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GAIT ANALYSIS USING A SINGLE WEARABLE INERTIAL MEASUREMENT UNIT

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ABSTRACT

Procedures for quantitative walking analysis include the assessment of body segment movements within defined gait cycles. Recently, methods to track human body motion using inertial measurement units have been suggested. It is not known if these techniques can be readily transferred to clinical measurement situations. This work investigates the aspects necessary for one inertial measurement unit mounted on the lower back to track orientation, and determine spatio-temporal features of gait outside the confines of a conventional gait laboratory.

Apparent limitations of different inertial sensors can be overcome by fusing data using methods such as a Kalman filter. The benefits of optimizing such a filter for the type of motion are unknown. 3D accelerations and 3D angular velocities were collected for 18 healthy subjects while treadmill walking. Optimization of Kalman filter parameters improved pitch and roll angle estimates when compared to angles derived using stereophotogrammetry. A Weighted Fourier Linear Combiner method for estimating 3D orientation angles by constructing an analytical representation of angular velocities and allowing drift free integration is also presented. When tested this method provided accurate estimates of 3D orientation when compared to stereophotogrammetry.

Methods to determine spatio-temporal features from lower trunk accelerations generally require knowledge of sensor alignment. A method was developed to estimate the instants of initial and final ground contact from accelerations measured by a waist mounted inertial device without rigorous alignment. A continuous wavelet transform method was used to filter and differentiate the signal and derive estimates of initial and final contact times. The technique was tested with data recorded for both healthy and pathologic (hemiplegia and Parkinson’s disease) subjects and validated using an instrumented mat.

The results show that a single inertial measurement unit can assist whole body gait assessment however further investigation is required to understand altered gait timing in some pathological subjects.

ABSTRACT

L’analisi quantitativa del cammino include la definizione del movimento di segmenti corporei durante il ciclo del passo. Recentemente, sono stati proposti diversi metodi che studiano tale movimento utilizzando unità inerziali. Non è ancora chiaro se queste tecniche possano essere facilmente trasferite in ambito clinico. Il presente lavoro ha come obiettivo lo sviluppo e la validazione di metodi per la stima dell'orientamento di un’unità inerziale posizionata sulla pelvi e per la determinazione delle caratteristiche spazio-temporali durante il cammino.

Le principali limitazioni relative alla stima dell'orientamento mediante unità inerziali possono essere superate utilizzando metodi quali il filtro di Kalman, i cui risultati sembrano dipendere dal compito motorio, o eliminando errori di deriva dall’integrazione della velocità angolare tramite algoritmi quali il Weighted Fourier Linear Combiner. Accelerazioni e velocità angolari 3D sono state misurate durante il cammino in 18 soggetti sani e i risultati validati tramite stereofotogrammetria. La stima dell’orientamento mediante un filtro di Kalman ottimizzato per il cammino e l’utilizzo di tecniche per la correzione della deriva forniscono stime dell'orientamento dell’unità inerziale con un’accuratezza dell’ordine di 1°.

I metodi per determinare le caratteristiche spazio-temporali durante il cammino a partire dai dati misurati da un’unità inerziale posizionata sulla pelvi richiedono l’allineamento dell’unità rispetto all'anatomia del soggetto. È stato sviluppato un metodo per stimare gli istanti iniziali e finali di contatto del piede al suolo senza la necessità di effettuare un allineamento rigoroso. Il metodo si basa sul filtraggio e la differenziazione dei dati di accelerazione tramite l’uso di Wavelet. Questo metodo è stato testato su 18 soggetti sani e 23 patologici (esiti da ictus e malattia di Parkinson) e validato utilizzando un tappeto strumentato.

I risultati del presente lavoro mostrano che è possibile effettuare una valutazione quantitativa del cammino mediante l'uso di un’unità inerziale posizionata sulla pelvi.

SUMMARY

This thesis describes work performed to investigate the use of a single inertial sensor, mounted on the lower back, to measure features of gait for use in the assessment of pathologies, and direction and evaluation of treatment.

The initial chapter provides an introduction to the importance of locomotion to human quality of life. Reasons why it is beneficial to understand the movement patterns of the body during walking are outlined. The concepts of qualitative and quantitative assessment of gait are introduced. The problem of characterising complex integrated patterns of motion with numbers is described along with the issue of quantitatively describing walking in a general sense. Use and limitations of the commonly accepted “Gold standard” of quantitative gait assessment, i.e. stereophotogrammetry, is portrayed. Inertial measurement units and the methods by which they have been used to characterise walking patterns it outlined. Finally the ways these assessments can be used to characterize healthy gait and changes in walking patterns that may be due to pathologies is provided.

Chapter 2 provides a more detailed description of accelerometer and gyroscope components that comprise an inertial measurement unit. A background to how they provide measurement of linear acceleration and angular velocity is given. The second section of this chapter reviews uses of inertial measurement units that have been portrayed in the literature. Methods by which inertial measurement units can be used to provide kinematic measures are described. The use and limitations of the Kalman filter in the context of gait assessment is reviewed. The use of wavelet analysis to identify the time of occurrence of particular events within a signal, based on the identification of a particular wavelet form is introduced, along with its current application to motion analysis. Other ways through which temporal gait features have been identified from inertial signals are reviewed. The application of inertial signals to inverted pendulum models to measure spatial parameters of walking is considered, along with the use of this information in the assessment of walking characteristics as a possible predictor of fall risk. Finally, the methods by which an alternative approach of assessing balance and fall risk, along with the effects of aging and pathology from upper body motion, are reviewed to provide a background for the work presented in later chapters.

Chapter 3 provides a brief physical description of the inertial measurement device used to obtain data for the studies in this thesis, along with the components of which it is comprised. The second section of this chapter outlines the aspirations for the inertial

measures required. Reasons for choosing to locate one inertial measurement unit on the lower back to record data are given.

Chapter 4 explains how data collected with an inertial measurement unit (IMU) can be used to estimate segmental orientation. A Kalman filter is commonly used to fuse the information provided by multiple inertial sensors, to overcome deficiencies in both signals, and provide a more accurate estimation of orientation. The importance of providing the optimum parameters for the filter to properly select and fuse data recorded during a walking task is shown. An experiment is described whereby the parameters used in the filter to fuse data collected from subjects walking on a treadmill are optimized, and the beneficial effects of the optimization on the resulting angle estimates is shown.

The second section of chapter 4 introduces an alternative method to derive orientation information from inertial measurement data. This method, called a Weighted Fourier Linear Combiner (WFLC), generates a mathematical representation of the angular velocity signals to allow their drift free integration and, therefore, the estimate of the change in orientation of the sensing unit relative to its initial pose. This method was applied to the same data set as was used for the Kalman filter optimization mentioned previously. The estimated orientation angles obtained using the WFLC algorithm were compared with those derived from stereophotogrammetric marker data and those estimated using the Kalman filter.

Also included in this chapter is a section outline the ability of the Kalman filter and WFLC to provide accurate information regarding angles and angular velocities for extended periods of time.

Chapter 5 characterises the use of a single waist mounted inertial measurement unit to provide temporal information about the walking pattern. A new method of estimating temporal gait features from a waist mounted inertial sensor is outlined. This method uses a property of wavelet transforms to smooth the signal without distorting the timing of the desired events. This is performed by using a feature of wavelets to differentiate and smooth the data. From the smoothed signal, peaks that were assumed to coincide with initial and final contact times of the feet with the ground were extracted. The use of wavelets to smooth the signal removes the requirement of accurately placing and aligning the inertial measurement unit. Data were collected for healthy subjects to test the accuracy of this method. The estimated event times were compared with the same information measured using a pressure sensing gait mat, and with two previously published methods which use filtering and zero crossing techniques to identify windows of data from which the timing of gait events are estimated.

The next section of the chapter describes an experiment to assess the wavelet method of gait event estimation for use with pathologic data. Data were collected from stroke and Parkinson's disease sufferers with the same IMU location and fixation method as for the healthy subjects. The same gait mat was also used for comparison. The accuracy of the results obtained, did not compare favourably with those obtained for healthy subjects. It was observed that higher errors where a result of a difference in the timing of the events, with respect to the peaks in acceleration, than that observed for healthy subjects. It was also observed that this was not apparent for all subjects irrespective of pathology, walking speed, or cadence. A further investigation, using harmonic analysis, showed differences in the medial lateral acceleration pattern, and this difference was used to delineate subjects and provide more accurate estimation of initial contact.

This chapter concludes with an assessment of the ability of simple inverted pendulum models to estimate step length using vertical acceleration measurements from a point near the centre of mass.

Finally in chapter 6 the results of the investigations outlined in the previous chapters is reviewed. The ability of an IMU to furnish the information required to provide a useful assessment of walking function in light of these results in discussed. Ways in which the signals recorded by an IMU might be further exploited to provide appropriate information with which to evaluate gait are promoted.

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This thesis is dedicated to my mother,
Audrey.

The memories of your love, kindness, and support,
I will treasure always.

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CHAPTER 1: INTRODUCTION

THE WALKING TASK

Bipedal walking with an upright posture has long been considered one of the features that separates humans from other animal species. The ability to move from one location to another, while having upper limbs free to carry objects, is important to enable the performance of many tasks specific to humans, and it is an essential element of human capacity. It is generally assumed that the way humans ambulate is to transfer from one location to another while expending the least amount of energy (Saunders et al., 1953). Understanding this ability in healthy persons is important for the maintenance of mobility in humans. All people walk differently and even healthy individuals may vary their manner of walking (Inman et al., 1981) due to internal or external, physical or mental reasons.

Interest in the way in which the human body moves has ancient roots. Borelli was the first to write about locomotion in terms that can be related to what is now called biomechanics, in the seventeenth century. The study of the movement patterns exhibited when people walk is a field that uses technologies adapted from many areas, alongside some that are specifically designed for the required task. The measures used range from observational scales, or simple measurements such as walking velocity, to measures such as joint powers with more complex derivation. The tools required to acquire such a range of measures are consequently diverse as well.

The walking task requires a high level of both upper and lower body coordination to control the trajectory of the centre of mass (COM) and keep the trunk erect as the body progresses forward. Cappozzo et al. (1978) emphasises that during walking the upper body, consisting of the head and truck, moves in such a way that reduces the mechanical energy variation during each cycle than would be the case if these segments where fixed rigidly to the pelvis. It is also noted (Cappozzo 1978) that this results in a movement pattern at the level of the head that is smoother than that of the trunk. This smoothing effect has a moderating effect on the mechanical stimulus applied to brain and to the sensory organs of the head (Cappozzo, 1981), in addition to decreasing the inertial loads acting on the musculoskeletal system. Simultaneously, while modulating movement of the head, it is also necessary to maintain balance of the whole body mass over the small base of support provided by one limb in contact with the ground while the other limb swings to a new point of ground contact.

These observations suggest the possibility of drawing information concerning important determinants of the locomotor strategy, i.e. energy variations, maintenance of balance, and mechanical loads, from the movement of the upper body. These global determinants of gait, once they are quantified, may allow the effective assessment of the locomotor ability of an individual.

Walking requires the combination of a number of musculo-skeletal functions. This can be achieved by using different motion strategies, which will use different combinations of these functions. The combination of functions necessary to generate a chosen motor strategy will be subject to the structural and functional limitations of the locomotor system, and the strategy which is put into action will govern the quality of the gait outcome. Thus, two factors determine the quality of the gait outcome: the limitations of the components within the system, and the patient's ability to select an appropriate motion strategy, which combines the functional components effectively. Quality of gait is related to the reliability of the locomotor act, and its consistency in terms of the above-mentioned determinants, i.e maintenance of balance, mechanical load on tissues, and energy expenditure (Cappozzo, 1984).

Winter (Winter, 1995) outlines in some detail the challenges that must be overcome by the central nervous system to achieve stable walking. He noted that in steady state walking the COM is always outside the base of support during single stance, which he described as "dynamic balance". It is considered that a desirable walking pattern is one that is regular and consists of smooth and continuous movements. Minimising abrupt changes in direction of body segments while acting to reduce energy consumption will also lessen the loads on the joints of the body and the muscles forces required to move them. The sequence of repeated movements, requiring the coordinated activation of many muscles, in the correct sequence, and to the correct level, to provide forward motion, is still far from completely understood.

The requirements of protecting the sensory organs contained within the head and mediating to loads to the musculoskeletal structure become more challenging as walking speed increases. Thus it is apparent that the patterns of motion of both the upper and lower body over a range of walking speeds must be considered to achieve a fuller understanding of locomotion task and how it is affected by changes in all areas of the musculoskeletal system.

To properly assess the gait of a person it is not just important to measure a particular function or to compare the mechanical patterns they generate with a perceived normal patterns, but we need to assess the ability of the person to ambulate within the limitations of their own locomotor system. Thus the question which needs to be answered, to achieve effective gait assessment, is why a patient walks in a particular way, not just how he/she walks. This type of approach, as suggested in Cappozzo (1984), constitutes the conceptual basis of the present study.

ANALYSIS OF GAIT

Since this thesis aims at providing some alternative methods to be used for the analysis of gait, it is important to first understand what it is that is generally meant by gait analysis and how this relates to the locomotive task described above.

Cappozzo (Cappozzo, 1984) suggests that the following be described when undertaking a gait assessment: symmetry and simplicity of the movement; maintenance of balance; mechanical load on tissues; and energy expenditure.

When aspects of walking are considered, average values are usually used to show relationships that exist between the segments of the lower limbs, and other body segments, during gait analysis. Murray and others (Murray et al., 1964) noted how consistent many features of walking were for healthy male individuals, and how similar the patterns were between groups of men. This apparent similarity may be a factor why a change in a particular feature of walking might be assumed to indicate an overall change in the locomotive capacity. What first must be appreciated, is the relationship between the feature of interest, and the overall movement pattern, and how changes in what is measured, may be compensated and adjusted for within the whole locomotor system. Mündermann and colleagues (Mündermann et al., 2008) have shown how increased upper body medio-lateral trunk sway can lead to lower adduction moments at the hip and knee, showing the interrelationship between just one aspect of upper body motion and lower body kinetics. Cappozzo (Cappozzo, 1984) provides this summary: “gait evaluation is the assessment of the ability of the subject to move through space by ambulation”.

Notwithstanding the stated need for a “whole of body” approach to the assessment of gait, many studies have attempted to use the apparent similarity in walking patterns within groups to assess apparent differences between groups, and relate observed changes in pattern to specific changes in the body due to aging or pathology. Researchers have shown how aging (Callisaya et al., 2010; Grabiner et al., 2001; Paterson et al., 2011; Pecoraro et al., 2007; Prince et al., 1997) or the presence of pathology (Balasubramanian et al., 2009; Hass et al., 2012; Manor and Li, 2009; Myers et al., 2009; Nanhoe-Mahabier et al., 2011; Snijders et al., 2007) can lead to altered walking patterns.

While the presence of many pathologies, or dysphoric mood, may be detected by observation of gait patterns, it is generally assumed that a more accurate assessment of the type and severity of pathologies may be available through quantitative assessment. Many forms of gait assessment are available, which vary between simple, convenient, observational assessment, to more complicated, and time consuming, but informative, biomechanical methods.

The simplest tools available are based on observation. Rancho Los Amigos Hospital developed an observational gait analysis system (Gronley and Perry, 1984; Perry, 1992) to meet clinical needs, by systematically assessing motion, and differentiating gait deficits from compensatory actions. Studies have shown that, while this method of gait assessment may be convenient, it is only moderately reliable (Eastlack et al., 1991; Krebs et al., 1985; Saleh and Murdoch, 1985). Assessment methods also include functional tests (e.g. 6 minute walk test (Steffen et al., 2002), physical performance battery (Guralnik et al., 1994)). More recently, further functional gait assessment tools have been developed to assist in the assessment of fall risk associated with walking (Marchetti and Whitney, 2006; Whitney et al., 2000; Wrisley et al., 2004). These tests have shown to provide useful assessments of fall risk for persons with peripheral vestibular disorders (Hall and Herdman, 2006), Parkinson's disease (Leddy et al., 2011), and stroke (Jonsdottir and Cattaneo, 2007; Lin et al., 2010). These tests are inexpensive, easy to administer, and well accepted by the test subjects. However, they rely primarily on observations that are either subjective or semi-quantitative, or at the most, on time and distance measures. In addition they exhibit low sensitivity to disability level variation. While such tests are useful for assessing therapeutic interventions, they have a limited ability to direct such interventions.

The quantitative biomechanical analysis of suitably selected motor tasks, carried out using stereophotogrammetry, dynamometry, electromyography, indirect calorimetry or multi-segment human body modelling provides thorough and objective information. However, these approaches are awkward to apply for subject-specific evaluation in clinical practice by reason of the complexity of both instrumentation and experimental protocols. Therefore, the question arises as to whether methods may be devised that join objectivity with field applicability.

As will be better specified later, this study aimed at contributing to answering this question. We shall move from the basic idea that, for a compromise between the two approaches to be pursuable, a minimum number of biomechanical variables should be measured during the execution of the selected motor task and these quantities should be acquired using an experimental apparatus least perceivable to the test subject and the cost of which is moderate. However, since data thus obtained do not necessarily lend themselves to straightforward interpretation in terms of functional status assessment, a model of the portion of the musculo-skeletal system involved that embodies the invariant aspects of both the modelled system and the motor task will be devised. Through such a "minimum measured-input model", richer, physiology-related, and thus easier to interpret, information is expected. It is also expected that, for a global evaluation of the motor act, this model will be no less informative than more demanding multi-segment models associated with complex experimental approaches. Although information on specific musculo-articular functions will not be available, the more compact information yielded by this model, is expected to facilitate subject and/or disability classification.

The studies that will be discussed later in this thesis fall into the category of what is generally characterised as “quantitative gait analysis”. Baker (Baker, 2006) identified two areas of investigation, to which quantitative gait analysis is applied: Those used to develop an understanding of a condition that may affect gait or to better understand the effects of an intervention which is expected to change gait patterns; and those used to assist in clinical decision making. Four reasons for performing clinical gait analysis have been outlined (Brand, 1989), which are all related to the patient and patient outcomes: to distinguish between disease entities (i.e., diagnosis); to determine the severity of disease or injury (i.e. assessment or evaluation); to select among several treatment options; and to predict prognosis. These reasons relate to finding *why* a person ambulates in a particular manner whereas quantitative gait analysis generally measures *how* a person walks as a numerical difference between a gait parameter, or parameters, of interest, and an average value that is measured for “normal” walking. Quantitative gait analysis measures might be considered to measure symptoms, while often the clinician would like to know the cause, of an altered walking pattern.

Measurement of gait quantities usually involves an assignment of direction to the result. Is it a larger or smaller value than a previous or a “normal” measurement of the same parameter? Usually it is assumed if there is a change that is towards “normal” than this is better, irrespective of the limitations that may be placed on the subjects locomotor system by existing musculo-skeletal pathologies. Consider a lower limb amputee who wishes to walk normally. This might be possible but at what cost to energy expenditure? Conferring a numerical value to a feature of the locomotion task may not fully provide an appreciation of how well that task is performed. Nevertheless quantitative gait assessment is generally believed to be effective in characterising motion patterns during gait (Baker, 2006), and as an effective clinical evaluation tool (Davis et al., 1991) to determine how a person walks. It has been shown to be useful for measuring the changes that occur due to aging (Mazzà et al., 2008), and pathology (Schwartz and Rozumalski, 2008) as well as following rehabilitation (Baker, 2006). Lofterød and colleagues, state that compared to clinical examination, laboratory gait assessment improves detection of abnormalities and enables better treatment decisions, but there is no evidence that it improves outcomes (Lofterød et al., 2007).

The measures used in assessing walking patterns must be evaluated in a manner that takes into account the role of the feature of gait that is measured plays in progressing the body through space, and appraised by the ability of the locomotor system to adjust for the measured differences. An awareness must also exist of effects the measuring system itself will have on the measurement taken.

Stereophotogrammetric gait analysis

Stereophotogrammetric gait analysis can provide accurate measurements and a wealth of information about patterns of motion during gait, but it is not without limitations.

The use of photogrammetry for movement analysis can trace its origins to Muybridge and Marey in the 1800s (Cappozzo, 1984), however it is not until much more recently that the use of multiple, infra-red cameras, and retro-reflective markers, in conjunction with force platforms, has enabled the gait analysis laboratories of today (Baker, 2006) to exist. The speed and accuracy of data collection has advanced greatly from the first systems, to the point where markers can now be located in three-dimensional space with accuracies lower than 1 mm (Baker, 2006; Chiari et al., 2005). However, other factors can limit greatly the derived parameters such as joint angles which are calculated from the marker trajectories (Cappozzo et al., 1996; Della Croce et al., 2005; Leardini et al., 2005). It has been noted (Buczek et al., 2006) that studies accurately determining moments generated at particular joints, and attributing changes in gait to these factors can be contradicted by similarly detailed studies that deduce opposite effects. Using different versions of the same popular “off the shelf” software can provide significantly different kinematic and kinetic results (Larsen et al., submitted paper). Calculating accelerations by double differentiation of position data has inherent errors, however techniques for doing so have advanced along with the use of motion capture systems.

Stereophotogrammetry provides much information, which must be distilled into an understanding of the gait pattern that is being assessed. While many of the models used for stereophotogrammetric analysis have the ability to investigate upper body movement patterns as well, analysis is usually restricted to the lower limbs, reducing the amount of information that must be assessed and understood. Indexes have been developed to further distil the information provided by stereophotogrammetric gait analysis to a single value (Baker et al., 2009; Schutte et al., 2000; Schwartz and Rozumalski, 2008). The availability of gait laboratories with stereophotogrammetric systems for use in gait analysis is limited by factors including cost, the need for dedicated laboratory space, and the time and expertise needed to perform and assess the measurements. When assessing gait the subject must remain within a confined area defined by the camera setup so only a limited number of steps can be assessed. This means that assumptions are necessary to translate results into more generally understood gait performance parameters. These limitations are of special concern when the persons of interest for a gait study have limited mobility and may have difficulty attending a laboratory even when it is situated within a medical institution. Notwithstanding these limitations, stereophotogrammetry is normally assumed to be the gold standard for assessment of gait.

Inertial measurement units

An alternative tool for gait assessment which has the potential to provide much useful quantifiable information without the need for expensive equipment or intensive training is through the use of inertial sensing instruments such as accelerometers or gyroscopes. The use of accelerometers as a tool in the analysis of movement has been suggested for some time. In their often cited paper, Saunders and others (Saunders et al., 1953) attempted to use electrical accelerometers but found them inferior to differentiation of displacements for the determination of accelerations. Cappozzo (Cappozzo, 1984) also suggested that using accelerometry had problems, and could not compete with stereophotogrammetric methods. Since these papers were written advances in miniaturization have enabled the development of tools known as microelectromechanical systems (MEMS). Within this class are sensors that measure linear accelerations (accelerometers) and angular rate (gyroscopes) which are collectively referred to as inertial measurement units (IMUs). These types of IMUs are highly portable and relatively inexpensive yet accurate devices.

