Methods and models in signal processing for gait analysis using waist-worn accelerometer: A contribution to Parkinson's disease

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A thesis submitted for the degree of

Doctor of Philosophy in Interactive and Cognitive Environment

April, 2015

Acknowledgments

This PhD Thesis has been developed in the framework of, and according to, the rules of the Erasmus Mundus Joint Doctorate on Interactive and Cognitive Environments EMJD ICE [FPA n° 2010-0012] with the cooperation of the following Universities:

Alpen-Adria-Universität Klagenfurt – AAU

Queen Mary, University of London – QMUL

Technische Universiteit Eindhoven – TU/e

Università degli Studi di Genova – UNIGE

Universitat Politècnica de Catalunya – UPC

According to ICE regulations, the Italian PhD title has also been awarded by the Università degli Studi di Genova.

.....my parents, Md. Sadeque and Nurjahan Sadeque, my wife Nabila Noor and my child, Lubanah Taufique

ACKNOWLEDGEMENT

I would like to thank my supervisors Albert Samà, Joan Cabestany and Martin Hitz for their continuous and invaluable support throughout the course of this work. Their excellent leadership and supervision have been really helpful to achieve the objectives of my research. Special thanks goes to my former supervisor Andreu Català who also encouraged me and supported me all the time.

I would like to specially thank the group of researchers from both of my research centers: the CETpD and Interactive systems. They always supported me both in research and personal life. Daniel Rodriguez, Wilbert Aguilar, Jaume Romagosa, Carlos Perez, David Ahlström, Gerhard Leitner, Uwe Dutschmann, Ekaterina Peshkova are just few of them.

ABSTRACT

Parkinson's disease (PD) is a neurodegenerative disease that predominantly alters patients' motor performance and compromises the speed, the automaticity and fluidity of natural movements. After some years, patients fluctuate between periods in which they can move almost normally for some hours (ON state) and periods with motor disorders (OFF state). Reduced step length and inability of step are important symptoms associated with PD. Monitoring patients' step length helps to infer patients' motor state fluctuations during daily life and, therefore, enables neurologists to track the evolution of the disease and improve medication regimen. In this sense, MEMS accelerometers can be used to detect steps and to estimate the step length outside the laboratory setting during unconstrained daily life activities. This thesis presents the original contributions of the author in the field of human movement analysis based on MEMS accelerometers, specifically on step detection and step length estimation of patients with Parkinson's disease.

In this thesis, a user-friendly position, the lateral side of the waist, is selected to locate a triaxial accelerometer. The position was selected to enhance comfortability and acceptability. Assuming this position, first, a new method for step detection has been developed for the signals captured by the accelerometer from this location. The method is validated on healthy persons and patients with Parkinson's disease while compared to current state-of-the-art methods, performing better than the existing ones. Second, current methods of selected step length estimators that were originally developed for the signals from lower back close to L4-L5 region are modified in order to be adapted to the new sensor positions. Results obtained from 25 PD patients are discussed and the effects of calibrating in each motor state are compared. A generic correction factor is also proposed and compared with the best method to use instead of individual calibration. Despite variable gait speed and different motor state, the new step detection method achieved overall accuracy of 96.76% in detecting steps. Comparing the original and adapted methods, adapted methods performs better than the original ones. The best one is with multiplying individual correction factors that consider left and right step length separately providing average error of 0.033 m.

Finally, an adapted inverted pendulum (IP) model based step length estimators is proposed using the signals from left lateral side of waist. The model considers vertical displacement of waist as an inverted pendulum during right step. For left step, the displacement during single support and double support phase is considered as an inverted pendulum and a standard pendulum respectively. Results obtained from 25 PD patients are discussed. Validity and reliability of the new model is compared with three existing estimators. Experimental results show that ICE-CETpD estimates step length with higher accuracy than the three best contenders taken from the literature. The mean errors of this method during OFF state and ON states are 0.021m and 0.029m respectively. The standard deviation and RMSE shown as (SD) RMSE are (0.02)0.029m during OFF state and (0.027)0.038m during ON state. The intra-class correlations of proposed estimator with reference step length are above 0.9 during both motor states. The calibration of model parameters in each motor state is tested and found that the training sessions done with patients in ON state provide more accurate results than in OFF state. Given that training is in ON state, the advantage of this approach is that patients would not need to attend without medication in order to train the method.

