turning, passing obstacles) which may be more demanding for subjects affected by some gait pathologies with respect to others. For example, difficulties in turning during gait are often encountered in movement disorders such as Parkinson disease, and could often result in an increased fall risk. In these contexts, the accurate estimate of the changes of direction during gait along with an

exhaustive analysis of gait parameters during turnings becomes essential. Similarly, tripping over obstacles is one of the most common causes of reported falls in the elderly. In this context, the development and optimization of algorithms for the analysis of turnings strategies and obstacle crossing parameters should be carried out. Data acquisition from groups of Parkinson's disease and elderly subjects while performing such tasks using MIMUs and stereo-photogrammetric system as gold standard is in progress.

In addition, the MIMU based analysis of further gait tasks such as "tandem gait" generally used in the diagnosis of ataxia, since sufferers of these disorders will have an unsteady gait, are now under analysis and validation.

Improvement of the inter-foot distance measurement and applications

The determination of the inter-foot distance associated with the recordings of the MIMUs located on the feet (or ankles) may potentially improve the determination of some of the most common gait spatial parameters. It is known in fact that the measurements of two MIMUs located on the lower limbs cannot be spatially related. The periodic determination of the timing of minimum inter-foot distance and its value distance (twice in a gait cycle) and of the timing of minimum could facilitate the development of algorithms for the estimation of the entire 3D foot trajectory during a gait cycle. In this context, many efforts should be taken in validating the system and in developing data fusion algorithms to obtain the maximum amount of information from both the inertial and the IRR wearable systems.

Application of machine-learning based techniques to gait parameters estimation in pathological gait

Recently, foot-worn sensors were also considered in association with methods based on hidden Markov models [1]. Pathologic gait has not been tested yet with that statistical method. In a recent study [2] we performed preliminary tests to verify if the use of Hidden Markov Models based methods for gait phases determination could be extended to pathological gait conditions (traumatic brain injury, Parkinson’s disease and polyneuropathy patient). Two MIMUs were attached to the subjects’ shanks about 20 mm above the lateral malleolus and reference data from a stereo-photogrammetric system were acquired. The results obtained in this preliminary study were satisfying in terms of accuracy obtained in detecting GEs (<20ms). A more extensive study which includes different gait pathologies (Parkinson's disease, Huntington's disease, Post-stroke) is currently in progress.

9.2.2. Clinical applications

Analysis of gait variability in long term walking

Gait variability, described as stride-to-stride fluctuations, is related to the underlying neural control of gait. These fluctuations, typically quantified through standard deviation or coefficient of variation of chosen quantities, allow identifying changes in the postural control system due to aging, intervention, or pathology. Stride time variability has also been proposed as a fall risk predictor. The 2-minute walk test is a common tool to assess walking functional capacity, which can be combined with wearable sensors to enhance the understanding of gait pattern related variability. could be The evaluation of the gait variability using MIMUs based approaches of a large sample of pathological subjects would be an interesting clinical application of the proposed methods.

Further clinical applications

The clinical applicability of the gait spatio-temporal parameters evaluation provided by measurement with shank worn sensors was show for patients affected by Parkinson's disease, Huntington's disease, Post-stroke and TBI. This approach can be extended to other gait pathologies implying changes in the gait patterns which result in sensor signals variation with respect to the normal gait pattern. We could expect that for pathologies implying similar alterations the proposed methods may be used in clinical assessment in order to measure the extent of the gait impairment and eventually track the effectiveness of rehabilitation programs.

In the framework of a project run by our clinical partner at University of Genova, the gait spatio-temporal parameters estimation methods proposed in this thesis are currently applied to the evaluation of subjects with advanced Parkinson's disease treated with high-frequency subthalamic nucleus deep brain stimulation (STN-DBS). The goal of the study is to compare the effects of various STN-DBS parameters on freezing of gait and to determine whether such effects are more related to stimulation energy or frequency.

Finally, the gait parameters estimation methods using shank worn MIMUs are also currently applied for the clinical evaluation of children with cerebellar ataxia and children with Developmental Coordination Disorder in the framework of a project run in collaboration with the University of Groningen and Istituto Superiore Sant'Anna.

References

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[2] Mannini A., Trojaniello D., Della Croce U., Sabatini A. M.. **Gait phases determination using markov models applied to the recordings of a shank-worn gyroscope**, Proceedings of 25th SIAMOC-23th ESMAC 2014, p.69, Rome, Italy, October 2014