Systems consisting of multiple IMUs and magnetometers are available in wired or wireless configurations. The techniques required to set up and record data with such systems is generally simpler that that required for a stereophotogrammetric system which needs accurate marker placement as well as anatomic and system calibration. The use of systems consisting of multiple devices still requires a level of technical expertise to calibrate and synchronise the individual sensing units. As well, the more devices, and the more apparent the presence of these devices is to the subject, the more likely they are to alter movement patterns as a result, especially over longer recording periods. Powering multiple devices for longer tests can also become an issue. It is apparent that for IMUs to be accepted as a gait assessment tool for use beyond university and large hospital based laboratories, they must provide additional useful information in a timely manner, that does not require a high level of extra technical knowledge on the part of the user. Assessments such as six- and ten- minute walk tests are commonly used to give an indication of the walking ability of subjects. Such a test may provide a much more detailed assessment of many aspects of walking patterns such as step/stride variability and upper body motion, if it were enhanced by the attachment of an IMU. Also, walking patterns may be compared across a wide variety of situations, both indoor and outdoor if a self-contained inertial recording unit were fixed to the subject in an unobtrusive manner.

An IMU capable of measuring 3D accelerations and 3D angular velocities is the instrument on which this report is focused and will be described in more detail in the subsequent chapter.

Effects of aging and pathology

As people age, their gait patterns change due to many factors which are not fully understood (Kavanagh et al., 2004). Understanding the rate and effect of these changes helps provide an understanding of the effects aging has on limiting mobility, and increasing instability. The ability to maintain a stable walking pattern is important to people of all ages so that they have independence and quality of life (Berg et al., 1997) while a lack of stability may lead to falls which cause injury and further reduce mobility. The risk of falling while walking is present at any age and level of disability but the increases as walking patterns become less symmetrical and double support increases (Hill et al., 1999).

To be able to assess and understand how a pathological walking pattern is different from normal, the importance of differences which are measured requires first a comprehensive understanding of healthy patterns. If a healthy gait pattern is considered the most energy efficient form of walking for an individual, it is important to understand the mechanisms by which this walking pattern is generated so that rehabilitation can targeted to achieve a similarly efficient pattern. Pathologies which alter walking patterns may not be restricted to the lower limbs thus, a full knowledge of the effects requires an understanding of how the whole body moves and not only lower limb motion (Cappozzo, 1981; Winter, 1995). It is necessary to identify and quantify parameters that give an indication of the level of disability involved to understand the changes in walking patterns that occur due to aging or disability. Different measurement systems provide many and diverse measures which relate to the walking pattern in general such as gait speed, or to very specific aspects such as joint range of motion. One aspect of walking that has received attention, as it relates to gait stability and the likelihood of falls leading to injury, is the temporal and spatial variability of steps and strides (Lord et al., 2011). To properly assess such variations an accurate measure of the temporal and spatial aspects of individual gait cycles is necessary. This can be performed in a variety of ways but generally requires a significant instrumental component. More recently the use of inertial measurement units to evaluate these walking parameters has received attention. While gait events and spatial measurements can be derived using inertial data recorded at different locations of the body (Martin, 2011a; Najafi et al., 2009) useful information has been derived using trunk mounted devices (Hartmann et al., 2009). Another aspect of gait stability is the stabilization of the head and trunk during gait (Mazzà et al., 2008). Stabilization of the vestibular system is assumed to be an important feature of healthy walking. To achieve this requires attenuation of the movements of the lower body to prevent unstable patterns from being transferred cranially. To properly perform this task requires the locomotor system to adjust trunk angles with the correct timing and in the proper manner.

It is therefore apparent that if it is possible to accurately assess spatio-temporal features and also track the movement of the trunk much useful information with become available. This information can subsequently be used for the assessment of changes in walking patterns which might occur due to aging or disability and be precursors to events that could pre-empt falls causing injury.

PURPOSE OF THE STUDY

Many forms of quantifiable gait analysis provide information relating to the level of function of the subject but do not provide useful information regarding the cause or type of disability. Other forms of analysis provide a great amount of information but often at high cost and requiring extensive technical expertise. In addition, collection of such information may be uncomfortable physically and mentally for subject concerned. It may be assumed that if accurate quantifiable measurements or assessments are performed that can distinguish between healthy and disease specific gait patterns, assess the severity of disease, and/or track rehabilitation without causing discomfort this will be of some benefit. It will be of further advantage if accurate information can be collected without requiring a high level of technical expertise and assessed using simple to implement methods.

Modern inertial measurement units appear to provide useful information for the analysis of gait for a relatively low cost. Numerous methods of providing quantitative information concerning gait, using IMUs and similar MEMS devices in multiple locations on the body, have been promoted especially in the period since such instruments have become more freely available.

The aim of this work is to enhance the ability of signals recorded by a single waist mounted IMU to provide optimal information about gait patterns from movements of the lower trunk during walking. It will also enhance the use of these signals to determine temporal and spatial parameters of gait. The methods devised will be simple to implement and robust for use with pathological subjects to enable a better understanding of pathological walking that will be beneficial to the rehabilitation outcomes of patients. The potential to improve estimations of orientation available from a Kalman filter will be investigated through optimization of filter input parameters. Estimation of angles in all dimensions by integrating an analytic representation of angular velocities created using a Weighted Fourier Linear Combiner method will also be assessed. A method of determining temporal features of walking will be proposed and its ability to withstand variations in pathologic walking patterns will be investigated. Current models for determination of spatial gait parameters from centre of mass motion will be tested to observe the potential benefit from improved temporal input information.

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CHAPTER 2: INERTIAL MEASUREMENT UNITS

INTRODUCTION

The application of inertial measurement to motion analysis has been considered for some time. Early attempts at direct measurement of accelerations (Saunders et al., 1953), concluded that measurements taken using accelerometers were inferior to the differentiation of displacement data for the calculation of accelerations. Morris (Morris, 1973) determined that early accelerometers were unsuitable for biomechanical measurement but that six accelerometers would be sufficient to allow determination of the movement of a body with respect to a reference coordinate system. With the advent of microelectromechanical systems (MEMS), modern IMUs now however, have an advantage of compact size along with the ability to capture motion related signals with little restriction in location. They are also relatively inexpensive when compared to more established gait analysis tools such as gait mats, or stereophotogrammetric systems. In addition to the multiple accelerometers and gyroscopes that can make up an IMU, MEMS magnetometers, and GPS units can also be housed in the same compact unit to make a powerful sensing device. MEMS devices have now pervaded modern life to the point where it is expected that they will be carried by one billion people, by the year 2016 (Panzarino, 2012), due to their presence in smart phones and tablet computers.

IMU COMPONENTS

Inertial sensors use the principle of inertia of a mass to enable the measurement of linear acceleration and angular velocity. The quantities measured are with respect to the reference frame of the sensor, which is not a fixed reference. The sensing axes of the accelerometer and gyroscope components define this reference frame. When three sensors of a type are mounted together in one device the sensing axis of each sensor is arranged orthogonally to the others to make up a 3D sensor.

The vestibular system within the inner ear is a sensitive biological 3D inertial sensor with components sensing rotation movement and linear accelerations of the head and contributes to the maintenance of balance of the body.

Accelerometer

The measurement of linear acceleration can be achieved in a number of ways but most commonly uses the principle of a mass on a spring attached to a housing. When the housing is subjected to an acceleration the inertial force of the mass displaces the spring. The displacement is proportional to the mass and stiffness of the spring: $F = kd$, where F is the force, k the spring constant, and d the displacement of the mass. Combined with Newton's second law: $F = ma$, where m is the mass displaced, and a is the acceleration applied, acceleration can be calculated as:

$$\alpha = \frac{kd}{m} \qquad [2.1]$$

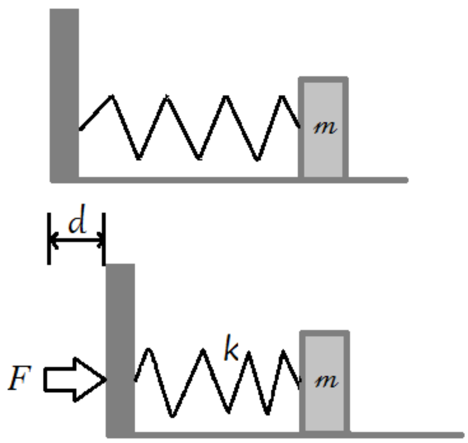


Figure 2.1 Spring mass model for measurement of acceleration

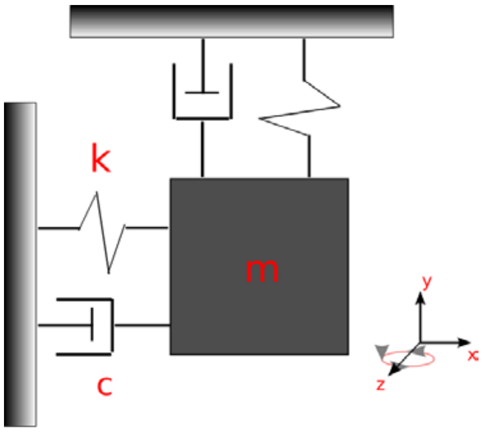
Gyroscope

A gyroscope provides a means to determine angular velocity. Conventionally they are mechanical devices consisting of a spinning mass mounted on a gimbal. Due to the Coriolis effect the mass will attempt to maintain its orientation in space when the mounting frame changes orientation.

This effect can be observed in many situations. It is the principle by which a spinning top remains upright and a single engine propeller driven aircraft will attempt to veer to the side when accelerating along a runway.

The effect also applies to a vibrating mass. A mass *m*, moving at a velocity *v*, in a frame of reference rotating at angular velocity ω will be subject to a force F_c according to the equation:

$$F_c = -2m(\omega \times v) \qquad [2.2]$$



(14-1-2013) http://wikis.controltheorypro.com/images/Generic_two_axis_mass-spring-damper_MEMS_gyro.png

Figure 2.2 Simplified model of a vibrating mass gyroscope

In the simple model shown in figure 2.2, if the mass is vibrating in the x-direction, and subjected a rotation around the z-axis (out of the page) an alternating force is generated in the y- direction. Measurement of the y-direction force provides a measure of the rate of rotation around the z-axis.

Gyroscopes are one of the most complex, high volume MEMS devices (Bogue, 2007), which sense vibration orthogonal to the line of resonation to measure angular velocity (Roetenberg, 2006; Woodman, 2007).

ANALYSIS OF GAIT USING IMUs

Notwithstanding the limitations of early accelerometers and the previous lack of suitable gyroscopes for use in human movement analysis, the advent on MEMS devices has led to a rapid increase in applications which make use of the advantages of their low cost and portability. Modern IMUs combine the measurement of both linear accelerations and angular velocities within one small device. Their use for analysis of walking ability, fall into a number of broad and sometimes overlapping categories. Measurements have been recorded using numerous combinations of sensors applied to most regions of both the upper and lower body in an attempt to characterise the walking task.

The investigations described below show that while inertial measurement devices can be used to measure gait parameters previously assessed using systems such as stereophotogrammetry and gait mats, their advantages lie in the ability to make these measurements in situations that are more representative of normal function. IMUs also provide the ability to quantify features of walking that are not easily determined using other tools, and have potential to provide researchers and clinicians with an improved understanding of the walking task.

Kinematic assessments

IMU portability allows the measurement of parameters normally associated with a laboratory based gait analysis, such as joint angles, to be performed under more varied conditions. This can enable quantitative assessment of function without the requirement of a visit to a gait laboratory. Early application of accelerometers for gait analysis (Hayes et al., 1983) showed multi-axial accelerometers fixed to the lower limbs could be used to assess three-dimensional leg motions during swing, however the application was limited by the accelerometers that were then available. As smaller, more useful devices became available, eight uniaxial accelerometers mounted in pairs on the upper and lower leg (Willemsen, Van Alsté, et al., 1990) were used to calculate two-dimensional knee angles in real time. Angles derived using this same arrangement of sensors were compared to angles obtained using a stereophotogrammetric system (Heyn et al., 1996) with reported indistinguishable results. In a later work (Favre et al., 2008) three-dimensional joint angles were obtained using two IMUs consisting of combinations of 3D accelerometers and 3D gyroscopes.

Orientation measurement, Data fusion

The ability of accelerometers to sense orientation, and of angular velocity measurements to provide information about changes in orientation over time, has received much attention for the potential that exists to provide useful information about human walking. Accelerometers can provide information about the orientation of the device relative to the horizontal plane when the only acceleration present is due to gravity. Gyroscopes provide angular velocity information, which in theory can be integrated to give rotations, however this information is limited by the presence of drift over time in the integrated signal due to offsets. A difficulty lies in how best to fuse data from multiples of two different types of sensor to provide the most accurate output by using information from the most reliable source depending upon the state of the system.

Farve et al. (Favre et al., 2006) compared using a strapdown navigation technique to estimate orientation with two alternative methods to fuse acceleration and gyroscopes signals and remove integration drift errors. The strapdown technique, used gravitational acceleration to determine an initial orientation quaternion for the body at rest, and updated this for each instant using rotations obtained by integrating the angular velocity. The first method of drift error removal, used the inclination estimated from accelerations, to correct the orientation when the body was only subjected to accelerations due to gravity or undergoing slow rotations. This correction was only applied to the characteristic samples. The second method proposed applied a linear interpolation between two corrected samples to correct all the intervening samples. Both methods showed a more than seven fold reduction in tilt angle estimation error. The second method of correction was shown to provide the most accurate estimations, however these were not available in real-time.

Other alternative methods to determine orientation angles (Giansanti et al., 2005; Kunze et al., 2009) have been proposed but the most common is the use of a Kalman filter (Grewal and Andrews, 2002; Kalman, 1960; Sabatini, 2006). The principle of updating the orientation estimation based on accelerations measured when the body is undergoing little or no acceleration except that due to gravity is used in the Kalman filter which will be described in a later section of this work.

The Kalman filter is used extensively in other fields such as robotics (Rehbinder, 2004; Vaganay et al., 1993) as a means to combine information from different sensors within an IMU. Manufacturers of IMUs now provide software which uses variations of Kalman filters to provide real time orientation information, however the accuracy of some of these methods has come into question (Brodie et al., 2008; Godwin et al., 2009; Picerno et al., 2011). The ability to determine orientation accurately by fusing inertial signals recorded by an IMU using an extended Kalman filter is reviewed in more detail in a latter part of this thesis where the benefits of optimizing the input parameters of a Kalman filter are investigated.

The ability of IMUs to enable the determination of orientation has led to their being tested extensively for physical activity monitoring, and the characterisation of body posture and assessment of activity levels. Early attempts to assess physical activity (Meijer et al., 1991) were limited by the devices available, however improvements in sensor technology has allowed postures (Veltink et al., 1996, 1993), and activities (Bussmann et al., 1998), to be determined using devices mounted on the thigh and sternum with little discomfort to the subject. One sensor consisting of two accelerometers and one gyroscope and mounted on the sternum (Najafi et al., 2003, 2000) was shown able to detect posture transitions and walking periods. This latter method uses wavelets (Bruce et al., 1996) to determine the timing of transitions. Wavelet analysis was also used to discriminate between walking patterns (Ibrahim et al., 2007; Wang et al., 2007) and differentiate between level walking and walking up and down stairs.

Estimation of temporal parameters

Analysis using wavelets has extended to other assessments of gait that require the accurate identification of the timing of a particular event in the measured inertial signal. Initial and final ground contacts have been detected from shank angular velocity using wavelet transformations (Aminian et al., 2002). Temporal parameters were also been successfully determined by filtering and peak detection of signals recorded using uniaxial accelerometers mounted just above the knee (Aminian et al., 1999) for healthy subjects and patients before and following hip arthroplasty as well as below the knee (Selles et al., 2005) for healthy subjects and amputees. Four one-dimensional accelerometers attached to the lower leg (Willemsen, Bloemhof, et al., 1990), were used to detect four phases within the gait cycle, however, when this method was tested with hemiplegic subjects, it was found that it might not be applicable for all walking patterns. These four gait phases were also detected using angular velocities measured using a single axis gyroscope attached to the instep of each foot (Sabatini et al., 2005). Jasiewicz and others (Jasiewicz et al., 2006) compared initial (heel-strike) and final (toe-off) contact events determined using linear accelerations measured at the foot, and with angular velocities at the foot and shank, against footswitch data. They determined that all locations provided results that were as accurate as footswitches for normal gait patterns but that shank angular velocity was less accurate for spinal-cord injured patients.

While the lower limbs and feet may be expected to provide the most detectable signals relating to ground contact events as well as some kinematic information for the lower limbs from sensors mounted on the shank and thigh other investigations have addressed pelvis and trunk motion as an avenue to determining temporal features of walking. This is the approach used in the studies outlined in this thesis and the rationale for this approach will be outlined in the next chapter. Evans and colleagues (Evans et al., 1991) 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 (Auvinet et al., 2002) were likewise able to identify event related features within the gait cycle from vertical acceleration signals recorded at the L3-L4 level for 282 healthy subjects. A number of studies have addressed the issue automatically detecting gait events (González et al., 2010; Hartmann et al., 2009; Mansfield and Lyons, 2003; Menz et al., 2003a; Zijlstra and Hof, 2003) from accelerations recorded at the lower back. These and other studies will be examined in more detail in chapter 5 when a proposed new algorithm for IC and FC detection using a single waist mounted IMU is outlined. As an alternative to locating the sensor on the lower back Kose and colleagues (Kose et al., 2012) chose to position a single inertial measurement unit at the right hip to detect temporal events. They decomposed the cranial-caudal and anterior-posterior accelerations using a wavelet decomposition to identify regions of interest within the signals from which they determined IC and FC events. The potential of wavelet analysis to assist in temporal event estimation using a single IMU mounted at the lower lumbar region is investigated further in a chapter 5.

Spatial parameter estimation

In conjunction with estimation of temporal gait features investigators (Alvarez and Gonzalez, 2008; Alvarez et al., 2006; Brandes et al., 2006; González et al., 2009; Jahn et al., 2010; Zijlstra and Hof, 2003) have assessed the ability to estimate spatial parameters from knowledge of the temporal parameters and estimations of COM motion. This work is assessed in more detail in a chapter 4. Other researchers have used IMUs attached to the lower limbs for this same purpose. A gyroscope attached to the thigh was used to detect angular velocity in the sagittal plane (Miyazaki, 1997) as a means of determining stride length using a pendulum model. In another method, thigh and shank angles where obtained using gyroscopes data and used to obtain stride length using a multi segment model (Aminian et al., 2002). This method was also used (Salarian et al., 2004) to assess patients with Parkinson’s disease. The measurement of stride length during walking has been used to calculate variability as a possible predictor of fall risk in the elderly (Callisaya et al., 2011; Hausdorff, 2005) and has consequently received attention. The ability of IMUs to record movements for an extended period provides an important additional tool to this area of investigation (Galna et al., 2012). While this area of research can benefit from the temporal and spatial measurements derived from IMUs data it is also possible to assess gait variability more directly from inertial signals recorded on the upper body.

Upper body motion

While interest in upper body acceleration patterns for assessment of gait began long before the advent of MEMS (Cappozzo, 1981), measurements using modern accelerometers have advanced this area of research. Changes that relate to balance and the effects of aging and pathology may be observed in upper body motion. Mündermann and collegues (Mündermann et al., 2008) reported the relationship between medio-lateral trunk motion and hip and knee moments. They showed that increased upper body sway led to lower hip and knee adduction moments. The RMS of medial lateral acceleration at the L3 level has been used to investigate how lateral balance changes at different walking speeds in healthy elderly persons (Helbostad and Moe-Nilssen, 2003) while unbiased autocorrelation coefficients were reported (Moe-Nilssen and Helbostad, 2005) for all axes of a similarly positioned device to differentiate between fit and frail older persons. This study showed that variability observed in the accelerations at the trunk was not reflected in the step width of the subjects. Further investigation using autocorrelation coefficients (Moe-Nilssen et al., 2010) has indicated that variability in AP accelerations relates to step length variability, and variability in vertical accelerations relates to variations in step time, when measured for elderly subjects. Harmonic ratios have been used to measure the rhythmicity of trunk motion and these ratios were compared to stride parameters as an indication of stability for healthy older adults and person with Parkinson’s disease (Lowry et al., 2009). A further investigation of harmonic ratios (Lowry et al., 2012) determined from accelerations measured at the trunk showed little difference between harmonic ratio for accelerations in all directions and age or walking speed except for old-old adults and young and old-old adults walking at fast speeds. In an attempt to relate fall risk to measures derived from lower trunk accelerations (Senden et al., 2012) compared spatio-temporal parameters, harmonic ratios, amplitude variability, and RMS, with a subjective measure of fall risk, the Tinetti scale. While measures derived from inertial data correlated with the subjective scale they showed no correlation with fall history.

As well as providing an avenue for understanding trunk motion, the small size and light weight of IMUs also provide the opportunity to record acceleration patterns of the head during gait to better understand the relationships that may exist between falls and instability, and the ability of modulate movements of the upper body while walking. Studies have examined and compared signals recorded at the lumbar region with head accelerations to investigate age related changes (Kavanagh et al., 2004; Menz et al., 2003a) and the effect of walking on different surfaces for healthy (Menz et al., 2003b), and impaired older people (Menz et al., 2004). Control of upper body motion during walking has also been assessed from accelerations recorded at three levels, the head, shoulder, and pelvis, to observe age and gender differences (Mazzà et al., 2009, 2008), whether gender differences were also present in children (Mazzà et al., 2010) and the effect of stroke (Iosa et al., 2012) and facioscapulohumeral dystrophy (Iosa et al., 2010).

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CHAPTER 3: DEVICE

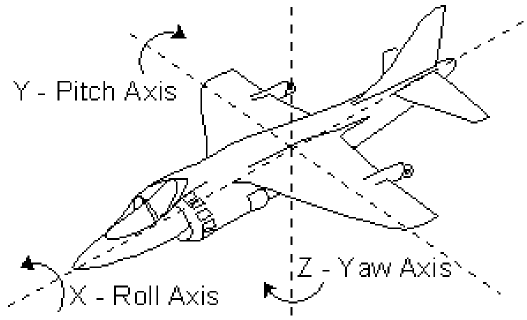
DESCRIPTION OF THE DEVICE

The device used for studies reported in this work was a FreeSense (Sensorize Ltd, Italy) IMU which contains a triaxial accelerometer for sensing linear accelerations and two biaxial gyroscopes, sensing angular velocities. The accelerometer was a MEMS, solid state, capacitive unit and the gyroscopes were MEMS, monolithic, capacitive units. The gyroscopes were mounted such that one axis of one gyroscope is aligned with an axis of the second to allow 3D angular velocity recording. Axis alignments are shown in figure 3.1 These sensors are contained in a polycarbonate housing 8.79 cm x 5.14 cm x 2.47 cm (HxWxD) and weighing 93 g. The accelerometer has a settable full scale range of ±2 g or ±6 g and the gyroscopes a full scale range of 300 deg/s. For the studies reported the range was set to ± 6 g and data were recorded at 100 Hz. Data were transmitted in real time via Bluetooth to a laptop computer for recording.

Figure 3.1 The Freesense (Sensorize) device and the alignment of axes.