RESUMEN

La enfermedad de Parkinson (EP) es una enfermedad neurodegenerativa que altera, de forma predominante, la capacidad motora de los pacientes y, además, afecta la velocidad, la automaticidad y la fluidez de los movimientos naturales. Tras varios años, los pacientes fluctúan entre unos periodos en los cuales pueden moverse de forma casi normal durante varias horas (periodos o estados ON) y periodos donde los desórdenes del movimiento aparecen (periodos o estados OFF). Entre otros síntomas, los pacientes con la EP sufren una reducción de la longitud del paso y una inhabilitación de la marcha. Monitorizar la longitud del paso contribuye a inferir el estado motor de los pacientes, a conocer las fluctuaciones durante su vida diaria y, en consecuencia, permitiría a los neurólogos realizar un seguimiento de la evolución de la enfermedad y mejorar la pauta terapéutica. En este sentido, los acelerómetros MEMS pueden ser usados para detectar pasos y estimar la longitud del paso más allá de las instalaciones de los laboratorios, es decir, en entornos no controlados. Esta tesis presenta las contribuciones originales del autor en el campo del análisis del movimiento humano basado en acelerómetros MEMS, específicamente en la detección de pasos y la estimación de la longitud del paso en pacientes con la EP.

En esta tesis, se ha seleccionado una posición amigable en la cual localizar un acelerómetro MEMS triaxial. La posición, que consiste en el lateral de la cintura cerca de la cresta ilíaca, fue seleccionada para mejorar la comodidad y la aceptabilidad desde el punto de vista del paciente. Asumiendo esta posición, en primer lugar, se presenta un análisis de los distintos métodos existentes en la literatura para la detección de pasos y, además, se presenta una nueva técnica de detección. Los métodos se han testado en usuarios sanos y en pacientes con Parkinson, mostrando que el nuevo método obtiene un porcentaje de acierto en la detección más alto que el resto de métodos. En segundo lugar, se han seleccionado aquellos métodos de estimación de la longitud de paso que fueron desarrollados mediante un sensor situado en el centro de la espalda, cerca de las vértebras L4-L5. Estos métodos fueron modificados con el fin de ser adaptados a la nueva posición del sensor y validados en señales obtenidas de 25 pacientes con EP. Además, se propone un factor de corrección genérico, el cual se compara con el mejor de los métodos obtenidos, para

ser usado en lugar de una calibración individual. A pesar de la variabilidad en la velocidad de la marcha debida a las fluctuaciones motoras, el nuevo método alcanza un 96,76% de precisión en la detección de pasos y, respecto la estimación de la longitud del paso, los métodos modificados obtienen mayor precisión que los originales. El mejor de los métodos obtenidos consiste en el uso de un factor de corrección multiplicador que considera los pasos de cada lado por separado, proporcionando un error medio de 0,03 m.

Finalmente, se presenta un nuevo modelo de la marcha representada como un péndulo invertido modificado que se emplea para analizar las señales de acelerometría obtenidas desde el lateral izquierdo de la cintura. De forma más concreta, este modelo considera el desplazamiento vertical de la cadera como un péndulo invertido durante el paso derecho (lado contrario del sensor). Para el paso izquierdo, el desplazamiento durante la fase *single support* y *double support* se model iza como un péndulo invertido y un péndulo simple, respectivamente. Los resultados obtenidos en 25 pacientes con EP son presentados y discutidos. La validez y fiabilidad del nuevo modelo son comparados con tres modelos distintos. Los resultados experimentales obtenidos muestran que el nuevo modelo, llamado ICE-CETpD, estima la longitud del paso con una precisión mayor que el resto de métodos seleccionados de la literatura. El error promedio de este método durante el estado OFF y ON es de 0,021 m. y 0,029 m., respectivamente, con una correlación intraclase superior a 0.9 en ambos estados motores. La calibración de los parámetros del modelo en cada estado motor ha sido evaluada, concluyendo que una calibración en ON proporciona más precisión en los resultados. En consecuencia, la ventaja de la aproximación propuesta residiría en no requerir señales en OFF de los pacientes con EP, por lo cual no sería necesario que los pacientes prescindieran de tomas de medicación.