DESCRIPTION OF PITCH, ROLL AND YAW

With the transference of techniques used commonly for navigation of unmanned vehicles and in robotics to the field of movement analysis, for the fusion of data from different types of sensors, so to, have some of the terms used in these and the field of navigation transferred. The terms *roll*, *pitch*, and *yaw*, are commonly used to describe changes in orientation of ships and aircraft, relative to the direction of travel, but not usually to describe human movement. (figure 3.2)



[http://bf2tech.org/index.php/File:Roll-pitch-yaw.gif (14-1-2013)]

Figure 3.2 Depiction of the Roll, Pitch, and Yaw axes relative to the principle direction of motion.

When compared to the ISB recommendations (Wu et al., 2002) for the axes used to describe the orientation of the pelvis, the Y- and Z- axes in figure 3.2 are reversed. Roll describes rotations in the coronal plane, pitch refers to rotations that occur in the sagittal plane, and yaw refers to those rotations which occur in the horizontal plane.

LOCATION OF THE DEVICE

In considering the location or locations on the body it is necessary to determine where the most useful and reliable movement patterns will exist to provide information regarding the parameters of interest. The ambition was to obtain information valuable to the assessment of how walking patterns might be affected by aging and pathology. This assessment requires measurement of both upper and lower body motion (Cappozzo, 1981; Winter, 1995). The aspiration was to determine if particular motion patterns of the upper body could be recorded accurately using an IMU and at the same time estimate temporal and spatial features that could be used in conjunction with the upper body motion to assess walking function. A second aspiration was that the data collection and analysis procedures would be easy to implement by persons unfamiliar with the technical requirements normally associated with accurate data collection.

Saunders (Saunders et al., 1953) states that "the displacement pattern of the centre of gravity may be regarded as constituting the summation or end result of all forces and motions acting upon and concerned with the translation of the body from one point to another during locomotion." It was also considered that, in the future, the data collected might be used to make estimation on energy cost of walking. To this end, a location close to the centre of mass (COM) was considered most appropriate. While measurement of COM motion has limitations for assessment of work done while walking (Winter, 1979), it is considered sufficient for many outcome assessments (Meichtry et al., 2007). A further aim was for the device to be attached in a manner that had a high likelihood of being adopted in a clinical environment. For reasons of simplicity in adoption of the investigated measuring technique and data analysis, it was determined that one device, mounted simply, in a location that could provide both clinically and biomechanically relevant information, should be selected. With this in mind, the IMU was mounted over the lower back using an elasticized belt. The belt enabled the device to be positioned over the clothing worn by the subjects in a way that allowed easy attachment and removal with minimal discomfort to the subjects during data collection. Another aim was to investigate whether information could be collected which was of benefit, without the need for precise positioning and alignment, or rigid fixation. A limitation to the adoption in clinical practice of many useful measurement techniques may be attributed to complicated or technically demanding setup procedures. To this end the method of mounting was made as simple as possible and accurate alignment was not required, nor was it attempted. Notwithstanding this aim, the IMU was positioned over the lower back.

Recording gait parameters with the least discomfort to the subjects as possible is believed to be most likely to allow subjects to ambulate in the most natural manner. The method of attachment and location met those aims.

Figure 3.3 Photograph showing fixation and approximate location of the IMU. The device was attached over the clothing.

The positioning of an IMU over the lower back has been chosen previously by other researchers to record acceleration patterns during walking. A 2008 review by Kavanagh (Kavanagh and Menz, 2008) into the use of accelerometry to quantify movement, lists a number of papers that recorded data at the lower trunk level for the assessment of a variety of gait characteristics. As in our case, the most often quoted reason for selecting positions over the lumbar spine or sacrum is that this region on the body surface is closest to the location of the COM within the body during upright stance or while walking. It is considered that this position provides movement patterns that are the end result of all the forces and movements as the body moves from one position to another (Floor-Westerdijk et al., 2012).

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CHAPTER 4: ESTIMATING ORIENTATION

USING INERTIAL MEASUREMENT UNITS TO ESTIMATE ORIENTATION

An IMU containing multiple accelerometers is able to sense the acceleration due to gravity. Through simple trigonometry, and if no other accelerations are present, i.e. when the sensor is stationary or when it moves at constant speed (Hansson et al., 2001; Kemp et al., 1998; Willemsen et al., 1991), it is possible to determine the tilt of the accelerometer from these acceleration signals. In other circumstances, changes in orientation may be calculated by the numerical integration of the angular velocity signals provided by gyroscopes. These integrated signals, however, are subject to drift (Bortz, 1971; Woodman, 2007), which over time introduce errors in the estimated orientation. There is also no information about the initial conditions when angular velocities are integrated unless this information is obtained from acceleration signals, and this information must be obtained while the accelerometers are not subjected to forces other than gravitational forces. Another source of error in the derived information is instrument noise. The goal is to fuse the information from both types of sensors in a way that uses the most reliable information and at the same time accounts for the noise component of each signal.

Many methods have been presented for the fusion of signals from different types of sensors to improve the accuracy of orientation estimation. Some of these have been outlined in a previous chapter. One common of fusion is by the use of a Kalman filter (Kalman, 1960). In the first part of this chapter, the optimization of a Kalman filter to improve orientation estimation during walking is presented.

A limitation of Kalman filtering is that there is no heading reference from which to determine initial conditions and provide updates to correct for integration drift around the vertical axis. An alternative is to represent angular velocities in a manner that will allow integration without drift caused by gyroscope errors. The Weighted Linear Fourier Combiner (WFLC) finds a mathematical representation of a signal if the signal is cyclical without being necessarily periodic. This method can be applied to all three gyroscope axis signals to allow drift free integration of these angular velocities and give an accurate estimate of orientation relative to all three axes.

In the second section of the chapter a WFLC is described and tested using the same gyroscopes data as were used to optimize the Kalman filter. The accuracy of the obtained orientation angles is compared to those obtained by stereophotogrammetry and using the Kalman filter.

AN OPTIMIZED KALMAN FILTER FOR THE ESTIMATE OF TRUNK ORIENTATION FROM INERTIAL SENSORS DATA DURING TREADMILL WALKING

Background

The use of accelerometers to detect and quantify human motion has been considered for many years (Morris, 1973). More recently, the use of this type of sensor to collect movement data has increased rapidly (Kavanagh and Menz, 2008). Modern inertial measurement units are small and self-contained, enabling their use for extended periods outside the confines of a laboratory.

Previous studies have outlined the potential for simple IMUs to determine gross body motion as a means to quantify differences in activities of daily living (Foerster, 1999). Other studies have used IMUs to calculate inter-segment forces and moments (Van Den Bogert et al., 1996) as well as spatial (Moe-Nilssen and Helbostad, 2004)and temporal (Aminian et al., 1999) features of gait.

Accelerometers can be used as inclinometers when accelerations are small (Kemp et al., 1998), however once accelerations increase the use of accelerometers alone is limited. This restriction can be overcome by the addition of other devices such as angular rate sensors (Foxlin, 1996). These devices, however, are subject to drift over time which may jeopardize the time integration of their output signals while estimating orientation data (Sabatini, 2006). This problem can be overcome by using recursive filters, such as complementary (Gallagher and Matsuoka, 2004) or Kalman filters (Vaganay et al., 1993). The latter choice is widely adopted in human movement analysis (Luinge et al., 1999; Pongsak et al., 2003; Sabatini, 2006; Vaganay et al., 1993).

The Kalman filter predicts the state of a system based on its previous measurements and compares this predicted state value with actual measurements to determine an error value, which is then used to improve the next prediction. The use of a Kalman filter requires a number of input parameters to determine how the output signals from each component of the sensor are weighted in future filtering. Previous authors have noted the importance of correctly selecting the parameters (Luinge and Veltink, 2005; Luinge et al., 1999) of the filter for tracking motions such as head orientation (Foxlin, 1996), forearm motion (Sabatini, 2006;

Yun et al., 2005), and lifting crates (Luinge and Veltink, 2005). The benefits of having the filter act adaptively to account for the differing relative importance of the signals during periods of low or high acceleration have also been noted (Foxlin, 1996; Suh et al., 2006). Currently, many commercially available IMUs have algorithms available that use a Kalman filter to convert the sensor measurements into information about the kinematic state (i.e. the orientation in space) of the device. These algorithms use parameters based on the characteristics of the sensors, such as the noise of the signal measured during static conditions (Yun et al., 2005). Little has been reported detailing the implementation of a filter for the estimate of trunk orientations during walking and to assess the effects of altering its input parameters.

The purposes of this study are: a) to design a Kalman filter which could be used for the estimate of the lower trunk orientation angles during walking using accelerometer and gyroscope data; b) to determine, through a sensitivity analysis, the importance of selecting the correct parameters for the Kalman filter to obtain accurate orientations when walking on a treadmill at different speeds.

Materials and Methods

Subjects and data collection.

A total of 18 subjects (10 male, 8 female, age range 24-64) volunteered for the study. The subjects' self-selected "natural" walking speed was determined by measuring the time it took them to cover a distance of 10 metres walking along a straight, level path. An IMU (Freesense, Sensorize srl) was then secured to the lower back of the subjects using an elastic belt. This study did not require accurate measurement of actual trunk angles so alignment of the sensor precisely to the trunk anatomy was not considered necessary. However to ensure that the measured accelerations and angular velocities were representative of those expected for trunk angle measurements the sensor was positioned so that the unit local frame (ULF) axes were approximately aligned with the anatomical axes of the lower trunk. In addition, three 15mm diameter retro-reflective markers were attached to the unit case and defined a marker-cluster local frame (MLF).

Subjects were asked to perform three walking trials on a motorized treadmill. Trials were performed at natural walking speed, 80% of natural speed and 120% of natural speed, and each of them lasted 40s. Acceleration and angular velocity data were collected from the

IMU (fs=100 samples/s) while the marker trajectories were tracked by five infrared cameras (MX, Vicon, fs=100 samples/s).

Pitch and roll angles, describing the orientation of the ULF were estimated from the IMU data using the Kalman filter as illustrated below and those describing the orientation of the MLF were reconstructed using photogrammetric data. The time-invariant offset of the MLF orientation relative to the ULF orientation was mathematically removed through a rigid transformation while the subject was standing still. In this way both instruments could be assumed to provide pitch and roll angles of the same lower trunk anatomical frame. The axial rotation of the trunk was not investigated in this study, since the yaw angle could not be estimated from the available IMU data. Pitch and roll angles were also calculated by integration of the angular velocity data.

In order to synchronise the two measuring systems' data, the subjects were asked to perform a forward bending of the trunk at the beginning and end of the walking trials, and the signals were aligned using the corresponding peaks in the pitch angles.

Kalman filter implementation.

The Kalman filter (Kalman, 1960) is used to estimate the state of a system, which, for an IMU, is represented by its orientation, defined as the rotation of the ULF relative to another frame attached to earth. This orientation may be expressed by a set of Euler angles, by a 3x3 orientation matrix or by a quaternion. The latter representation was chosen in this study because it is compact, fast and numerically stable. The process used by the Kalman filter consists of two main steps: propagation of the state, and correction of the error.

For each sample of time, i, the state vector of the filter X is a combination of the attitude quaternion ($Att = [q_0\ q_1\ q_2\ q_3]$) and the gyroscope bias vector ($B = [b_x\ b_y\ b_z]$):

$$X = \begin{bmatrix} Att \\ B \end{bmatrix} = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ b_x \\ b_y \\ b_z \end{bmatrix}$$

The gyroscope vector measured at the instant i and defined in the body frame can be expressed as G = $(g_x \quad g_y \quad g_z)$. An estimation of the offsets $\Omega = (\omega_x \ \omega_y \ \omega_z)$ of the angular velocity vector, as expressed in the body frame, can be computed from the gyroscope data as:

$$\Omega = \begin{pmatrix} \omega_x \\ \omega_y \\ \omega_z \end{pmatrix} = \begin{pmatrix} g_x - b_x \\ g_y - b_y \\ g_z - b_z \end{pmatrix}$$

The prediction of the state at instant i+1 is obtained from the previous updated state with:

$$\begin{bmatrix} q_0^{i+1} \\ q_1^{i+1} \\ q_2^{i+1} \\ q_3^{i+1} \end{bmatrix} = \begin{bmatrix} q_0^{i} \\ q_1^{i} \\ q_2^{i} \\ q_3^{i} \end{bmatrix} + \frac{1}{2} \cdot \begin{bmatrix} 0 & -\varpi_x & -\varpi_y & -\varpi_z \\ \varpi_x & 0 & \varpi_z & -\varpi_y \\ -\varpi_y & -\varpi_z & 0 & \varpi_x \\ \varpi_z & -\varpi_y & -\varpi_x & 0 \end{bmatrix} \cdot \begin{bmatrix} q_0^{i} \\ q_1^{i} \\ q_2^{i} \\ q_3^{i} \end{bmatrix} \cdot \Delta t$$

and equation for the updated state:

$$X^{i+1} = X^i + f(X^i, G^i) \cdot \Delta t \quad \Rightarrow \quad X^{i+1} = f'(X^i, G^i)$$

The Jacobian matrix F:

$$\mathsf{F} = \begin{bmatrix} \frac{\partial f_0'}{\partial q_0} & \cdots & \frac{\partial f_0'}{\partial b_z} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_6'}{\partial q_6} & \cdots & \frac{\partial f_6'}{\partial b_z} \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{2}\varpi_x\Delta t & -\frac{1}{2}\varpi_y\Delta t & -\frac{1}{2}\varpi_z\Delta t & \frac{1}{2}q_1\Delta t & \frac{1}{2}q_2\Delta t & \frac{1}{2}q_3\Delta t \\ \frac{1}{2}\varpi_x\Delta t & 1 & \frac{1}{2}\varpi_z\Delta t & -\frac{1}{2}\varpi_y\Delta t & -\frac{1}{2}q_0\Delta t & \frac{1}{2}q_3\Delta t & -\frac{1}{2}q_2\Delta t \\ \frac{1}{2}\varpi_y\Delta t & -\frac{1}{2}\varpi_z\Delta t & 1 & \frac{1}{2}\varpi_x\Delta t & -\frac{1}{2}q_3\Delta t & -\frac{1}{2}q_0\Delta t & \frac{1}{2}q_1\Delta t \\ \frac{1}{2}\varpi_z\Delta t & \frac{1}{2}\varpi_y\Delta t & -\frac{1}{2}\varpi_x\Delta t & 1 & \frac{1}{2}q_2\Delta t & \frac{1}{2}q_1\Delta t & -\frac{1}{2}q_0\Delta t \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

and the gyroscope error matrix Q (where q is a parameter representing the gyroscope noise and I is an identity matrix):

$$Q = q \cdot I$$

can then be used to update covariance matrix P:

$$P^{i+1} = F \cdot P^i \cdot {}^T F + Q\,,$$

For this study, P^0 was set to a null value.

Correction of the error

The error in roll-pitch estimation is computed as:

$$E_{PR} = Z_m - Z_e$$

where the *measured* acceleration vector *Acc* = is expressed in the unit frame as Z_m:

$$Z_m = \begin{cases} \dfrac{a_x}{\sqrt{a_x + a_y + a_z}} \\ \dfrac{a_y}{\sqrt{a_x + a_y + a_z}} \\ \dfrac{a_z}{\sqrt{a_x + a_y + a_z}} \end{cases}$$

and the *estimated* vertical vector is expressed as Z_e:

$$Z_e = h(X) = \begin{cases} Z_{ex} = 2(q_1 \cdot q_3 - q_0 q_2) \\ Z_{ey} = 2(q_2 \cdot q_3 + q_0 q_1) \\ Z_{ez} = 1 - 2(q_1^2 + q_2^2) \end{cases}$$

In the proposed extended Kalman filter, the roll-pitch observation matrix is expressed as the Jacobian of the above function *h*:

$$H_{PR} = \begin{bmatrix} -2q_2 & 2q_3 & -2q_0 & 2q_1 & 0 & 0 & 0 \\ 2q_1 & 2q_0 & 2q_3 & 2q_2 & 0 & 0 & 0 \\ 0 & -4q_1 & -4q_2 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

Using H_{PR} the roll-pitch estimation error P_{PR} can be computed as:

$$P_{PR}^{i+1} = H_{PR} \cdot P^{i+1} \cdot {}^T H_{PR} + R_{PR},$$

with *R* representing the noise in the accelerometer data.

Finally, the Kalman gain, associated with the roll-pitch estimate, is computed as:

$$K_{PR} = P_{i+1} \cdot {}^T H_{PR} \cdot P_{PR}^{-1}$$

and is used to obtain the estimate of the state of the system:

$$X^{i+1} = X^{i} + K_{PR} \cdot E_{PR} \, .$$

To run the filtering procedure, estimates of the noise associated with the gyroscope (Q) and accelerometer (R) are needed. Bench trials were performed to record the sensor signals in six different positions, in which the positive and negative x, y and z axes of the accelerometers, were each made to coincide with the gravity acceleration. These trials showed that Q^0, and R^0 can be considered constant in all three directions. They were hence expressed as: $Q^0 = q \cdot I$ and $R^0 = r \cdot I$, with I being a 3x3 identity matrix, and q and r being two parameters that need to be set to run the process. Furthermore, the relevant contribution of Q and R to the computation of the estimate of the state must be established. This can be done using the following reliability criteria: if the system is in a “quasi static” state (Jurman et al., 2007) the magnitude (a) of the vector *Acc* must satisfy the following condition:

$$g - s1 < a < g + s2,$$

where g is the magnitude of the gravity acceleration vector, and $s1$ and $s2$ are two constants. If the above constraints are satisfied, the accelerometer signals are considered more reliable than the gyroscope signals and a higher relevance given to R. Otherwise, more reliability is placed on the gyroscope signals and a higher relevance given to Q.

To implement the above criteria, the matrix Q^i, representing the noise in the gyroscope data at any instant i, can be kept constant (and equal to Q^0), while the matrix R^i, representing the noise in the accelerometer data at any instant i, can be increased or decreased by a multiple of R^0 through a weighting coefficient w ($R^i = w * R^0$), which is changed according to the values of $s1$ and $s2$. In this study, we chose to represent the relationship between w and $s1$ and $s2$ through a ramp function, defined as:

$$w = s1, \text{ for } a \leq g - s1,$$

$$w = m \cdot (a - s1)/(s2 - s1), \text{ for } g - s1 < a < g + s2,$$

$$w = s2 \text{ for } a \geq g + s2$$

In summary, in order to run the above described Kalman process, the values of five parameters must be set: q, r, $s1$, $s2$ and m. On the basis of the previously described bench trials and on the authors experience, the following first approximation values were selected:

q = 1e-008 °/s (static gyroscope signal noise)

r = 1e-009 m/s2 (static accelerometer signal noise)

s1 = 0.5 m/s2

s2 = 0.5 m/s2

m = 200.

Optimization procedure

Data from nine trials recorded from three randomly selected subjects at three different speeds were used to run the optimization procedure. Orientation angles for the IMU (pitch P_K and roll R_K) were calculated using the described Kalman filter with the first approximation parameters listed above. These angles were then compared to the corresponding angles calculated from the stereophotogrammetric data (pitch P_S and roll R_S). The root mean square of the differences between P_K and P_S (RMS_P) and between R_K and R_S (RMS_R) was then calculated along with the correlation coefficients (r_P and r_R, respectively) between the same angle time histories. Mean root mean square (RMS=mean(RMS_P, RMS_R)) and mean correlation coefficient ($corr$ =mean(r_P, r_R)) were then computed.

The PatternSearch algorithm (Matlab®, Mathworks, Natick, MA) (Lewis and Torczon, 2000)was used to determine the optimum combination of parameters (q, r, s_1, s_2 and m) that minimized the quantity $J=RMS_P/r_P+ RMS_R/r_R$. The optimization procedure was repeated three separate times, once for each of the slow, natural, and fast speed trials. The corresponding *RMS* and *r* values were computed as the mean of the corresponding values for the data of the three subjects The combination of parameters that gave the lowest *J* was finally selected as the optimal solution.

Sensitivity analysis

Once the optimized parameters were found, a sensitivity analysis was performed to assess their role in determining the final results. The Kalman filter was run by using the 3125 (55) combinations obtained by multiplying the optimal q, r, and m values by 1/50, 1/5, 1, 5, and 50 and the optimal s1 and s2 values by 1, 50, 100, 500 and 1000.

The analysis of the relevant results was divided into two steps. First the effects of the variation of the product r·m (representing the accelerometer noise for a non-adaptive filter) and of q have been investigated. Second, the subsets of the combination of these values that provided the best results were used for investigating the effects of varying s1 and s2, which are the parameters that make the filter adaptive.

Filter accuracy assessment

The accuracy of the pitch and roll estimates obtained from the IMU data using the Kalman filter was assessed by comparing the data recorded in the 45 trials not used in the optimization process to those measured with the stereophotogrammetric system. Again, RMS and corr were used to this purpose, together with the offset values (computed as the difference between the mean values of the corresponding angles).

It should be noted that the stereophotogrammetric errors (Chiari et al., 2005) propagate to the angles of interest in this study causing a maximal inaccuracy of 0.5°.

Results

Results relevant to the optimization procedure are shown in Table 4.1. The use of the approximation parameters led to an improvement in the estimate of about 2° when compared to the data obtained by integrating the angular velocity signals without correction for drift using the filter. The residual error values, however, were still unsatisfactory, with RMS differences of about 4-5° between stereophotogrammetry angles and angles calculated using the Kalman filter, and correlation coefficients around 0.5 for the pitch and around 0.4 for the roll estimate.

Table 4.1: Results of the optimization procedure

		Pitch			Roll		
Trial Type	Filter	RMS (°)	*corr*	Offset (°)	RMS (°)	*corr*	offset (°)
Slow	Without filter	6.1 (1.2)	0.41 (0.32)	2.6 (0.6)	5.2 (1.2)	0.19 (0.34)	1.4 (0.4)
	First approximation parameters	4.7 (4.9)	0.53 (0.25)	2.9 (0.8)	3.6 (2.8)	0.39 (0.36)	1.6 (0.7)
	Optimized parameters	0.7 (0.4)	0.98 (0.01)	1.8 (0.7)	0.8 (0.2)	0.91 (0.03)	2.4 (0.4)
Natural	Without filter	7.1 (1.1)	0.41 (0.6)	2.8 (0.6)	6.2 (1.3)	0.09 (0.21)	1.5 (0.6)
	First approximation parameters	5.2 (2.2)	0.56 (0.05)	2.8 (0.7)	3.9 (0.3)	0.26 (0.05)	1.5(0.5)
	Optimized parameters	0.6 (0.4)	0.99 (0.01)	2.9 (0.5)	0.5 (0.1)	0.95 (0.01)	1.5 (0.6)
Fast	Without filter	7.7 (1.6)	0.32 (0.16)	2.7 (0.5)	7.6 (1.2)	-0.02 (0.21)	1.6 (0.4)
	First approximation parameters	5.4 (1.8)	0.49 (0.02)	2.8 (0.7)	5.2 (5.9)	0.13 (0.4)	1.5 (0.4)
	Optimized parameters	0.7 (0.1)	0.98 (0.01)	3.3 (0.4)	0.7 (0.4)	0.92 (0.02)	1.2 (0.3)

The optimization procedure produced an evident reduction of the *RMS* differences between the stereophotogrammetry and the Kalman angles (to less than 1°) and an increase of the mean correlation coefficients *corr* to values greater than 0.9. The best results were obtained for the natural speed trials. The corresponding values of the Kalman filter parameters were:

q = 2.4e-007 °/s,
r= 1.61e-006 m/s^2,
s_1 = 0.11 m/s^2,
s_2 = 0.10 m/s^2,
m = 80,

and the corresponding J was 1.46°. Similar values were found in the other experimental conditions.

Figure 4.1 shows the variability of the cost function index J as a function of the two parameters q and $r{\cdot}m$. As highlighted in the figure, very low values of J (black points) could be obtained not only for the optimum values of the parameters, but also for other combinations, all characterized by having a similar ratio $\frac{r \cdot m}{q}$ (with its values being equal to

544±26 in the trials with J<2). This means that if one of the parameters is varied, the other must vary as well in a proportional manner.

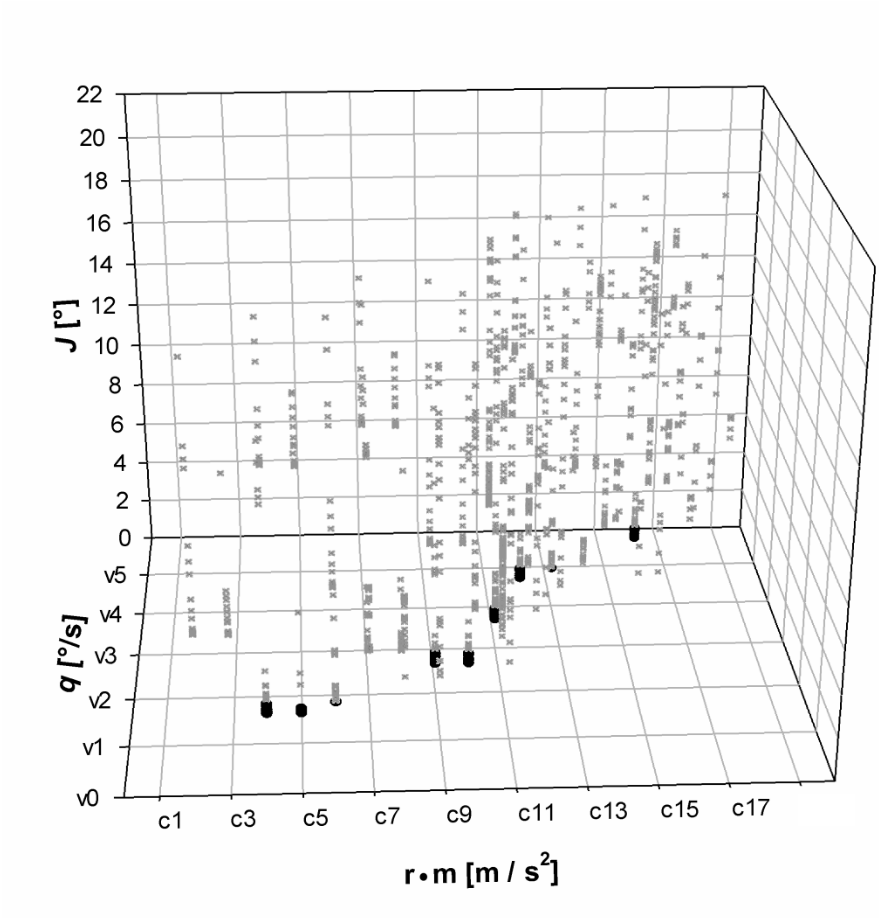

Figure 4.1: Results of the sensitivity analysis. For the sake of clarity, results have only been plotted for the combinations of parameters that gave J < 20°, and these J values have been plotted for the combinations of the $r \cdot m$ values (c1, …, c17) and of the q values (v1,…,v5) from which they were obtained. The results relevant to the combinations of the parameters leading to values J < 2° have been highlighted by plotting them in black.

Figure 4.2 shows the values of J obtained varying the parameters s_1 and s_2 for any combination of the parameters q, r, and m that gave the best results. Most of the solutions leading to the lowest J values were around the optimum values of s_1 and s_2, with J values increasing with the value of these parameters.

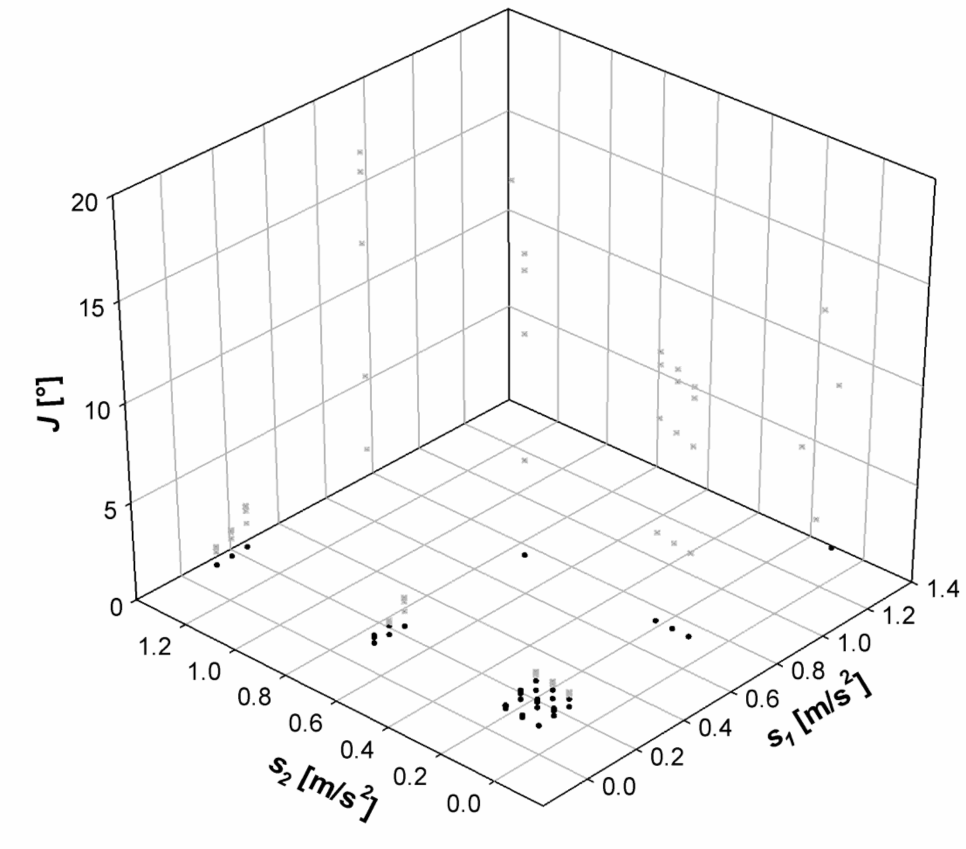

Figure 4.2: Results obtained for the sensitivity analysis. The values of the index J have been reported as a function of the values of the parameters s1 and s2. For the sake of clarity, results have only been plotted for the combinations of parameters that gave J<20°. Furthermore, the combinations of the parameters leading to values J<2° have been highlighted by plotting them in black.

The optimal configuration of the parameters of the filter led to very satisfactory results in terms of accuracy, as shown in Figure 4.3. The mean (standard deviation) *RMS*, *corr* and offset values for the 45 trials that were not used for the optimization are reported in Table 4.2. At all observed speeds, errors were around 0.6° with average correlation coefficients greater than 0.90.

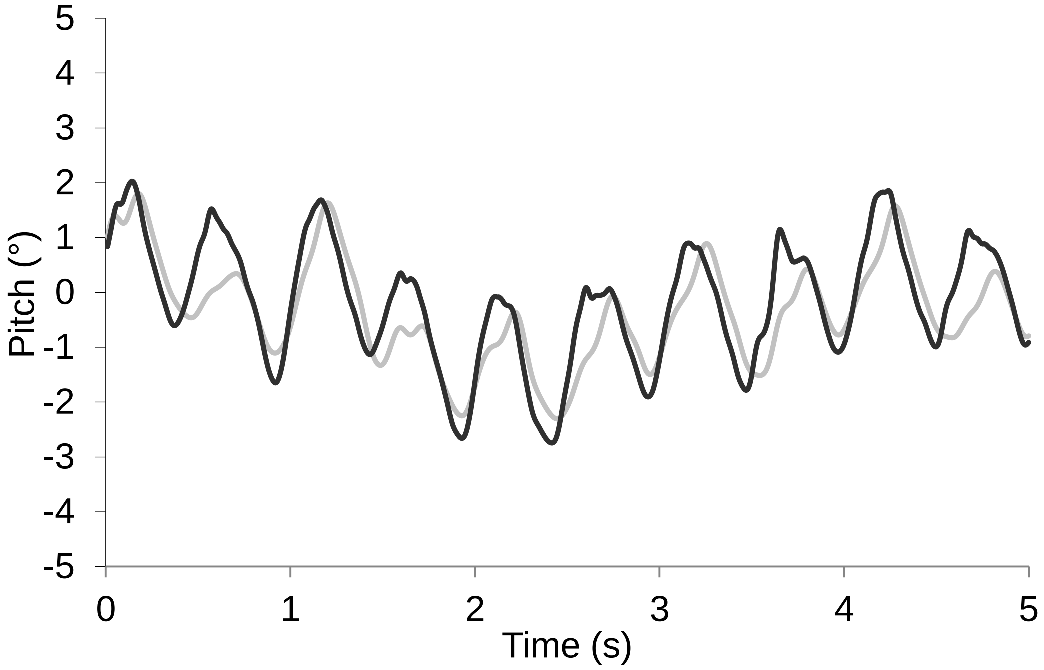

Figure 4.3**:** An example of the estimate of the angles obtained during a consecutive series of walking cycles extracted from a trial at natural speed. Angles estimated with photogrammetry are represented by the grey line and those estimated using IMU data and the optimized Kalman Filter are shown by the black line.

Table 4.2: Results of the accuracy analysis

		Pitch			Roll		
Trial Type	Filter	RMS (°)	*corr*	Offset (°)	RMS (°)	*corr*	Offset (°)
Slow	No	8.1 (0.9)	-0.26 (0.16)	3.4 (0.7)	6.7 (1.3)	0.04 (0.21)	1.3 (0.5)
	Yes	0.6 (0.1)	0.91 (0.04)	3.6(1.1)	0.5 (0.1)	0.93 (0.07)	1.3 (0.6)
Natural	No	9.6 (0.7)	-0.27 (0.22)	3.4 (0.7)	7.8 (1.5)	0.01 (0.16)	1.2 (0.5)
	Yes	0.6 (0.1)	0.91 (0.03)	3.5 (0.9)	0.5 (0.1)	0.93 (0.06)	1.3 (0.7)
Fast	No	10.6 (1.3)	-0.22 (0.21)	3.1 (0.9)	10.0 (1.9)	-0.09 (0.13)	1.4 (0.7)
	Yes	0.7 (0.2)	0.91 (0.03)	3.6 (1.0)	0.6 (0.1)	0.92 (0.05)	0.9 (1.1)

Discussion

This study proposed a Kalman filter for the estimation of the lower trunk movements during treadmill level walking and proved the importance of selecting proper parameters for it.

As reported for other motor tasks (Luinge and Veltink, 2005), the importance of the parameters selection has been highlighted by the results of the optimization procedure and of the sensitivity analysis. It has been shown, in particular, that the three parameters q, r, and m

must vary simultaneously, with the ratio $\frac{r \cdot m}{q}$ having to be constant and much greater than one. This means that for the investigated type of motor task the relative importance of the accelerometers and gyroscopes error is fixed, with the gyroscope generally being considered more reliable than the accelerometers, as already suggested by other authors (Suh et al., 2006).

Once the proper combination of q, r, and m is found, s1 and s2, have to be set to low values, ranging in between 0.05 and 0.2 m/s2, in order to obtain satisfactory angle estimates. This can be explained by the fact that the observed motor task is dynamic, and its “quasi static” parts do not actually require the use of an adaptive filter, as they are typically very short and hence do not strongly influence the results of the computations. The use of an adaptive filter and the proper selection of its parameters could be crucial when different movements, involving higher deceleration and acceleration phases, are investigated (Rehbinder, 2004). We expect, for example, that this would be the case in other locomotor tasks such as running.

Once the optimized parameters were selected, the filter proved to be very robust with respect to walking speed and subjects’ anthropometry, as shown by the very low residual differences to orientation data obtained with stereophotogrammetry. Since the difference between treadmill and overground walking mainly affects self-selected walking speed and, very mildly, stride length (Stolze et al., 1997), it can be hypothesised that the results of this study may be valid for the latter type of locomotion as well. However, evidence is required to confirm this hypothesis. RMS differences were lower than 1° and were close to the accuracy with which the same angles can be measured with the stereophotogrammetric system. As expected, the offsets between the curves, that were around 3.5° for the pitch and around 1.3° for the roll, were not modified by the filter and were not noticeably affected by the optimization procedures. This may also be a consequence of the fact that they were not included in the calculation of the cost function. This choice is justified by the fact that these values reflect possible misalignments of the global reference frames adopted for the two measurement systems and should hence have already been minimized during the calibration of the systems.

Whereas the importance of the selection of the correct parameters is a concept that can certainly be generalized, the specific values proposed in the study are only valid for the class of sensors used, since they depend on the electronic noise of their components, and for the investigated locomotor act, since they depend on the features of its accelerations and angular velocities. For the sake of practicality, a method not requiring the use of stereophotogrammetry as a concurrent measurement system needs to be developed for the tuning of the filter parameters. A mechanical device imposing a priori known rotations at predefined angular speeds which replicate those found in selected human movements could be a feasible alternative.

The purpose of this study was to show the value of optimizing the input parameters of an extended Kalman filter and as such it did not require the precise measurement of trunk angles. Nonetheless it did require the measurement of angular velocities and accelerations representative of those that would be apparent were the accurate measurement of trunk angles desired for a cross section of healthy subjects over various gait speeds. Moreover, somewhat varied inertial measurements will be obtained from different positions on the trunk where orientation angles might be assessed. Taking both these matters into consideration is was not considered necessary for the performance of this study to precisely position and align the sensor to anatomic axes as would be necessary for accurate assessment of trunk angles at a given position.

In conclusion, the proposed filter can be used for reliably estimating trunk lateral and frontal bending during walking over a wide range of speeds. This information, if used together with other parameters, derived from an inertial sensor output located on the lower trunk (such as temporal and spatial parameters and those describing the pelvis movements) is certainly of interest for assessing walking ability. Further studies are needed to determine the filter parameters that are most suited for other motor tasks.

ESTIMATING ORIENTATION USING GYROSCOPES DATA

Background

The previously described Kalman filter is only able to provide estimations of pitch and roll angles due to the lack of a reference for yaw angle. Magnetometers are often used to provide the necessary extra information to obtain yaw angle estimations (Gallagher and Matsuoka, 2004; Kemp et al., 1998) however these can be affected by the surroundings (Roetenberg et al., 2005). An alternative is to use a model based adaptive filter which can provide a reliable estimation of the shape and time evolution of the signal if there is previous knowledge of the type of signal (Tan et al., 2009). If the signal is periodic, Fourier Linear Combiner filters (Vaz et al., 1994; Vaz and Thakor, 1989) are effective. However in the case of human movement signals are rarely truly periodic. An alternative Weighted Fourier Linear Combiner (WFLC) filter was proposed (Riviere et al., 1998) for use with signals which exhibit time-varying oscillation patterns. It was proposed that this method may be used to characterize the gyroscope signals and allow drift free analytical integration to provide 3D orientation angles when applied to data recorded by three orthogonally mounted gyroscopes. The proposed filter has been described in detail elsewhere (Bonnet et al., 2012). An experiment was conducted to assess this method and compare the angles derived with the roll and pitch angles estimated using the previously described Kalman filter as well as those estimated from marker position data recorded using a stereophotogrammetric system.

Introduction

Inertial measurement units (IMUs) have gained in popularity as a tool to quantify human motion (Moe-Nilssen and Helbostad, 2004), thanks to their ease-of-use, robust design, and their small dimensions. In the same period, mass-market electronics companies have provided low cost devices, such as cell-phones, that contain embedded IMU devices along with recording and transmission capabilities. The characteristics of IMUs enable them to be used for extended periods outside the confines of a laboratory.

An IMU normally includes accelerometers and gyroscopes to measure three accelerations and three angular velocities, respectively. Theoretically, the determination of the position and orientation in space of such a device could be obtained by double and single integration of the above signals, respectively. Unfortunately, the IMU outputs are subject to drift over time, which jeopardizes the time integration of the raw signals (Sabatini, 2006). The additional use of magnetometers has been proposed to compensate for the integration errors, but their effectiveness is limited by their high sensitivity to magnetic disturbances (Caruso, 2000; Kemp et al., 1998).

The present study focused on the estimate of orientation and aimed at devising a data processing procedure that would compensate for the above-mentioned drift and provide an optimal estimation of the 3-D instantaneous orientation of the IMU and, therefore, of the body segment it is attached to.

As reported in the literature, the use of recursive filters, such as the Kalman filter, allows the real-time accurate estimate of lower trunk 2D orientation (pitch and roll angles) from the measurement of three accelerations and three angular velocities (Mazzà et al., 2012). A possible alternative is represented by model-based adaptive filters, which can be used when it is possible to formulate reliable hypotheses about the shape and the time evolution of the signal, which is plausible when the type of motor task performed is known (Tan et al., 2009). Among the most popular model-based adaptive filters are the Fourier Linear Combiner (FLC) filters (Vaz et al., 1994; Vaz and Thakor, 1989). These filters, which model the measured signal by a Fourier series, are effective when dealing with periodic signals, which is hardly ever the case in biomechanics in general and human movement in particular. For this reason, while dealing with the real-time analysis and for the cancellation of movements such as hand tremor, Riviere and his colleagues (Riviere et al., 1998) proposed the use of Weighted Fourier Linear Combiner (WFLC) filters. These filters are an extension of the FLC which can be used when investigating signals that display an oscillatory pattern but with a time-varying period. Human walking is a phenomenon that, although it is most of the time hypothesised to be periodic for analysis purposes, does exhibit minor features that vary from stride to stride and, as such, may be defined as quasi-periodic. WFLC filters can therefore be considered suitable for analysing gait related data.

This paper proposes the use of WFLC adaptive filter to perform drift-free orientation angle estimation in three dimensions starting from the measurement of three angular velocities as provide by three orthogonally mounted gyroscopes. The accuracy of the method was assessed using data collected using a device mounted on the lower trunk and collected while volunteers walked on a treadmill at different speeds, both at quasi steady-state, and in accelerating and decelerating conditions.

Methods

The proposed method for the estimate of the 3D sensor orientation is based on two main steps. First, each of the three measured angular velocity components is tracked by identifying the corresponding Fourier series coefficients using the WFLC. Then, the identified Fourier series are analytically integrated to estimate the three orientation angles.

The WFLC filter

As previously mentioned, the WFLC is an adaptive filter that allows the analytical tracking of a quasi-periodic signal. The architecture of the WFLC is presented in Figure 4.4. The input of the WFLC is the angular velocity signal as measured at the instant of time k (s_k). Depending on the instantaneous difference ε_k between the signal s_k and the output estimated by the WFLC ($\hat{s}_k$), the WFLC computes the Fourier series coefficients that will represent the measured signal at time $k+1$. This result is obtained by adjusting, at each iteration, the so-called filter weights, w_{0_k} (the frequency weight, taking into account for the fundamental pulsation) and w_k (the vector containing the amplitude weights), using the least mean squares (LMS) algorithm proposed by Widrow and Stearns (Widrow and Stearns, 1985). Initial values of the weights, w_{0_1} and w_1, need, of course, to be provided.

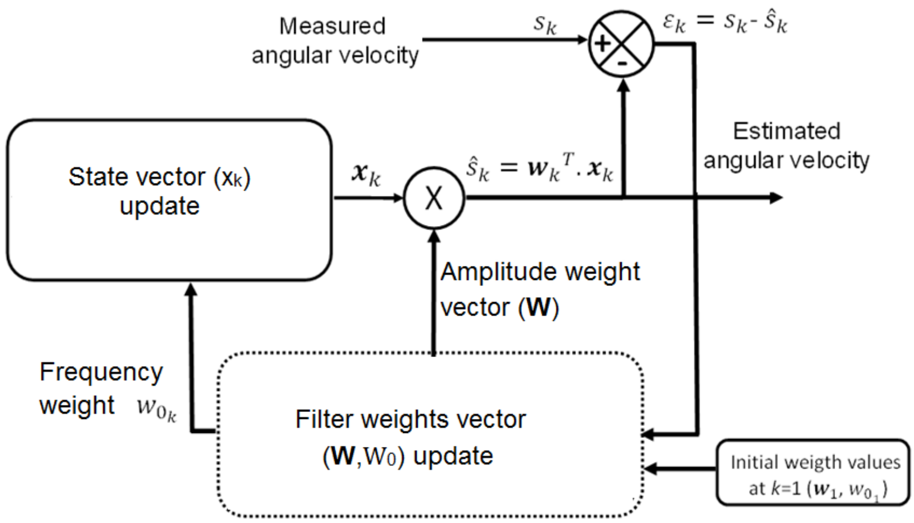

Figure 4.4:Block diagram of the Weighted Fourier Linear Combiner filter

The state vector $\mathrm{x_k} = [\mathrm{x_{1_k}} \dots \mathrm{x_{2M_k}}]^{\mathrm{T}}$ used by the WFLC is composed of the sine and cosine functions computed using the frequency weight $\mathrm{w_{0_k}}$ (Riviere et al., 1998; Vaz et al., 1994; Vaz and Thakor, 1989):

$$x_{r_k} = \begin{cases} sin\left(r \sum_{j=0}^{k} w_{0_j}\right), & 1 \leq r \leq M \\ cos\left((r-M) \sum_{j=0}^{k} w_{0_j}\right), & M+1 \leq r \leq 2M \end{cases} \tag{1a}$$

where *M* is the order of the Fourier series representing the measured signal s.

At each instant of time, $\mathrm{w_{0_k}}$ and $\mathrm{w_k} = [\mathrm{w_{1_k}} \dots \mathrm{w_{2M_k}}]^{\mathrm{T}}$ are computed using the following equations:

$$\varepsilon_k = s_k - \boldsymbol{w}_k^T \boldsymbol{x}_k - w_{b_k} \tag{1b}$$

$$w_{0_{k+1}} = w_{0_k} + 2\mu_0 \varepsilon_k \sum_{r=1}^{M} m(w_r x_{M+r} - w_{M+r} x_r) \tag{1c}$$

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k + 2\mu \boldsymbol{x}_k \varepsilon_k \tag{1d}$$

with μ_0 and μ representing the so called frequency and amplitude adaptation gains, respectively. $\mathrm{w_{b_k}}$ is introduced in the computation of ε_k to estimate the bias present in the signal (Gallego et al., 2010; Veluvolu and Ang, 2011; Widrow and Stearns, 1985), due to possible low frequency components and/or drift, and to remove it. And it is thus computed as:

$$w_{b_{k+1}} = w_{b_k} + 2\mu_b \varepsilon_k \tag{1e}$$

where μ_b is the so called bias adaptation gain.