RESUM

La malaltia de Parkinson (MP) és una malaltia neurodegenerativa que altera de forma predominant la capacitat motora dels pacients i, a més, afecta la velocitat, l'automatització i la fluïdesa dels moviments naturals. Després de diversos anys, els pacients fluctuen entre uns períodes en els quals poden moure's de forma quasi normal i que duren vàries hores (períodes o estats ON) i períodes on els desordres del moviment apareixen (períodes o estats OFF). Entre altres símptomes, els pacients amb la MP sofreixen una reducció de la longitud del pas i una inhabilitació de la marxa. La monitorització de la longitud del pas contribueix a inferir l'estat motor del pacient i a conèixer les fluctuacions durant la seva vida diària permetent als neuròlegs, en conseqüència, realitzar un seguiment de l'evolució de la malaltia i millorar la pauta terapèutica. En aquest sentit, els acceleròmetres MEMS poden ser utilitzats per tal de detectar passes i estimar la longitud del pas fora de les instal·lacions dels laboratoris, és a dir, en entorns no controlats. Aquesta tesis presenta les contribucions originals de l'autor en el camp de l'anàlisi del moviment humà basat en acceleròmetres MEMS, específicament en la detecció de passes i l'estimació de la longitud del pas en pacients amb MP.

En aquesta tesis, s'ha seleccionat una posició amigable en la qual localitzar un acceleròmetre MEMS triaxial. La posició, que consisteix en el lateral de la cintura prop de la cresta ilíaca, va ser seleccionada per maximitzar la comoditat i l'acceptabilitat des del punt de vista del pacient. Assumint aquesta posició, en primer lloc, es presenta un anàlisi dels diferents mètodes existents a la literatura en detecció de passes i, a més, es presenta una nova tècnica de detecció basada en acceleròmetres. Tots els mètodes han estat provats en usuaris sans i en pacients amb la MP; els resultats mostren que el nou mètode obté un percentatge d'encert en la detecció de passes més alt que la resta de mètodes. En segon lloc, s'han seleccionat aquells mètodes d'estimació de la longitud de pas que van ser desenvolupats per a tractar les senyals d'un sensor situat prop de les vèrtebres L4-L5. Aquests mètodes van ser modificats amb la fi de ser adaptats a la nova posició del sensor. Tots ells van ser validats en senyals obtingudes de 25 pacients amb la MP. A més, es proposa un factor de correcció genèric, el qual es compara amb el millor dels mètodes obtinguts per tal

de ser usat en lloc d'una calibració individual. A pesar de la variabilitat en la velocitat de la marxa deguda a les fluctuacions motores, el nou mètode assoleix un 96,76% de precisió en la detecció de passes i, respecte l'estimació de la longitud de pas, els mètodes modificats obtenen una major precisió que els originals. El millor d'ells consisteix en un factor de correcció multiplicador que considera les passes de cada costat per separat, proporcionant un error mig de 0,033 m.