The three adaptation gains, μ_0, μ, and μ_b determine the convergence time, the accuracy of the algorithm in tracking the measured signal, and the algorithm stability at each sample of time. It has to be noted that the algorithm convergence time cannot be analytically computed (Riviere et al., 1998) and that high values of the gains can improve tracking of the input signal, but can also cause the algorithm to diverge.

In order to allow the use of higher gains, the WFLC can be run twice (Riviere et al., 1998): the first time using high μ_0 and low μ value to identify the frequency weight $\mathrm{w_{0_k}}$ and the second time using the so identified w_{0_k} and a higher μ (μ_{FLC}) to identify wk. It has to be noted that this latter use of the WFLC algorithm, in which equation 1c is ignored, makes it equivalent to an FLC (Riviere et al., 1998; Vaz et al., 1994; Vaz and Thakor, 1989).

Analytical integration

The estimates of the IMU orientation requires an integration of the gyroscopes' data. Once the angular velocity is tracked with the above algorithms, its analytical and instantaneous representation is provided by the identified Fourier series. The analytical integration of this Fourier series should eliminate drift issues, and can be computed at each sampled instant of time using the following method (Tan et al., 2009; Veluvolu and Ang, 2011; Veluvolu et al., 2010): first the vector $w_{i_k} = [w_{i_{1_k}} \ldots w_{i_{2M_k}}]^T$ (where the subscript "i" represents the integral and is computed using the identified amplitude, and frequency weights:

$$w_{i_{r_k}} = \begin{cases} -w_{r_k}/(r w_{0_k} f_s), & 1 \leq r \leq M \\ w_{r_k}/((r-M) w_{0_k} f_s), & M+1 \leq r \leq 2M \end{cases} \quad (2)$$

where fs is the sampling frequency. The instantaneous estimate $\hat{s}_{i_k}$ of the integral of the measured angular velocity is then obtained as [2], [11-12]:

$$\hat{s}_{i_k} = \boldsymbol{w}_{i_k}{}^T . \boldsymbol{x}_k \quad (3)$$

The above angle represents the result of the integration of each single angular velocity component along its corresponding sensor axis, which does not necessarily coincide with the actual rotation of the corresponding axis of the IMU local frame. To overcome this issue, an estimate of the actual rotation can be obtained through a rigid transformation that accounts for the fact that at every instant of time there is a rotation of the local system of reference (x, y, z) fixed to the IMU with respect to the one computed at the previous instant of time.

Experimental session

A total of 18 volunteers (10 male, 8 female, age range: 24 - 64 years, stature: 1.76 ± 0.09m, mass: 78 ± 11 kg) were included in the study after signing an informed consent. They were asked to perform three walking trials at natural walking speed (as measured over level ground), 80% and 120% of natural speed on a motorized treadmill. The subjects initially stood on the treadmill, which was then accelerated to the desired velocity. After 35s of steady state walking, the treadmill was decelerated and stopped for 5s, before being reaccelerated to the same velocity for additional 35s and then stopped again, for a total recording time of 80s. The transition and stopping phases were used to assess the ability of the proposed algorithm to provide accurate estimates also during non-periodic motion over a short interval of time.

An IMU (Freesense, Sensorize srl) was located on the lower back of the subjects so that the unit local frame (ULF) axes were aligned with the anatomical axes of the lower trunk. In addition, three retro-reflective markers were attached to the IMU sensor in order to define a marker-cluster local frame (MLF).Acceleration and angular velocity data were collected from the IMU (fs=100 samples/s) while the marker trajectories were tracked by five infrared cameras (MX, Vicon, fs=100 samples/s).

Pitch, roll and yaw angles, describing the orientation of the ULF, were estimated from the IMU data using the WFLC algorithm and those describing the orientation of the MLF were reconstructed using stereophotogrammetric system. The time invariant offset of the MLF orientation relative to the ULF orientation was mathematically removed through a rigid transformation while the subject was standing still. In this way both instruments could be assumed to provide pitch, roll, and yaw angles of the same lower trunk anatomical frame. Pitch, roll and yaw angles, can hence be associated with lower-trunk frontal and lateral bending and axial rotation, respectively.

It should be noted that in this study the stereophotogrammetric errors (Chiari et al., 2005) propagate to the angles of interest causing a maximal inaccuracy of 0.5deg.

Tuning of the algorithm parameters

The order of the Fourier series M, representing the measured signal s, was set to M=1. This conservative choice was initially made following the literature (Riviere et al., 1998; Tan et al., 2009) and was supported by a preliminary analysis, in which higher values of M caused convergence problems, leading to very inaccurate and unrealistic estimates for some of the investigated trials. Also a value of M > 1 will not necessarily achieve more accurate estimates because the filter weights (Fourier coefficients) are continually adjusted. Adding more coefficients makes the identification process more complex and less stable. Conversely, the choice of M = 1 guaranteed the stability of the algorithm for all trials and all subjects.

In order to provide the best trade-off between accuracy, stability and robustness of the above described method, data recorded from three randomly selected subjects at three different speeds were used to determine the optimal combination of the WFLC gains μ_0, μ, and μ_b for each angular velocity. To this purpose, the three combinations of gains were searched to minimise three cost functions defined for the pitch, roll, and yaw angles, J_P, J_R, J_Y, respectively. Each of these cost functions was calculated as the average over the nine trials of the root mean square (RMS) differences between the angle calculated from the stereophotogrammetric data and the one calculated from the IMU. The WFLC is run separately for each angular velocity and a separate set of parameters was found to be optimum in each case. This is understandable when it is considered that while the motion is considered "quasi-periodic" the amplitude varies across each axis and the fundamental frequency about the anterior posterior and vertical axes will be twice that of the medial lateral axis.

Knowing that all the gains need to be positive, noting that previous implementations of the FLC algorithm suggest that in most cases a value of $\mu < 0.5$ is most likely to ensure convergence (Vaz et al., 1994; Vaz and Thakor, 1989), and on the basis of the authors experience, the following range of values were considered in the gain identification process:

$$\mu = 0.01 + i0.025, \qquad i = 1, 2, 3, \ldots 10$$

$$\mu_{FLC} = 5\mu$$

$$\mu_0 = \mu_b = [5e^{-8}; 1e^{-7}; 5e^{-7}; 1e^{-6}; 5e^{-6}; 1e^{-5}; 5e^{-5}; 1e^{-4}; 5e^{-4}; 1e^{-3}]$$

The WFLC algorithm requires an initial estimate of the value of the frequency weight w_0 (equation 1c and Figure 4.4). A sensitivity analysis of the effects of varying w_0 was performed to choose this value by searching for the frequency value that minimised the cost function $J_{RMS} = (J_P + J_Y + J_R)/3$.The tested range of frequencies was 0.1-5 Hz, which is expected to include all possible walking related frequencies.

Assessment of estimate accuracy

The accuracy of the WFLC in the estimate of the pitch, roll, and yaw angles was assessed by comparing them to the corresponding angles obtained from the stereophotogrammetric data in the 45 trials that were not used in the gains identification process. The RMS, correlation coefficient r, and offset values between estimated and measured angles were calculated for the whole trials (80s), for the steady-state sub-phase (25s), and for the transient sub-phase, which included the deceleration, stopping and acceleration phases (15s) (Figure 4.8).

Results

Results of the gains identification procedure are shown in Figure 4.5. The red circles indicate the optimum weight combination for pitch (a); roll (b), and yaw (c) angles, respectively. The optimum gain values, which will be used on all the following computations, were:

Pitch: μ = 0.160, $\mu0$ = 1e-5, μ_b = 5e-4;

Roll: μ = 0.160, $\mu0$ = 5e-5, μ_b = 1e-3;

Yaw: μ = 0.135, $\mu0$ = 1e-3, μ_b = 5e-4.

The corresponding RMS values were:

Pitch: J_P = 0.8 ± 0.2deg,

Roll: J_R = 0.4 ± 0.1deg, and

Yaw: J_Y = 1.0 ± 0.5deg.

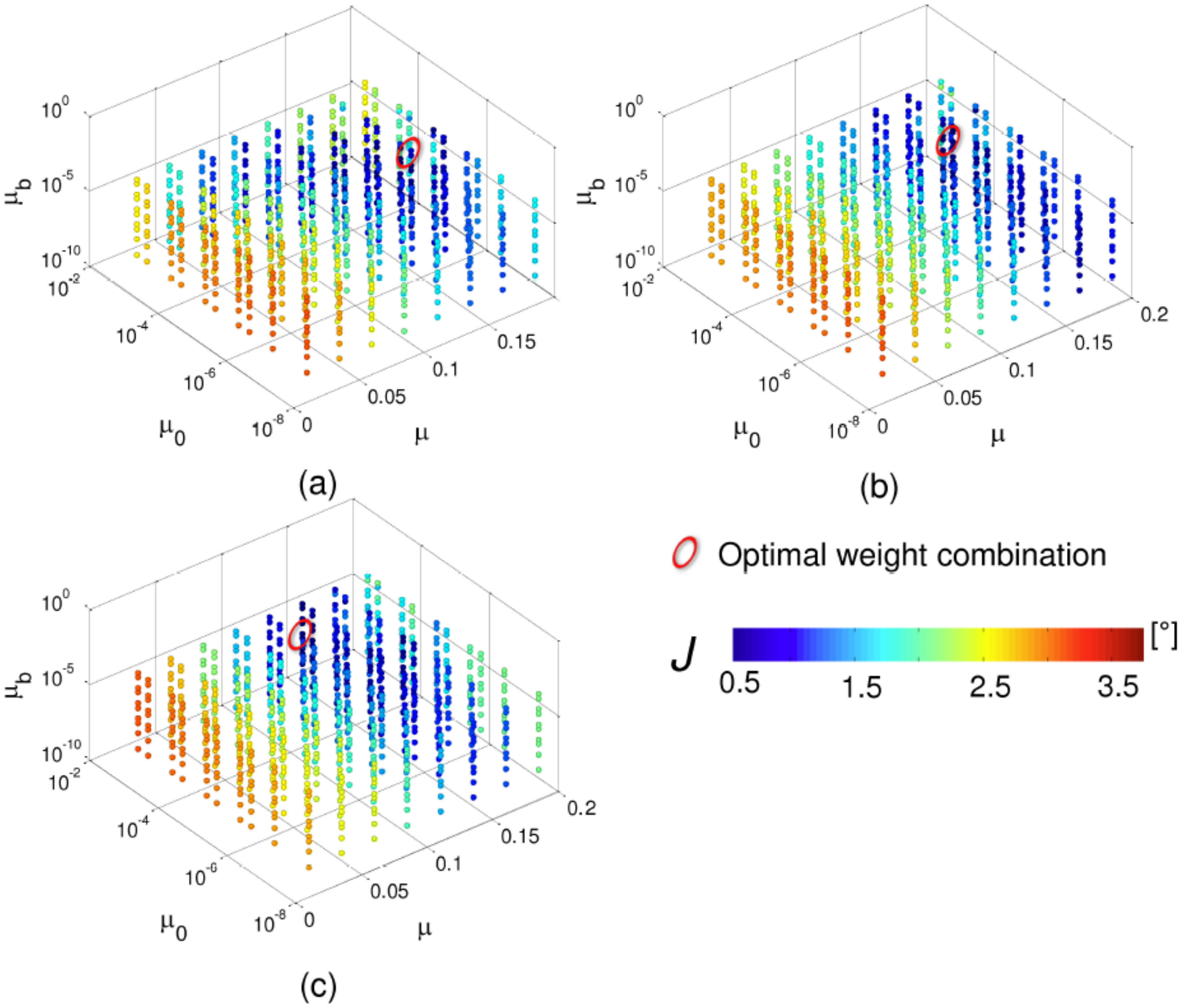

Figure 4.5:Results of the sensitivity analysis: weight parameters
Results of the gains identification process: values of JP for pitch (a), JR for roll (b), and JY for yaw (c) angles are shown. Data have been plotted for the combinations of the 3 parameters μ, μ0, μb, with the corresponding J-values represented using a color scale. The red ellipses indicate the optimum weight combinations

The results of the sensitivity analysis concerning the choice of w_0 are shown in Figure 4.6. The values obtained for J_{RMS} ranged from 1.3 to 0.65deg, with very small variations observed for w_0 varying in the range of 1-3 Hz, indicating a low sensitivity of the outputs to this initial condition.

The minimum J_{RMS} value was found for w_0 =2Hz.

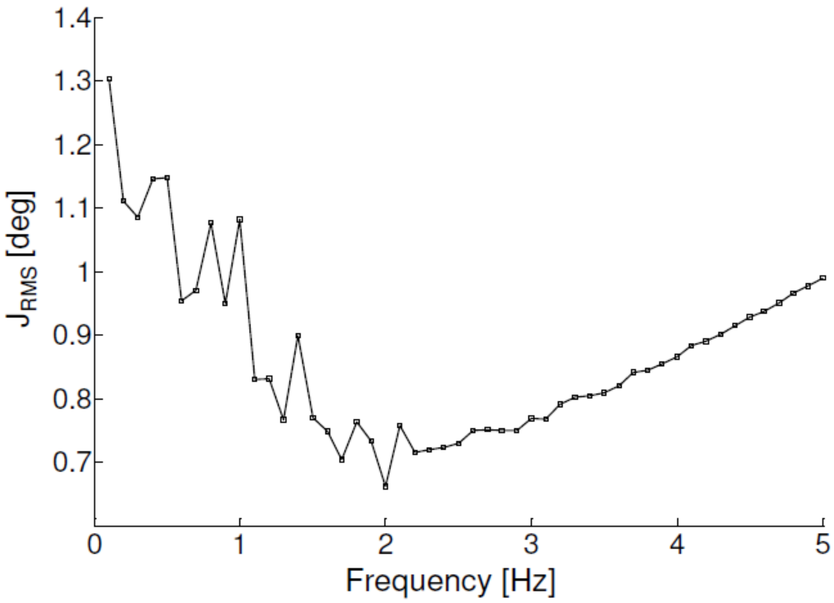

Figure 4.6:Results of the sensitivity analysis: initial frequency weight

The ability of the WFLC algorithms to track a measured angular velocity is depicted in Figure 4.7, where the results are shown for one randomly selected trial. It should be noted that, after the stopping phase, the algorithm rapidly re-converges as soon as the subject starts walking again.

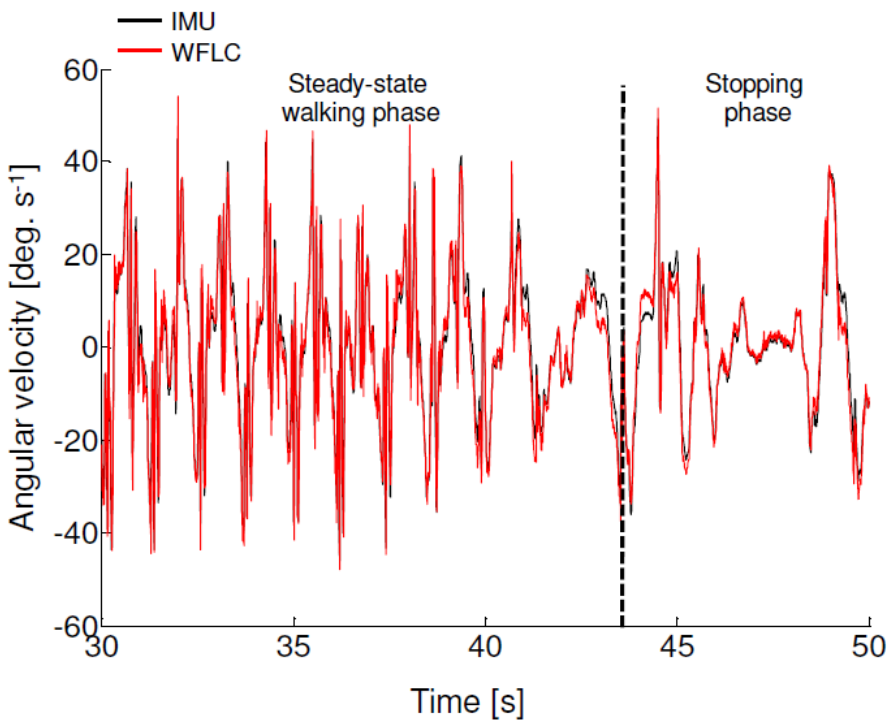

Figure 4.7. Angular velocity tracking. Representative results of one walking trial showing the estimated (red line) and measured (black line) angular velocity components

As shown in Figure 4.8 for one randomly selected trial, the proposed algorithm led to very satisfactory results in terms of accuracy for the pitch, roll, and yaw angles, not only in the steady-state walking phase (from 10s to 35s), but also during the decelerating (from 40s to 42s), stopping (from 42s to 45s), and accelerating (from 45s to 48s) phases (Table 4.3).

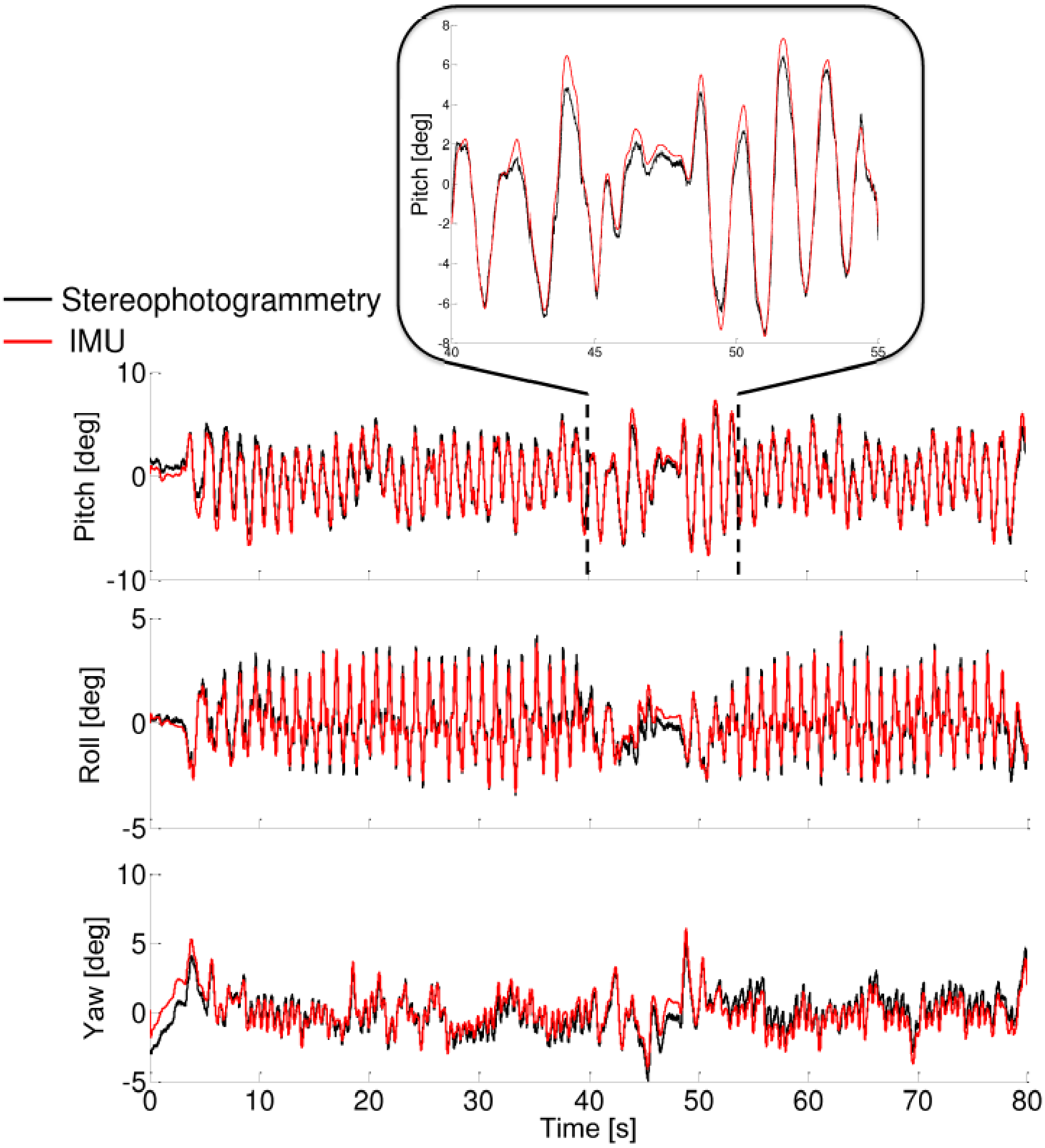

Figure 2.8: Representative trunk angles estimate. Representative results obtained for one randomly selected trial. The lower trunk orientation angles, as obtained from the stereophotogrammetric system (black curves) and using the proposed method (red curves) are shown. Angles are expressed in the ULF

The mean (standard deviation), *RMS*, *r* and offset values for the 45 trials that were not used for the gains identification are reported in Table 1. At all the observed speeds, all the investigated angles were estimated within an average of less than 1.2deg and with average correlation coefficients greater than 0.90 (with the highest values found for the yaw angles). This applied to both the whole trials and to their sub-phases. An average offset of less than 3deg was found, with lowest values observed for the roll angle.

Table 4.3 Results of the accuracy analysis

		Pitch			Roll			Yaw		
	Trials	***RMS* (deg)**	***r***	**Offset (deg)**	***RMS* (deg)**	***r***	**Offset (deg)**	***RMS* (deg)**	***r***	**Offset (deg)**
Whole trial	Slow	0.9±0.3	0.93±0.04	2.2±1.6	0.5±0.1	0.92±0.04	0.7±0.4	1.1±0.6	0.80±0.16	2.4±3.0
	Natural	0.8±0.2	0.95±0.03	1.4±1.4	0.4±0.1	0.94±0.02	0.9±0.0	1.1±0.7	0.82±0.14	2.6±2.6
	Fast	0.9±0.3	0.93±0.03	2.4±1.5	0.4±0.0	0.95±0.02	0.9±0.0	1.2±0.7	0.82±0.19	2.9±2.8
Steady state	Slow	0.7±0.2	0.97±0.02	2.0±1.6	0.4±0.1	0.95±0.03	0.8±0.4	0.7±0.4	0.86±0.14	2.9±2.9
	Natural	0.8±0.2	0.96±0.02	1.4±1.4	0.4±0.1	0.97±0.02	0.9±0.0	1.1±0.7	0.83±0.17	2.6±2.6
	Fast	0.7±0.3	0.96±0.03	2.7±1.7	0.4±0.1	0.96±0.05	0.7±0.6	1.1±0.8	0.86±0.24	2.9±2.4
Stopping Phase	Slow	0.6±0.2	0.98±0.01	2.4±1.9	0.4±0.1	0.96±0.02	0.8±0.7	0.7±0.4	0.93±0.04	2.9±3.4
	Natural	0.8±0.2	0.98±0.02	2.4±1.4	0.4±0.1	0.95±0.01	0.9±0.0	1.1±0.7	0.94±0.03	2.6±2.6
	Fast	0.7±0.2	0.98±0.01	2.3±1.5	0.4±0.1	0.96±0.03	0.7±0.0	1.2±0.8	0.89±0.06	2.9±3.1

Discussion

The aim of this study was to validate a method based on the use of a WFLC adaptive filter approach, to obtain a drift-free estimate of the 3D orientation of a sensor attached to the lower trunk for a prolonged period of time during treadmill walking, from angular velocities recorded using only one IMU.

A tuning of the WFLC was initially performed, to find optimal values for the gains. A sensitivity analysis was then performed to assess the effects of changes in algorithm frequency weight w_0, which is crucial for ensuring that equation 2, and hence the output of the proposed method, are determinable. Results of this analysis showed that the outputs were always determinable for frequencies ranging between 0.1 Hz and 5 Hz, and that frequencies ranging from 1 Hz to 3 Hz led to very similar results. It has to be noted that these frequencies are actually those expected to be of interest when dealing with human locomotor tasks.

After the above tuning process, the method proved to be very accurate in estimating all of the three angles, for all the observed speed conditions and also when the subjects were not walking at a steady state. Interestingly, the convergence time of the algorithms, which generally depends on the signal properties, appeared to be negligible for the specific investigated application, as shown by the fact that the results obtained for the transition phases were almost identical to those obtained in the steady state phase (Table 1). This ability of the method to provide accurate angle estimations during non-periodic motion (acceleration and deceleration phases) and during short intervals of almost no motion (stopping phase) opens the way to future applications, such as uncontrolled walking.

The accuracy of the estimates of lower trunk bending in the sagittal (pitch) and frontal (roll) planes is similar to that obtained in a previous study using a properly optimized Kalman filter (Mazzà et al., 2012). A clear advantage of the proposed method is that, conversely to the Kalman filter approach, it uses only the angular velocity signals. Nevertheless, the Kalman filter approach is expected to be more robust for non-periodic motions than the proposed method, since it does not require any a-priori assumption about the signal characteristics.

It has been previously shown that when tracking signals that have a frequency content composed of many frequencies that are close to each other, the performance of the WFLC can be degraded [8]. A Band-limited Multiple Fourier Linear Combiner (BMFLC) (Latt et al., 2011; Veluvolu and Ang, 2011) can be used to overcome this problem. However, the BMFLC filter requires an *a priori* determined set of frequencies, which is not always available when dealing with movement analysis application (Balasubramanian et al., 2009; Pecoraro et al., 2006). Numerical integration, as associated with WFLC-BMFLC adaptive filters, has been recently successfully used for tremor cancelation (Latt et al., 2011). This numerical approach, however, requires the use of a high-pass filter, which allows easy separation of the tremor oscillations (high frequency) from the voluntary motion (low frequency). Unfortunately, this approach is not suitable for lower trunk angular velocity data recorded during walking, when the determination of high-pass filter cut-off frequency is not straightforward due to the variability of walking speed, and to the fact that most of the gyroscope signals power is within the low frequencies, which hinder the determination of a proper high-pass cut-off frequency

In conclusion, this study proved the effectiveness of the WFLC method in accurately reconstructing the 3D orientation of an IMU located on the lower trunk of a subject during treadmill walking. This method is expected to also perform satisfactorily for overground walking data. The small differences in the values of the measured angular velocities which might be observed between treadmill and level walking data, might require a minor adjustment to the identified values of the algorithm gains. Further studies are needed to test the suitability of the method for the assessment of pathological gaits and to examine if the method can be generalized to other “quasi-periodic” tasks, such as squatting, rowing, running, or swimming.

ACCURACY OF ORIENTATION ESTIMATION FOR EXTENDED TIME PERIODS

Introduction

One of the benefits of using an inertial sensor to measure features of walking is portability. Many such devices can record data without requiring a computer connection, and the devices are also not sensitive to their surroundings. These features make them particularly suitable for making measurements away from the controlled environment of a laboratory.

While most of the literature describing the development and implementation of various Kalman and other filters provides validations of the outputs with respect to a reference standard many of these validations are performed for a limited period of, in most cases, of less than two minutes duration. Likewise, the performance of the optimized Kalman filter and the Weighted Fourier Linear Combiner described previously were shown for durations of less than two minutes.

It may be important for many aspects of walking assessment to detect the presence, or lack thereof, of changes in walking patterns that occur when the walking period is of a longer duration than one or two minutes. In many aspects of daily living it is necessary to walk for much longer periods. Common gait assessment measures include the six-minute and ten-minute walk tests. If it is possible to accurately record truck orientations for a period of six minutes or longer it will allow a much enhanced assessment of the walking patterns of the persons who perform this test and others of a similar or longer duration.

Methods

Data were recorded for two subjects using a single trunk mounted IMU (as described previously) while walking outdoors along a straight level path at a normal speed for a period longer than 12 minutes. During this period subjects walked in one direction for a period of slightly greater than six minutes and then turned and walked in the opposite direction for a similar period. Data recording commenced with a five second period of quite standing and walking was continuous throughout the trial. Due to technical constrains it was not possible to perform such a test and have a stereophotogrammetric measurement of sensor orientation available for reference.

Acceleration and angular velocity data were filtered using the optimized Kalman filter described previously. Angular velocity data were also input to the WFLC described in a previous section. Output of the Kalman filter was assessed for drift and results of the WFLC were compared to the recorded angular velocities be means of RMSE and correlation coefficients and offset.

<u>Results</u>

Orientation angles obtained from the data of one trial by integrating the angular velocities are shown in figure 4.9a. It can be seen that the amount of drift is high. The angles derived using the Kalman filter are shown in figure 4.9b). Pitch is shown as the angle of the vertical axis of the sensor relative to the horizontal plane.

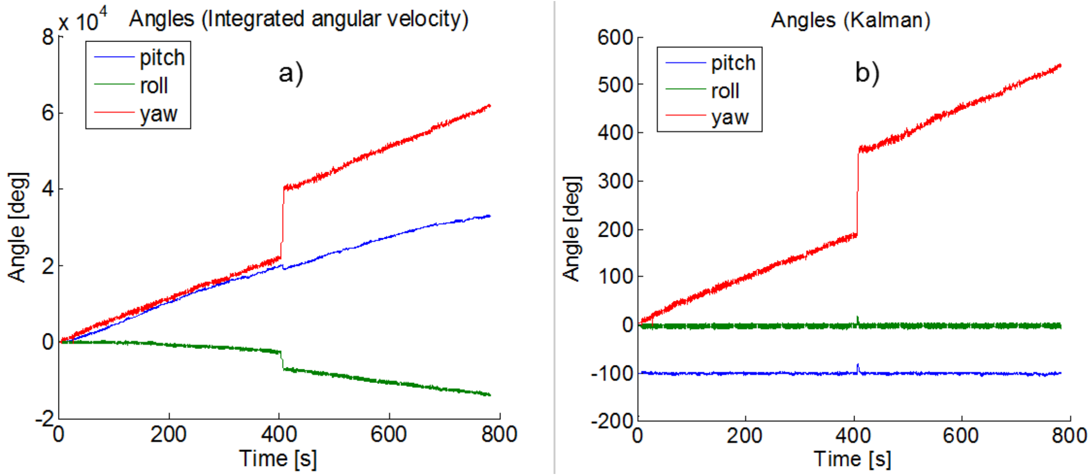

Figure 4.9. Pitch, roll and yaw angles calculated by a) integrating angular velocities for each axis and b) the Kalman filter. The step at approximately 400 seconds corresponds to the 180 degree turn at the end of the first period of straight level walking.

It is apparent from both the figures, and also from analysis of the orientation values obtained, that the drift in orientation angles due to integration has been removed for both roll and pitch angles for the period recorded. As the device used and the filter applied has no reference to use for correcting drift in yaw angles a drift remains around this axis after filtering. Figure 4.9b also shows that the filter is able to return appropriate pitch and roll values after the device is rotated 180 degrees.

Figure 4.10 shows the results of using the WFLC to provide an analytical representation of the recorded angular velocities. Intervals at the commencement (figure 4.10a) and the end (figure 4.10b) of one representative trial are shown.

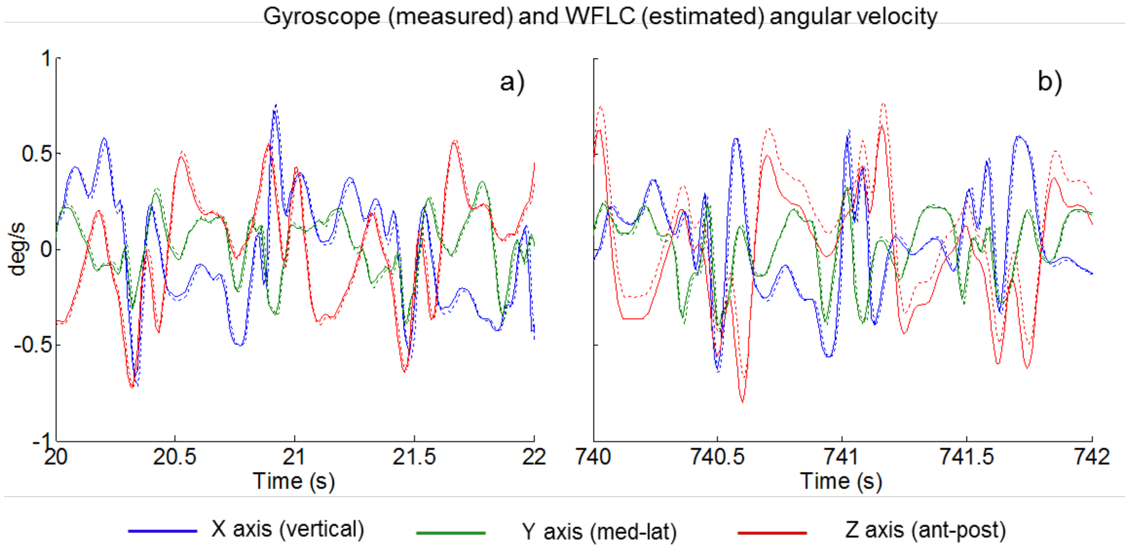

Figure 4.10. Plots showing the measured (solid lines) and WFLC estimated (dashed lines) angular velocities. Figure 4.10a shows velocities for a two second period commencing 20 seconds after recording commenced. Figure 4.10b shows velocities for a two second period after a further 12 minutes of walking.

The figure shows no difference in the performance of the WFLC for the angular velocities corresponding to the pitch, roll and yaw, for the duration of the trails. The angular velocity corresponding to the pitch axis showed some divergence after 12 minutes in the data shown in the figure but this was not apparent in the other trial.

Discussion

The results of this test show that both methods of determining orientation angles are able to provide useful estimations of these angles for the periods in excess of those normally required for a commonly used walking assessment. It can be expected from the results that these methods will also be able to provide estimates for periods longer than those which were recorded during this test. While the results show that angles can be estimated for periods of walking in a straight line interspersed with a brief turning period it remains to be determined if this is also possible when changes in walking direction are more irregular. A further enhancement may be to fuse the results of both Kalman filter and WFLC methods and use yaw and roll axis results of the WFLC to overcome the drift in yaw angle that is present when the Kalman filter is used to fuse inertial data and the accuracy of the Kalman filter to overcome inconsistencies in the y-axis (pitch) angular velocity estimation from WFLC.

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CHAPTER 5: MEASURING WALKING TEMPORAL AND SPATIAL PARAMETERS WITH WAIST MOUNTED IMUs

INTRODUCTION

Walking is a sequence of repeated movements that vary with time and from subject to subject (Perry, 1992). A characteristic of bipedal walking is that there are periods when the body is supported by both lower limbs, and periods when support is provided by only one limb. It is these periods that provide the simplest and most common subdivisions to the gait cycle and differentiate periods of greater and lesser stability during double and single support. Consistently identifying the same instant within each cycle, is therefore important to enable the observer to assess and compare cycles. A readily identifiable point in each cycle is the instant when one of the feet begins to touch the ground. This point also identifies when support for the body changes from one limb to two limbs and provides a more stable support mechanism. Another important point within the cyclical pattern is when the foot leaves the ground and the body again loses stability. The period from the instant when one foot contacts the ground until the same foot again contacts the ground is generally used to define a gait cycle which is also referred to as a stride. Each gait cycle is then be divided into two periods: double support, when both feet are in contact with the ground, and single support, when only one or the other limb is in contact with the ground (figure 5.1). Gait cycles are also defined by whether they are identified for the right or the left limb. It should be noted that during pathological gait there are often instances when a foot will contact the ground briefly, during what is normally swing phase for that limb. This is not a normal part of a healthy walking pattern and cannot be described as such. Sub phases of stance and swing have been described elsewhere (Perry, 1992), but are not the subject of this investigation.

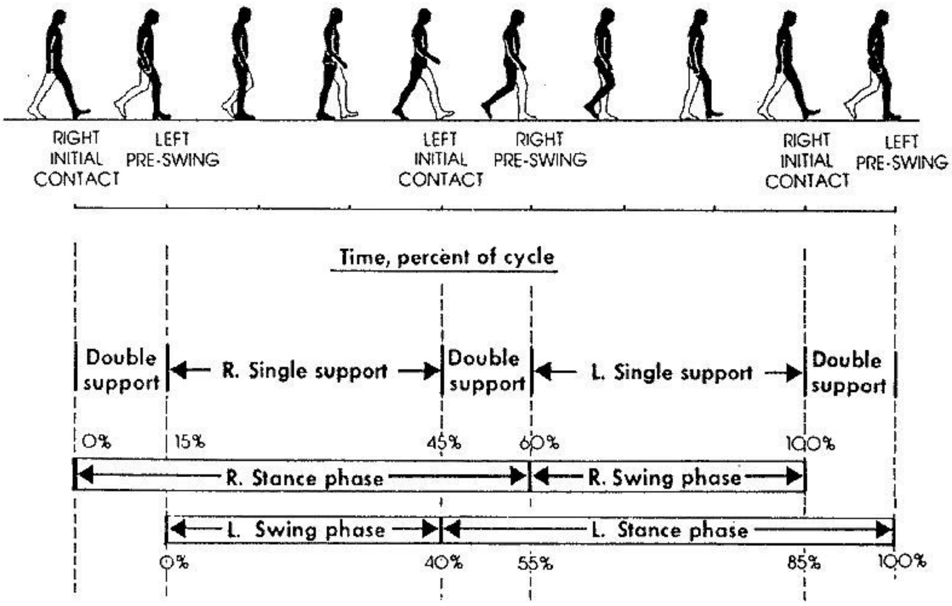

Figure 5.3. The gait cycle and phases of gait

The literature uses different terms to describe the instant of foot contact (heel strike, foot strike, foot contact), but for the purposes of this work the term initial contact (IC) will be used. Right initial contact (RIC) defines the instant when some part of the right foot contacts the ground and left initial contact (LIC) describes the same occurrence with left foot. The term used to describe the end of the double support phase also varies within the literature (toe off, foot off, end contact, etc.), but for this work the term final contact (FC) will be used.

The detection of consecutive initial contact times for both limbs or a single limb allows the calculation of step and stride intervals respectively. Additionally, knowledge of when final contact occurs allows calculation of the time spent in stance and swing phase, and of the periods of double and single support. All these parameters have been shown to be important in assessing changes in gait patterns caused by aging or disability. While the parameters themselves are important the variability which is apparent is also an important indicator of the presence and level of disability and provide useful information about the stability of the walking pattern (Berg et al., 1997).

This chapter consists of three parts. In the first section a description of a new method of estimating IC and FC instants from an acceleration signal recorded by an IMU attached at the waist is presented. This method takes advantage of the properties of wavelet transformations to estimate IC and FC instants. The method is tested using data collected from healthy younger adults and the results compared to those obtained using two other methods described in the literature. The second section applies the method developed to estimate ICs and FCs for healthy subjects to data recorded for subjects suffering from hemiplegia and Parkinson’s disease. Estimated instants are compared to those measured using a gait mat and possible enhancements to the method discussed. The third and final part gives a description of calculation of step length using acceleration signals recorded at near the centre of mass and assesses the two currently available models for this purpose.

AN ENHANCED ESTIMATE OF INITIAL CONTACT AND FINAL CONTACT INSTANTS OF TIME USING INERTIAL SENSOR DATA

Introduction

The ability to estimate the timing of IC and FC using inertial sensors mounted on one or both lower limbs has been well established for both healthy (Morris, 1973; Willemsen, Bloemhof, et al., 1990) and pathological gait, such as before and after hip arthroplasty (Aminian et al., 2004), after spinal cord injury (Jasiewicz et al., 2006), and as a consequence of Parkinson's disease (Esser et al., 2011). Other authors have also observed that these same features may be estimated using acceleration patterns recorded using an IMU mounted at the waist. Evans and colleagues (Evans et al., 1991) noted that the instants ICs could be observed in vertical and anterior-posterior (AP) accelerations, measured using a device consisting of three orthogonal accelerometers held against the sacrum with a belt. Identification of right or left IC could be determined from the direction of lateral acceleration. They further noted that FC could be identified by an inflection in vertical acceleration signal. No estimation of the accuracy of these observations was reported. Menz and collegues (Menz et al., 2003c) observed that IC accurately coincided with peaks in vertical pelvis acceleration. Mansfield and Lyons (Mansfield and Lyons, 2003) collected data from four subjects for accelerations perpendicular to the lumbar spine. They compensated for the gravity component of these accelerations by measuring the tilt of the accelerometer during quiet stance and, after low pass filtering (2Hz), determined IC events for one limb occurred when the slope of the acceleration signal changed from negative to positive. False events were removed manually. When compared to footswitch data, Mansfield and Lyons observed that the accelerations were more reliable in detecting IC events and also that there was a 147±91ms delay between footswitch and acceleration detected events. Zijlstra and Hof (Zijlstra and Hof, 2003) used a previously described inverted pendulum model (Zijlstra and Hof, 1997) to predict IC for subjects walking at a range of speeds on a treadmill. Using this model, they suggested that anterior-posterior acceleration would undergo a rapid reversal at IC. They tested this using a tri-axial accelerometer positioned over the second sacral vertebra, and aligned to International Society of Biomechanics specifications (Wu et al., 2002), while the subject was standing in anatomical position. Forward accelerations were initially low-pass filtered (fourth-order, 20 Hz, Butterworth). The first procedure described (based on the pendulum model), predicted IC would occur when the sign of the AP acceleration (after further filtering at 2Hz) changed from positive to negative (zero crossing). The second method used the peak in acceleration preceding the zero crossing to estimate IC. The estimations were validated by comparison to ground reaction forces. The zero crossing method systematically predicted IC over the range of walking speeds with a delay of 4.6±1.2% of the stride duration, while the peak detection method had a mean error of 0.5±1.2% delay. The peak detection method described by Zijlstra and Hof was subsequently used with a slight modification to estimate IC for 20 children aged between 3 and 16 years. The modification consisted of adjusting the cut-off frequency for filtering the acceleration signal to correspond to the step frequency determined by a Fourier transformation (Brandes et al., 2006). For this study the temporal accuracy of the IC estimations was not reported. The peak detection method for estimating IC was also tested with 23 older adults (77±5 years) (Hartmann et al., 2009). These investigators assessed the concurrent validity of temporal parameters with those estimated using a gait mat (GAITRite®) and reported their results as interclass correlation coefficients for step durations ranging from 0.81 to 0.88 over slow, preferred, and fast walking speeds. Ratio limits of agreement were 10s for individual step durations.

A more recent study (González et al., 2010) has developed a method for estimation of both IC and FC events in real time using both vertical and AP accelerations. This multi-step procedure is also based on zero crossings of the AP acceleration, but, in this method, signals were filtered using an 11^{th} order FIR filter. If the area under the curve preceding a zero crossing is greater than a given threshold, then the IC is determined from a peak in raw AP acceleration which fall within a window where the vertical acceleration is greater than gravity and less than 99% of maximum. Contralateral FC was determined to occur at the first local minimum in vertical acceleration that followed the first local maximum subsequent to IC. After determination of the necessary threshold, this method was tested for six healthy subjects, using a sensor recording 3D accelerations placed close to L3 and aligned to anatomical axes. IC errors were reported as 13 ± 35ms and FC errors as 9 ± 54ms

All the above described methods rely on filtering the signal and some form of zero crossing, or absolute value determination, before estimation of the timing of the IC of FC events. Any change in orientation of the sensor, changes the gravitational component contained within the recorded signal, so that such methods require accurate alignment of the sensor axes and minimal deviation from this alignment during gait. Previous research has shown that this may not be the case (Moe-Nilssen, 1998), with inclination during walking differing from that while standing, and varying with walking speed. A goal of this work was to develop and test a method which could be applied in a clinical environment without the need for accurate alignment and that could be used for pathological subjects, which may have irregular and varied postures during gait. The previous authors have shown that the events of interest occur at or close to peaks in the acceleration signals, so it was anticipated that, if the signal could be filtered such that the required peaks emerged without distortion in timing of these peaks, this would provide a more robust method of event timing estimation.

Continuous Wavelet Transform

Analysis of frequencies contained in human walking have been successfully analysed previously using Fourier analysis (Cappozzo, 1982), which involves decomposing the signal into a series of sine waves of different frequencies. This type of analysis is useful to analyse patterns of walking (Lowry et al., 2009; Pecoraro et al., 2007), but provides little information about timing of events within the cycle.

An alternative method of signal decomposition has been proposed more recently using wavelets. The continuous wavelet transforms (CWT) can resolve a signal in both time and frequency and can show the timing of a particular feature within the signal.

Previous applications within human movement analysis has included removing noise (Wachowiak et al., 2000) from biomechanical data and smoothing (Ismail and Asfour, 1999) as well as classification of walking patterns (Sekine et al., 2004, 2000; Wang et al., 2007) and long term gait and activity monitoring (Aminian and Najafi, 2004; Najafi et al., 2003). The usefulness of CWT in identifying transients within a signal (Najafi et al., 2001) has led to gait temporal parameter identification using gyroscopes mounted on the lower limbs (Aminian et al., 2002) and waist (Martin, 2011b). Luo (Luo et al., 2006) proposed a method whereby the properties of wavelet transforms could be used to differentiate and smooth signals.

A mother wavelet $\psi(x)$ is a finite energy function which has an average of zero (Messina, 2004):

$$\int_{-\infty}^{+\infty} \psi(x)dx = 0 \qquad [5.1]$$

From which analysing wavelets can be obtained that are weighted by $1/\sqrt{a}$

$$\psi(x)_{a,b} = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \qquad [5.2]$$

Where “a” and “b” are the scaling and translation parameters respectively

The CWT function of a signal $y(x)$ can be written as:

$$y_\omega(a,b) = \int_{-\infty}^{+\infty} y(x) \frac{1}{\sqrt{a}} \psi\left(\frac{x-\bar{b}}{a}\right) dx \qquad [5.3]$$

If a mother wavelet $\psi(x)$ having a fast decay is defined by the *m*th derivative of a smoothing function $\theta(x)$.

$$\psi(x) = (-1)^m \frac{d^m \theta(x)}{dx^m} \qquad [5.4]$$

The smoothing function has fast decay and a nonzero constant integral (Luo et al., 2006; Messina, 2004).

$$\int_{-\infty}^{+\infty} \theta(x) dx = K \neq 0 \qquad [5.6]$$

It has been shown (Luo et al., 2006) that the CWT $y_\omega(a,b)$ is the derivative of the signal $y(x)$ smoothed be a weighted average corresponding to the smoothing function dilated through a weighted though $1/\sqrt{a}$ and turned over through $-x$. The following holds:

$$\lim_{a\to 0} \frac{y_\omega(a,b)}{K_s^{3/2}} = \frac{dy(x)}{dx} \qquad [5.7]$$

So that the derivative can be approximated by: $\frac{y_\omega(a,b)}{K_s^{3/2}}$ [5.8]

The mathematical application of CWT has been outlined in detail in texts and literature (Bruce et al., 1996; Mallat and Hwang, 1992; Mallat, 1989; Rioul and Vetterli, 1991).

It was proposed to test this method of smoothing to determine if it could remove the unwanted peaks from acceleration signals recorded at the waist and preserve the timing of peaks corresponding to temporal events, thus providing a reliable method of estimating IC and FC times.

Methods

Eighteen healthy volunteers (10 males, age: 26±7 years, stature: 1.76±0.09m, mass: 70±11kg) participated in the study, having signed an informed consent. Participants walked three times at a self-selected speed along a 12m walkway. A validated (Pecoraro et al., 2006) 4m instrumented mat (figure 5.2) located in the central part of the walkway was used to measure left and right IC, FC, and stride duration (T_m). One IMU (Freesense, Sensorize), positioned over the lower lumbar spine of each participant by a waist belt, was used to acquire linear acceleration and angular velocity local components. Data for both systems were recorded at 100 samples per second. Fifteen steps were analysed for each participant.

Figure 5.2 Instrumented mat for recording instants of initial and final contact

Continuous Wavelet transform method for estimation of contact events.

A method (M1) was proposed, whereby the vertical acceleration measured in the sensor reference frame was smoothed by integrating (Zok et al., 2004) and then differentiating, the acceleration signal using a Gaussian CWT, implemented in Matlab (Mathworks, USA). The differentiation procedure has been described elsewhere (Luo et al., 2006) and the Matlab code is freely available. A Gaussian wavelet [5.9] (figure 5.3) scale of “16” was chosen to give a wavelet shape to best identify instants of contact and the frequency of healthy gait (Martin, 2011b).

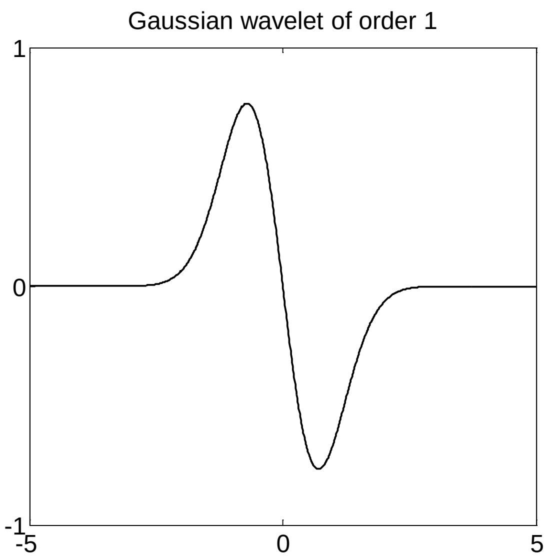

Figure 5.3 Plot of Gaussian wavelet of order 1

Gaussian wavelet function: $\psi(x)_1 = -2xe^{-x^2}\sqrt[4]{2/\pi}$ [5.9]

IC events were identified as the times of the minima of the smoothed signal. FCs were identified as times of the maxima of the signal obtained from a further CWT differentiation (Figure 5.4). Right and left ICs were designated by the sign of the filtered (4th order, Butterworth, 2Hz) vertical axis angular velocity at the instant of IC (Figure 5.5).

Comparison of Estimation Methods

Results were compared to those obtained with two previously proposed methods (M2, M3) (Zijlstra and Hof, 2003), (González et al., 2010) respestively. In M2, the AP acceleration is filtered with a 4th order Butterworth low pass filter at 20Hz, then a 4th order 2Hz Butterworth filter. IC is estimated as the time of peak forward acceleration preceding the change in sign from positive to negative, of the 2Hz filtered signal. In M3, a multi-step process is designed, whereby initial windows are detected when the filtered (11th order, finite impulse response filter) AP acceleration is positive, and then sub-windows are isolated, where the vertical acceleration is greater than 1g and less than 99% of its maximum. IC is finally estimated as the time of peak AP acceleration within the latter windows and FC as the instant of the first minimum in vertical acceleration following the maximum subsequent to IC.

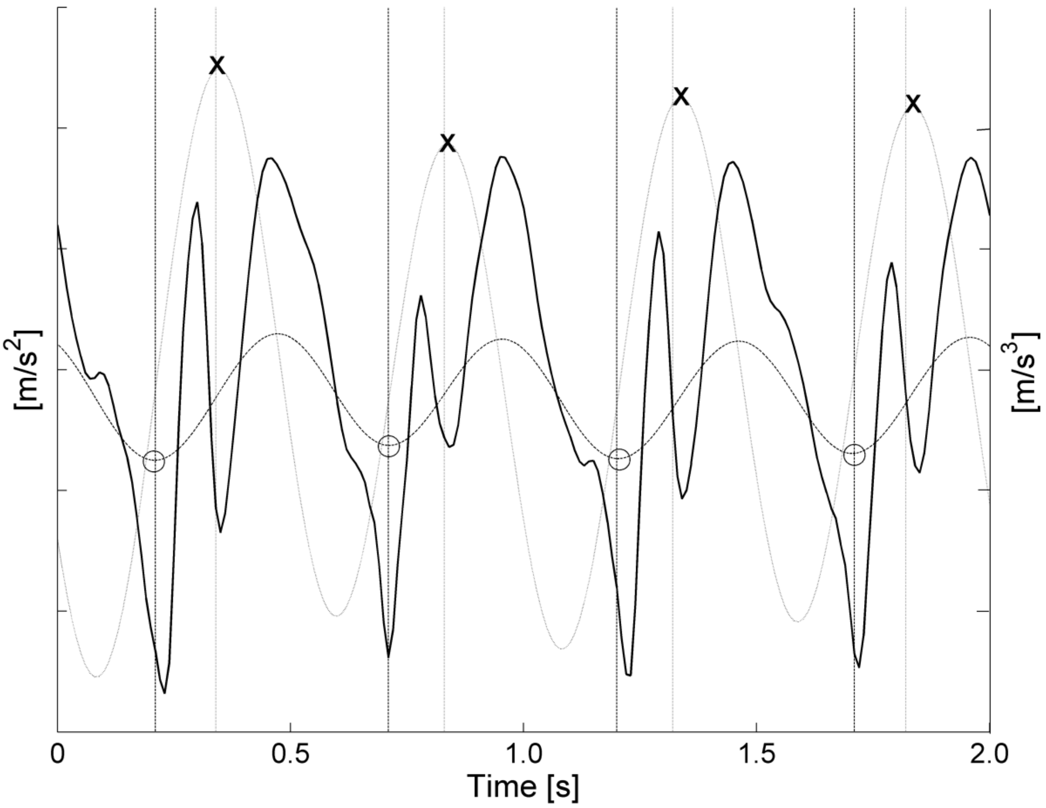

Figure 5.4. Proposed method (M1) for determining gait event times. Vertical acceleration (solid line) is integrated and then differentiated using CWT (dashed line). Minima from this signal correspond to the ICs. Further differentiation (dotted line) provides jerk maxima which correspond to the FCs. Vertical dashed and dotted lines indicate the ICs and FCs measured from the mat, respectively

A Friedman repeated measures ANOVA (significance level p=0.050) and Wilcoxon tests with Bonferroni correction (p=0.017) were used to compare the FC and IC values obtained with the different methods. The differences (and their absolute values) between measured (instrumented mat) and estimated (M1, M2, M3) events, as well as the means and standard deviations of these differences, were computed. Limits of agreement were computed using a Bland-Altman analysis (Bland and Altman, 1986).

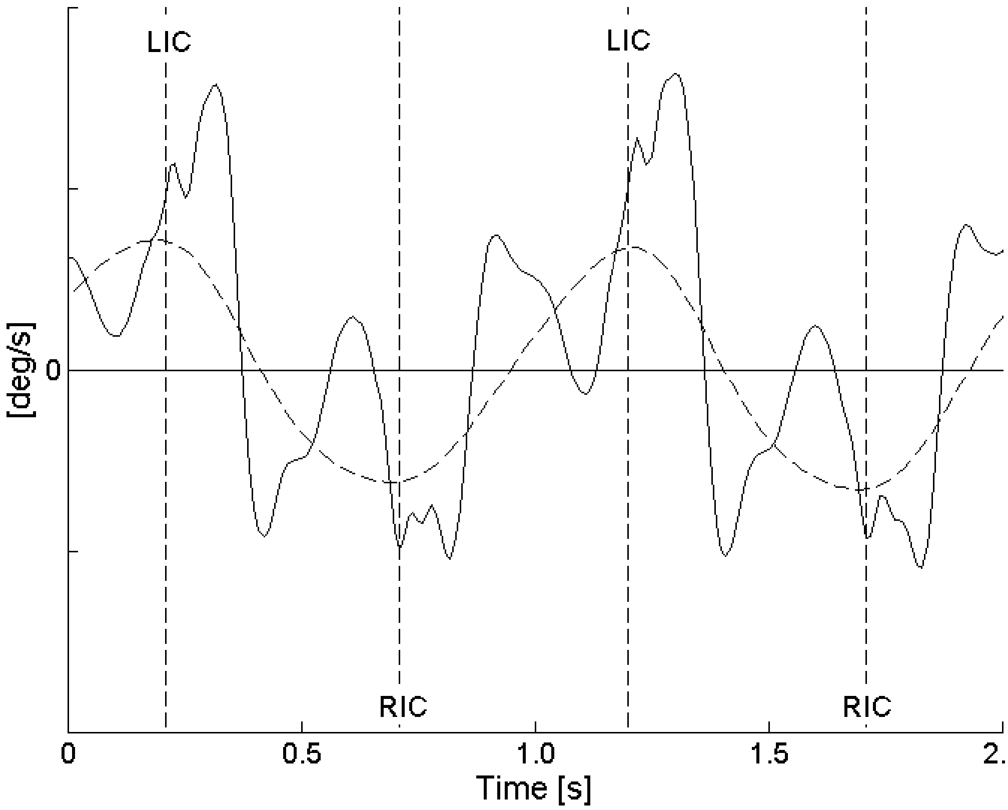

Figure 5.5 Proposed method for distinguishing left and right gait events. Angular velocity around the vertical axis (solid line) is filtered (dashed line). Positive or negative sign of the filtered signal indicates left and right ICs, respectively. Vertical dashed lines show the measured ICs.

<u>Results</u>

The range of observed gait velocities was 1.08-1.65m/s, with an average stride duration (T_m) of 1.07s. M1 detected 100% of both right and left IC and FC events. M2 was unable to detect 4 ICs and M3, 10 ICs. Furthermore, M2 detected 3 ICs, and M3 detected 12 ICs, that did not correspond to actual events. To properly compare the methods, these events were however included in the statistical analysis.

All the methods provided IC and FC values that differed significantly ($p<0.001$) from those measured with the mat. M1 provided the lowest estimation errors (approximately 2% and 3% of Tm, for IC and FC, respectively) and standard deviations, and consequently, tighter, upper and lower limits of agreement, more closely centred to zero, than M2 and M3 (Table 5.1).

Table 5.1. Comparison of errors in measurement for the methods. The mean of the differences (and of their absolute values) between measured (instrumented mat) and estimated ICs and FCs are shown, together with relevant standard deviations. Bland-Altman limits of agreement are also reported.

	Method	Mean difference (s)	Mean absolute difference (s)	Standard deviation (s)	Limits of agreement	
					Upper (s)	Lower (s)
IC	M1	-0.006	0.019	0.024	0.042	-0.053
	M2	0.019	0.032	0.033	0.086	-0.048
	M3	0.048	0.048	0.046	0.139	-0.044
FC	M1	-0.029	0.032	0.026	0.022	-0.088
	M3	0.030	0.033	0.030	0.089	-0.030
Step duration	M1	-0.004	0.018	0.024	0.045	-0.053
	M2	-0.004	0.028	0.042	0.080	-0.087
	M3	0.031	0.039	0.056	0.115	-0.109
Stride duration	M1	-0.004	0.017	0.025	0.045	-0.054
	M2	-0.001	0.020	0.033	0.065	-0.067
	M3	-0.005	0.035	0.054	0.113	-0.104

Discussion

The proposed method, based on the analysis of the vertical acceleration measured in the sensor local frame at lower trunk level, proved highly reliable, detecting 100% of the analysed events. This is likely to be the direct result of the fact that the vertical acceleration itself has reliable and repeatable features (Kavanagh et al., 2006; Mazzà et al., 2009).

Estimates from previously proposed methods were less accurate than those originally reported by the respective authors, likely caused by the inclusion of miss-detected events in our analysis, or simply reflecting the use of different measurement instruments and the fact that subjects walked along different length paths (Pecoraro et al., 2006). This study provided additional information about the ability of different methods to determine the timing of a single step within a series of steps and showed that the new method estimates stride duration with a level of accuracy suitable for detecting changes in gait variability (Hausdorff, 2005), which hints at possible future applications.

All subjects in this study were young and healthy and a limited range of walking speeds was actually observed. Because the proposed method does not rely on particular signal characteristics, it might be expected to be robust for a wider range of speeds and in the presence of pathologies affecting gait symmetry and regularity. Further studies are needed to test these hypotheses.

USING A SINGLE WAIST MOUNTED INERTIAL SENSOR TO ESTIMATE GAIT EVENTS TIMING FOR PATHOLOGICAL SUBJECTS

Introduction

Fundamental to the analysis of human walking is the ability to compare gait patterns between individuals and groups. The ability to correctly determine the phases of gait during human walking is recognised as being a useful tool to help provide understanding of the presence and changes in many pathologies which affect human walking (Hausdorff, 2005). To be able to do this requires the identification of repeatable temporal features within the cycles of motion. The most fundamental of these features are the instants when the feet contact or leave the ground. These instants of initial contact (IC) and final contact (FC) allow the gait cycles to be identified and divided into phases of single and double support which can be used to analyse many features of walking in both healthy and pathological subjects and provide understanding of pathological changes in human walking (Hausdorff, 2005; Hausdorff et al., 1995). It is often considered that the timing of these events are accurately determined by the measurement of ground contact forces using force platforms (Rueterbories et al., 2010). Other common methods of measurement involve using pressure switches positioned under the foot or the use gait mats (Hausdorff et al., 1995)(Pecoraro et al., 2006). An alternative is to determine event timing from kinematic data (Hreljac and Marshall, 2000). These forms of measurement and the devices used are not readily portable and are usually located in specialized laboratories. More recently the use of inertial measurement units has been proposed (Kavanagh and Menz, 2008). This has generally been performed using multiple sensors positioned on one or both lower limbs. These devices have been shown to estimate the timing of ICs with an error of 11-14ms for healthy subjects and 15-24ms for subjects with spinal-cord injury (Jasiewicz et al., 2006). It has also been shown that a single inertial sensor mounted over the lower back can be sufficient to provide estimates of IC and FC times (González et al., 2010; Zijlstra and Hof, 2003).

Specific groups of pathological subjects exhibit characteristic changes in gait as a result of their disability and accurate and quantifiable assessment of these changes can assist in understanding the progression of disease or the response to treatment (MacKay-Lyons, 1998). In patients suffering the after effects of a stroke, accurate determination of IC may be used to assist in walking by providing a trigger for electrical stimulation (Mansfield and Lyons, 2003). Patients suffering from Hemiplegia notably have high levels of gait asymmetry and quantifying the degree of asymmetry through measurements of temporal parameters may be useful in determining responses to physiotherapy (Olney and Richards, 1996). While post stroke subjects have been observed to walk more slowly than healthy subjects it has been suggested that step length asymmetry may offer more insight into underlying impairments and compensatory mechanisms than walking speed (Allen et al., 2011). Asymmetry is not always a prominent aspect of gait pathology. Parkinsonian gait is characterised by freezing of gait and this may be associated with stride variability and changes in gait between the freezing episodes (Hausdorff, 2009; Hausdorff et al., 2003). Stride time variability in subjects with Parkinson's disease has also been associated with likelihood of falling (Schaafsma et al., 2003). While step and stride interval characteristics are important features of pathologic walking, stance time variability has been observed to also provide information concerning level of impairment (Brach et al., 2008).

It is apparent that to properly understand the mechanisms by with patients respond to disability caused by aging or gait altering pathologies such as hemiplegia, or Parkinson's disease, that accurate measurements are available for both step and stride length as well as the step-to-step and stride-to-stride changes. It is also important to have full knowledge of the instants during walking when changes from double support to single support (and a return to double support) for each limb occur. The duration and variability between these events on a step-by-step basis can provide useful information concerning the presence and severity of pathologies how the motor control mechanisms are effected.

The methods used to estimate events from accelerations, generally, require filtering which can distort the signal and affect the accuracy of the subsequent estimate. Continuous wavelet transform (CWT) analysis has been advanced as an alternative way to process IMU data for the extraction of gait events (McCamley et al., 2012). We propose to test this method of estimating gait events times using an inertial sensor positioned over the lower lumbar spine with a group of patients suffering from hemiplegia and Parkinson's disease. The lower lumbar spine position was chosen to provide information from both lower limbs equally to better identify differences between limbs. It is also expected that compensatory effects of upper body motion transmitted to the lower limbs through the pelvis would be reflected in the accelerations recorded at this level.

Methods

Twenty three subjects with hemiplegia or Parkinson's disease visited a motion analysis laboratory. Subject details are listed in table 1. All subjects signed informed consent. Subjects walked back and forth along a 4m instrumented mat (McCamley et al., 2012; Pecoraro et al., 2006) a minimum of two times. Each subject wore their own clothing and shoes. Conductive tape was positioned under the heel and toe of the shoes to allow the mat to record the beginning and end of floor contact separately for each foot. One IMU (Freesense, Sensorize), positioned over the lower lumbar spine of each participant by a waist belt, was used to acquire 3-dimensional linear acceleration and angular velocity components in the sensor frame of reference. The sensor was positioned such that the x-axis was aligned cranio-caudally, the y-axis in the medial-lateral direction, and the z-axis in the anterior-posterior direction. Data for both IMU and mat were recorded at 100 samples per second. A minimum of eight steps were analysed for each participant. Data captured separately by a stereophotogrammetric system was used to calculate subjects' walking velocity, stride duration and stride length

Table 5.2. Subject demographics

Number	Hemiplegia	Parkinson's disease	Total
Total	12	11	23
Male	9	8	17
Female	3	3	6
Cane	5	1	6
AFO	2	0	2
Age	76 ± 7.5	74 ± 6.0	75 ± 6.7
Height (m)	1.64 ± 0.07	1.65 ± 0.09	1.64 ± 0.08
Body mass (kg)	73.8 ± 8.0	77.6 ± 9.7	75.6 ± 8.9

Figure 5.6 Instrumented mat for recording instants of initial and final contact

A previously described method (CWT - McCamley et al., 2012) was used to determine instants of initial IC and final (FC) contact, for each foot with the ground. This method smooths the cranio-caudal (x-axis) acceleration signal by first integration (Zok et al., 2004) and then differentiation (Luo et al., 2006). Instants of IC are estimated from the minima of the smoothed signal. Right and left events are determined from the sign of the filtered (4^{th} order, Butterworth, 2Hz) angular velocity around the x-axis at the instant of IC. Peaks in the signal derived from a second differentiation of the x-axis acceleration is used to estimate instants of FC.

Accuracy of event timing estimation was determined from the absolute error of the time estimated from the acceleration when compared to the time of the event measured using the mat.

Results

All subjects walked with a lesser velocity than normal healthy subjects (Table 5.4). Those with hemiplegia walked more slowly and with shorter stride lengths than those with Parkinson's disease, however all subjects walked with similar stride durations (time from initial contact to subsequent ipsilateral initial contact). A total of 543 initial contacts and 461 final contacts were recorded with the mat for comparison (Table 5.5). For some walking patterns the method detected extra peaks in the smoothed signal which did not correspond to IC events. This did not occur for FC events due to the smoothing effects of the differentiation. Initial contacts were estimated to occur a mean of 0.06 ± 0.08s after the measured event and with an absolute error of 0.08 ± 0.06s which is equivalent to 5 ± 8% of stride duration. Both hemiplegia and Parkinson's disease subjects had similar mean errors in initial contact time. Final contact timing was estimated with a mean error of -0.02 ± 0.1ms.

Table 5.3. Hemiplegia and Parkinson's disease subjects walking speed, stride duration, and stride length, measured using stereophotogrammetry.

	Hemiplegia	Parkinson's disease	Total
Velocity (m/s)	0.38 ± 0.15	0.70 ± 0.29	0.53 ± 0.28
Stride Duration (s)	1.4 ± 0.3	1.4 ± 0.5	1.4 ± 0.4
Stride Length (m)	0.52 ± 0.18	0.88 ± 0.30	0.69 ± 0.30

Table 5.4. Differences between initial and final contact time estimations and times measured using a custom mat.

	Hemiplegia	Parkinson's disease	Total
IC mean difference (s)	0.07 ± 0.08	0.06 ± 0.07	0.06 ± 0.08
IC absolute difference (s)	0.08 ± 0.07	0.07 ± 0.06	0.08 ± 0.06
FC mean difference (s)	-0.06 ± 0.14	0.03 ± 0.11	-0.02 ± 0.10
FC absolute difference (s)	0.12 ± 0.08	0.09 ± 0.07	0.11 ± 0.08

Discussion

The accuracy of the initial and final contact time estimation provided by the CWT method was 4% and 5% of stride duration for Parkinson's disease, and Hemiplegia subjects respectively. Parkinson's disease patients have been shown to exhibit stride to stride variability of 4% of stride duration for non-fallers and 6% of stride duration for fallers (Schaafsma et al., 2003). Stride time variability (standard deviation) for hemiparetic subjects has been measured as 0.05s for moderate and 0.13s for severe groups. The mean and standard deviations of the contact time estimations is thus of a similar magnitude to the differences that need to be measured. This suggests that the accuracy and precision of the estimations will need to be improved if groups such as the ones described are to be properly assessed.

After inspection of the results, graphs for subjects with the worst estimations, were plotted, showing the initial contact events recorded with the mat and the x-axis accelerations. This led to the observation that for a subgroup of subjects, which included both hemiplegia and Parkinson's disease patients, the timing of initial contact did not coincide with a minimum in acceleration similar to that observed with healthy subjects. A close examination showed that for these subjects, IC occurred prior to the minimum of the smoothed signal, and when the acceleration values was undergoing a rapid reduction. Further investigation showed a closer estimation of initial contact could be determined from maximum jerk in the x-direction (M2-IC) (figure 5.8). A small majority of subjects suffering from both pathologies however showed smoothed acceleration patterns similar to those of healthy subjects and the preferred method of estimation was from the smoothed acceleration signal (figure 5.9). If the time of maximum jerk was used to estimate the initial contact time for the total group of subjects, this led to estimations that were less accurate than those determined using the original method (table 5.5).

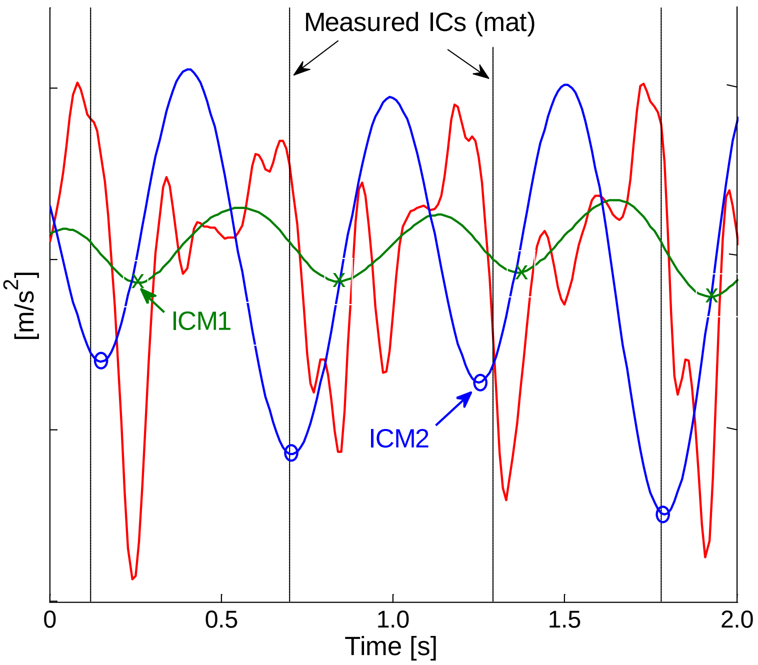

Figure 5.8 Vertical acceleration (red), smoothed signal (green), differentiated smoothed signal (blue) showing estimated IC events (x) for the original method, estimated IC events (o) for the alternative method and measured ICs from mat (vertical dashed line) for a representative subject for whom the published method produce good estimated event times

When the subjects were separated into groups based on the most accurate method of IC estimation comparisons were made to determine possible causes for the alteration in the relationship between to timing of IC and the craniocaudal acceleration signal. The groups contained a similar number of subjects with both pathologies and no observable differences were apparent in the normal walking speed or cadence of the subjects (table 5.6). Further investigation of the acceleration signals while exhibiting large variations within groups, showed no relationship between the groups, and the RMS or amplitudes of the signals for any axis, so it was decided to investigate alternative methods of signal analysis.

Table 5.5 Comparison of results obtained using the original method of IC detection (M1-IC) and the alternative (M2-IC) detection using filtered jerk signal

	M1-IC				M2-IC			
	Mean		SD		Mean		SD	
	(s)	(%)	(s)	(%)	(s)	(%)	(s)	(%)
Group1	**0.04**	**3**	**0.03**	**2**	0.13	10	0.08	6
Group2	0.11	9	0.06	6	**0.06**	**5**	**0.05**	**4**

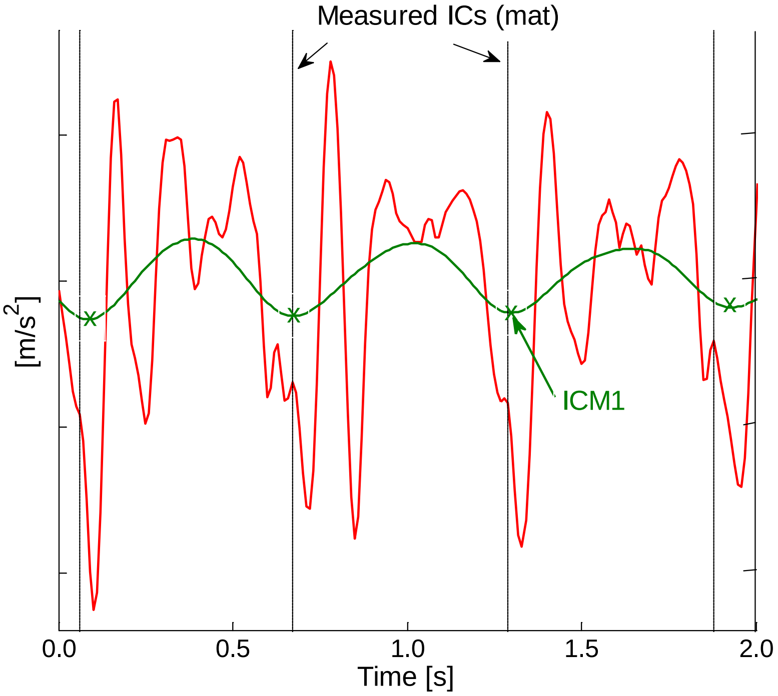

Figure 5.6 Vertical acceleration (red) and smoothed signal (green) showing estimated IC events (x) and measured ICs from mat (vertical dashed line) for a representative subject for whom the published method produce good estimated event times

Table 5.5 Data for groups of subjects which had differing IC detections

	Group 1	Group 2
Number	13	10
Pathology	8 Hemi, 5 PD	6 Hemi, 4 PD
Velocity (m/s)	0.55 ± 0.29	0.53 ± 0.28
Stride duration (s)	1.4 ± 0.3	1.4 ± 0.4

Harmonic analysis has been used (Cappozzo, 1981) to separate patterns of movement into intrinsic and extrinsic motion and it has been shown that harmonic analysis is reliable in detecting features of gait that may reveal information about differences in walking patterns (Pecoraro et al., 2007). Intrinsic motion identifies features of the movement pattern which are inherent in the locomotor act whereas extrinsic motion reflects the individual characteristics of each subjects movement while performing the act. For motion in the vertical or anterior-posterior direction the intrinsic patterns of motion will be reflected in the even harmonics related to the stride period. In the medio-lateral (ML) direction stride patterns will be reflected in the odd harmonics.

An harmonic analysis showed differences in harmonic ratios between Group1 and Group2, for accelerations in the ML direction ($p < 0.001$) however differences were not significant for the harmonic ratios calculated from acceleration signals in the sagittal plane. This may indicate that differences in the patterns of movement relate to the stride characteristics of the subjects. It may be though, that because many of the subjects, and especially those with hemiplegia, have large lateral differences in step characteristics, this variability masks differences between the two groups in sagittal plane accelerations.

A visual inspection of frequency spectrum plots showed that, subjects for which the original method of IC estimation did not perform satisfactorily, had a markedly higher amplitude in the first harmonic of the ML acceleration signal, than subsequent harmonics (figure 5.7). This difference was not observed to be as pronounced in amplitudes of the harmonics of the ML accelerations for subjects for which the smoothed acceleration signal gave more accurate estimations.

An attempt was made to classify the subjects according to the harmonic characteristics observed. This observed differences in harmonics correctly classified 72% of subjects (17/23) and in doing so provided the improved results for IC estimation shown in table 5.6

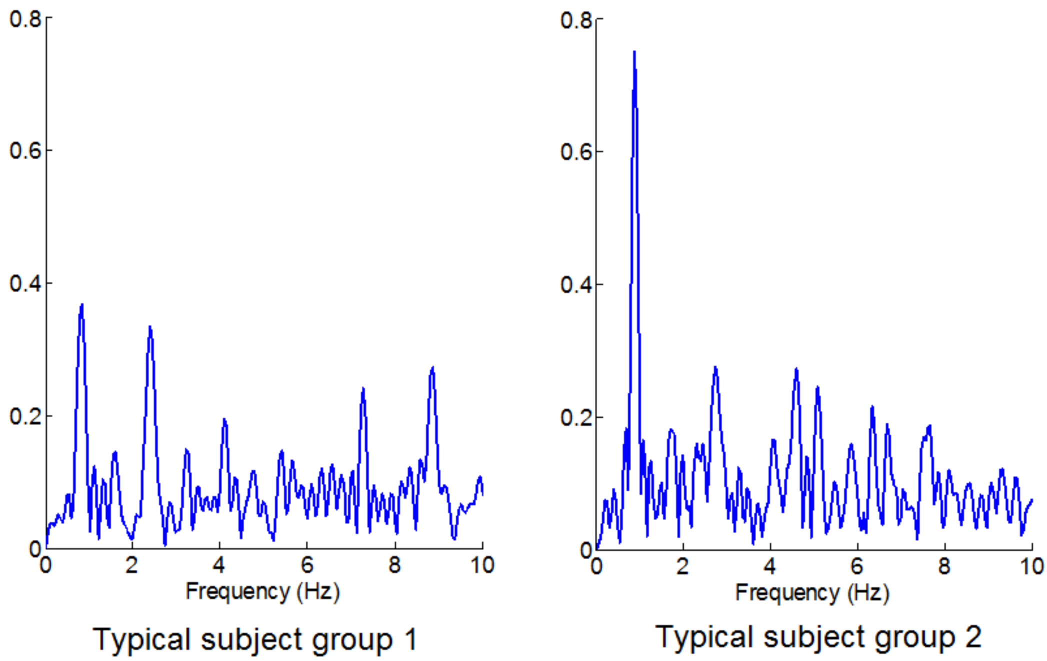

Figure 5.7 Frequency spectrum plots for typical subjects from group 1 and group 2 showing differences in amplitude of the first harmonic

Table 5.6 Table comparing IC estimation accuracy in seconds and as a percentage of stride interval if the optimum method of estimation is chosen or the harmonic amplitude is used to classify subjects

	Mean		SD	
	(s)	(%)	(s)	(%)
M1	0.08	6	0.08	6
Optimum	0.05	4	0.04	4
Classified	0.06	5	0.05	4

Conclusions

The accuracy of estimation of IC and FC events with pathological subjects was much reduced from that found previously for healthy subjects and it was noted that variations existed in results for patients with both pathologies. There appeared to be no simple or easily observed cause for this variation. A difference was found when an harmonic analysis was performed. Interestingly, this difference was apparent in the ML acceleration but not in the vertical signal that was used for estimating IC times. The alternative signal used for estimation of IC times is AP acceleration (Auvinet et al., 2002; González et al., 2010; Zijlstra and Hof, 2003) however this signal also showed no difference in harmonics between groups.

There is much information contained in the movement patterns of the lower trunk that reflects the complicated interrelationship between the support and propulsion functions of the lower limbs, and the control and balance provided by the upper body. It is apparent that for some pathological subjects this interplay masks and distorts some of the characteristics of motion that that indicate the instants of IC and FC and which are readily apparent in healthy movement patterns. It appears that to accurately determine IC and FC events using inertial measurements recorded at the lower trunk level will first require not just an understanding of the changes that occur to the lower limbs but also a better understanding of how the presence of pathology effects upper body movement patterns.

INDIVIDUAL STEP LENGTH ESTIMATION USING A SINGLE WAIST MOUNTED INERTIAL SENSOR

The assessment of step length and the variability of step and stride length have been shown to be important indicators of the likelihood of falling and the level of disability due to disease. Research has shown that increased stride to stride length variability (Maki, 1997) and increased step length variability (Callisaya et al., 2011) are associated with multiple falls and the risk of falling, respectively, in elderly people. Step length asymmetry may also be an indicator of the underlying impairments and compensatory mechanisms used by stoke sufferers (Allen et al., 2011). Others have shown a relationship between increased step length variability and fatigue (Helbostad et al., 2007). While it is possible to measure step and stride length using stereophotogrammetric techniques, or instrumented floors, these systems are restricted in the number of consecutive steps/strides they can record. Methods have been devised to estimate spatial and temporal parameters using inertial measurements recorded at the foot (Sabatini et al., 2005), shank (Aminian et al., 2002), thigh (Miyazaki, 1997), and waist (González et al., 2009; Zijlstra and Hof, 2003). These methods allow a greater number of step cycles to be measured, but the accuracy of step length estimations using simple pendulum models and accelerations measured at the waist may be limited (Alvarez and Gonzalez, 2008). While the more distal locations provide the highest sensitivity to inertial features which enable accurate estimations of step and stride length, these locations are restricted in the amount of information they can provide about other features of body motion during walking,

Inverted pendulum models

The estimation of step length from inertial measurements recorded at or near the centre of mass requires a model to relate the motion patterns at this location, with the forward progression of the body from one initial contact to the next ipsilateral one. One of the most simple and common models to describe walking is a simple inverted pendulum. Such a model has been described to to estimate step length using vertical displacement of the centre of mass (Zijlstra and Hof, 2003) (figure 5.8a). The estimation of step length using this model requires first an accurate assessment of the accelerations in the vertical direction. As the orientation of a waist mounted IMU alters continuously during gait this in turn requires accurate appraisal of the orientation of the device at the instant the accelerations are recorded. The step length estimation method described by Zijlstra and Hof was observed to underestimate step length and required correction by a factor of 1.25l. A modified model using an additional component to estimate forward displacement during double stance as a multiple of foot length (González et al., 2009) was subsequently devised (figure 5.8b).

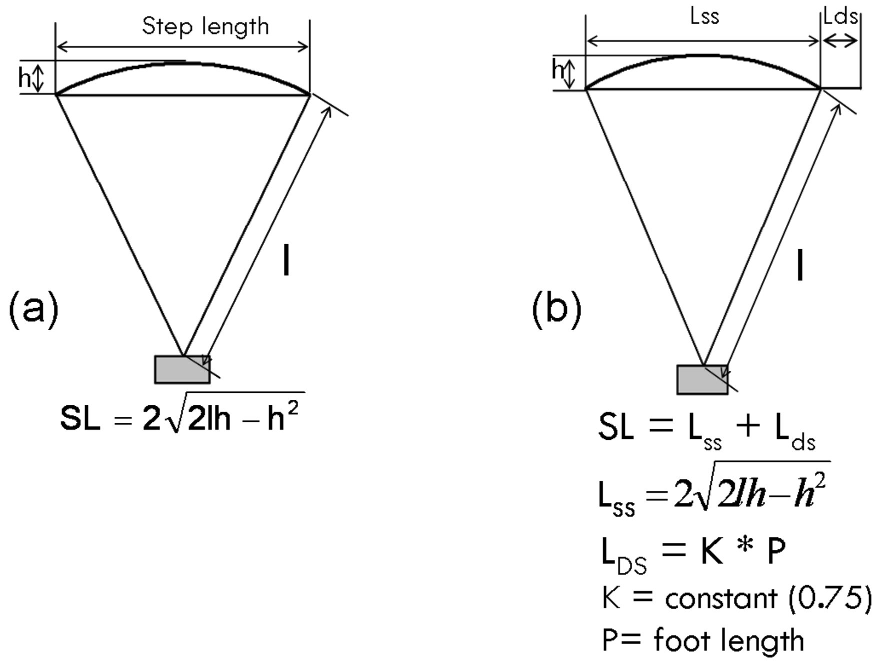

Figure 5.8 Inverted pendulum models to estimate step length from COM vertical excursion a) Zijlstra and Hof (2003), b) Gonzalez et al. (2009)

Model assessment

Prior to implementing the previously described models to estimate step length it is important to understand the ability of these inverted pendulum models to accurately determine individual step lengths. The accuracy of the models was tested by comparing the outputs calculated from vertical movements of the sensor location which measured by a stereophotogrammetric system which took place between the times gait events measured using the custom mat. These calculated step lengths were compared to the horizontal displacement of the same point determined directly from stereophotogrammetry. Contact times measured using the mat, and also the estimated contact times using the CWT method, and those estimated using the published methods, were input to the inverted pendulum models and step lengths were assessed.

Model Performance

The results of the calculations of step length using the two models and the different gait event times are shown in Table 5.7.

Table 5.7. Comparison of estimates of step length using different gait events estimation techniques and two simple inverted pendulum models

Method of event estimation	Mat		IMU+M3		IMU+M1	
Step length model	(a)	(b)	(a)	(b)	(a)	(b)
Absolute difference (mm)	55	43	80	67	70	47
Mean difference (mm)	43	-6	56	29	51	-14
Standard deviation (mm)	53	53	83	78	65	58

M1 – proposed wavelet method, M3 – Gonzalez et al., 2010
(a) – Pendulum model (Zijlstra & Hof, 1997), (b) – Pendulum + constant (Gonzalez et al., 2009)

It was found that, as would be expected the improved event estimations determined from stereophotogrammetry led to an improvements in step length estimation, however this improvement was not sufficient to overcome the inherent limitations of the models which were apparent from the errors in step length estimation observed when the actual measured contact events where input to the models.

To estimate individual step length using centre of mass motion and event times estimated accurately from inertial sensing without the necessity of individual calibration will require first an improvement in the model used to estimate step length. Development of a model that more directly uses the measures of linear acceleration and angular velocity obtained from a waist mounted sensor such as that applied for a hip mounted sensing unit (Kose et al., 2012) requires further investigation.

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CHAPTER 6:

DISCUSSION OF RESULTS

The aim of this thesis was to assess the ability of an inertial measurement unit to provide useful information which could be used for gait analysis. There have many previous examples of the successful use of inertial sensors for gait analysis, some of which have been described elsewhere in this document. One of the considerations of gait assessment is: What is the desired outcome from the assessment? When assessments are performed in a clinical location it is often in a situation where the assessment must be performed in a timely manner and by persons with little or no specific technical knowledge of the instrument. The size and nature of inertial measurement units make them suitable for this setting. Another consideration is the manner of attachment of the IMU. For the studies reported in this thesis the IMU was positioned on the lower back but no sensitive alignment procedures were performed. This was a conscious decision to simplify as much as possible the measurement procedure. While much of the information currently used in gait assessment can be provided by alternative tools, an IMU can gather information in situations where these other tools cannot. Information gathered outdoors, in the home, or over extended periods of time, cannot readily be reproduced from laboratory based assessments. These recorded data however, must be accurate to be useful for a gait assessment. A location on the lower back was chosen as the position from which to collect the data. This location was chosen as the one that is more likely to provide the most useful information concerning motion of the body as a whole during the walking task.

An objective of this thesis was investigate the means by which the signals recorded by a single waist mounted inertial measurement unit could be used to in an optimal way to provide information about lower trunk orientation during walking. Kalman filters are able to provide orientation information with good accuracy during motion when used to fuse data from different sensors. It was shown that improvements can be made to the predicted roll and pitch angles during walking, if the parameters of the filter are optimized for the movement. Errors of less than one degree are possible when angles calculated using the Kalman filter are compared to those derived from stereophotogrammetric data. Most commercially available inertial systems are provided with software to fuse the data recorded but these may not provide ouputs with the optimum accuracy. In order to provide the most accurate estimations of orientation that are possible using inertial sensors data, it is recommended that an optimization procedure be performed before using a Kalman filter. Further investigation is required to determine if it is necessary to perform the optimization procedure that was reported in this thesis, for other movements patterns, or for persons who walk with altered gait patterns due to aging or pathology.

The Kalman filter is limited by lack of a reference to correct for drift in the integration of angular velocities about the vertical axis. Thus reliable angles are only provided for pitch and roll. The alternative of generating a mathematic representation of the angular velocities signals by means of a Weighted Fourier Linear Combiner filter appears to avoid this problem. The WFLC requires a signal to be quasi-periodic (i.e. a signal that is cyclical but with a frequency that varies over time). Angular velocity signals recorded during walking fit this category. The angles provided by the WFLC exhibited errors of less than 1.2 deg. This method appears to provide a useful alternative for the estimation of orientation of an inertial measurement unit and requires further investigation for use with data for other subjects groups such as elderly or pathologic subjects or other quasi-periodic movement patterns. Both the Kalman filter and the WFLC are able to provide orientation estimations for extended periods of time which will allow the recording of data not readily available with current laboratory based measurement systems.

The location of the sensor at the waist, while convenient to provide information about upper body motion, is removed from the location of the feet for the estimation of gait events. However, previous authors have determined that acceleration patterns of the lower trunk can provide the necessary information from which to deduce the instants of initial and final foot contact with the ground. These methods were derived from an inverted pendulum model of the lower limbs and rely on knowledge of the alignment of the sensor and use the timing of "zero crossings" to help identify the required peaks in acceleration from which to estimate events. These methods are sensitive to changes in alignment of the sensor and irregular patterns of the peak accelerations. A CWT differentiation procedure provides a smoothing of the signal. This is intended to remove unwanted peaks while the combination of wavelet and scale chosen was intended to identify the dominant peaks in the acceleration signal that were related to the initial contact event, without distorting the timing of these peaks. The CWT method reported in this thesis was found to show improved accuracy when compared to previous published methods without needing accurate alignment procedures. Testing has shown that the CWT method has reduced sensitivity to alignment in the sagittal plane than methods that rely on zero crossing. Further testing is required to determine if this absence of sensitivity translates to alignment in the coronal plane.

When tested with pathologic data collected from hemiplegia and Parkinson's disease sufferers the accuracy of the CWT method of event detection was much reduced. Errors in the estimation of the events were largest for a particular group of subjects suffering from both pathologies. For these subjects the association between acceleration peaks and the gait events, was not the same as observed in healthy subjects. Some, pathological subjects exhibited a pattern of cranial-caudal acceleration whereby IC occurred at a time of maximum jerk. Attempts to identify the differences between the groups with different acceleration signal - IC timing led to the realization that they had different harmonic ratios in medio-lateral acceleration signals. While the differences in harmonic ratios between the groups was highly significant, it could not discriminate between all the individuals in the groups. Discrimination of subjects using ML acceleration signal harmonics data gave improved results. Using a combination of both methods of detection still did not provide estimates of IC timing with levels of accuracy provided by alternative event detection methods such as mats or force platforms. Wavelet transforms may be applied using different mother wavelets and different scales. Alternative mother wavelets may be more applicable to the shape of the acceleration peak at IC of different groups of subjects. Improvements in estimation of time may also be available through adjusting the scale of the wavelet to different walking cadences.

The problems observed for the detection of contact events using acceleration signals highlights problems of inferring outcomes at one location on the body, from actions at another location, without a full understanding of the systems linking the two locations. As well as being affected by movements of the lower limbs and the forces applied to them, motion of the pelvis will also be affected by motion of the upper body. When attempting to estimate event times using a waist mounted sensor there is no accurate way to model the mechanisms in play, between what we are attempting to estimate, and the output of the device we are using for measurement. Thus the estimations we make can only be expected to hold true, for patterns of motion is the same as, or very similar to, those that existed when the algorithms were devised.

This holds true for many measures of human motion. It does not mean we should not attempt to make the measurement but it highlights the need to be extremely appreciative of all the mechanisms which may contribute to the measure.

IMUs and other MEMS devices have become popular for use in movement analysis. They are devices which almost everybody is familiar with, because of their existence in mobile telephones and many games. Consequently they are readily accepted by the general community. They are not perceived as devices that are restricted to laboratories and as such they allow the field of gait analysis to move outside the boundaries of a laboratory or clinic. This allows the assessment of gait in ways that were not previously available. These assessments however require proper validation to ensure the parameters of interest are evaluated properly. The results of the studies performed and reported in this thesis emphasise the need properly understand the ability of IMUs to measure gait parameters by validating them against known techniques and tools so that they can be used to their full potential and advance the understanding of how people, healthy and unhealthy, young and old, ambulate.