Finalment, es presenta un nou model de la marxa representada com un pèndul invertit modificat que és utilitzat per analitzar les senyals d'accelerometria obtingudes des del lateral esquerra de la cintura. De forma més concreta, aquest model considera el desplaçament vertical del maluc com un pèndul invertit durant la passa dreta (costat contrari al del sensor). Durant la passa esquerra, el desplaçament durant la fase *single suport* i *double suport* es modelitza com un pèndul invertit i un pèndul simple, respectivament. Els resultats obtinguts en 25 pacients amb MP són presentats i discutits. La validesa i fiabilitat del nou model són comparats amb els de tres models diferents. Els resultats experimentals obtinguts mostren que el nou model, anomenat ICE—CETpD, estima la longitud de la passa amb una major precisió que la resta de mètodes seleccionats de la literatura. L'error mitjà d'aquest mètode durant l'estat OFF i ON és de 0, 021 i 0,029 m., respectivament, amb una correlació intraclasse superior a 0,9 en ambdós estats motors. La calibració dels paràmetres del model en cada estat motor ha estat avaluada, obtenint que una calibració en ON proporciona més precisió en els resultats. D'aquesta manera, l'avantatge de l'aproximació proposada residiria en no requerir de senyals en OFF dels pacients amb MP, per la qual cosa no seria necessari que els pacients prescindissin de preses de medicació.

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Chapter 1 Introduction

1.1 Background

Gait is one of the most important properties of human movement that could be affected by age, disease or psychological problems. Gait analysis and monitoring helps to evaluate the quality of human movement in order to use them for treatment, rehabilitation and training purposes. In medicine, its (gait's) monitoring /evaluation allows clinicians to diagnose and treat patients suffering from the disease that effect gait like stroke, falls risk, osteoarthritis, amputee, Huntington's disease and Parkinson disease (PD) [1][2][3]. Gait is also monitored to evaluate the rehabilitation process of patients [4]. Gait analysis is performed to increase physical activity and to diagnose neurological, degenerative and respiratory disorders [5]. In sports it is applied not only to identify injuries that affect movement and postures but also to train the athletes by recognizing the faults in athletic performance [6], to evaluate the performance of the runners [7] and to evaluate quantitative sport-skill of a person in golf [8] and swimming [9]. In the field of biometric person identification, gait is analyzed to extract gait patterns of a person for identification or tracking [10].

Nowadays, different techniques are developed for ambulatory monitoring of gait which extend it outside of the clinical environment [11]. This will help to monitor patients for long term without interfering in their natural daily activities. It is employed in many research applications within tele-health and ambient assistive living [12]. In the field of tele-health, patients' activity and health are monitored remotely. Gait analysis allows monitoring human activity, movement, sudden attack of illness like stroke, an epileptic fit, freezing of gait and falls to enhance the service [13]. Gait analysis is also used in the

field of ambient assisted living to enhance the quality of life of older people and to optimize the treatment of patients with PD [12].

Wearable sensors are currently the basis of monitoring and analyzing gait outside the clinical environment with, among others, tele-health and tele-care applications. Within this scope, this thesis seeks to analyze gait of the patients of Parkinson's disease (PD) to detect their steps and then estimate their step length during daily life using a triaxial accelerometer positioned on left lateral side of waist. The final aim is to improve diagnose and treatment of patients with PD.

Parkinson's disease (PD) is the second most common neurodegenerative disease in people aged over 40 years. It is a chronic progressive disorder of the nervous system due to the increasing death of the nerve cells in the substantia nigra located within the basal ganglia of the brain. These specific types of neurons are the source of dopamine that act as a neurotransmitter to communicate between neurons. The death of these specific types of neurons provokes the deficiency of dopamine and affects patients' motor performance and compromises speed, automaticity and fluidity of natural movements. The disease predominantly alters patients' motor control, causing tremor, reduced step length and walking speed, rigidity, muscle stiffness and impaired postural balance, among others [14]. Initially the symptoms are not noticeable. With the course of time, they are gradually visible.

Levodopa or similar medications are capable of reducing the motor symptoms of PD patients in the early stages. After some years of medication, patients fluctuate between ON and OFF states [1,2]. ON state is the state in which motor symptoms are almost invisible with the exception of dyskinesia (involuntary movements) and patients feel relatively clear and in control of their movements for some hours. When the effect of medication goes down, OFF state starts, and motor symptoms become more prominent. During OFF states, PD patients have less control of their movements, have increased risk of serious health problems and sometimes face sudden fall. An accurate detection of both ON and OFF states provides physicians proper information of advancement of disease to modify the medication regimen according to motor fluctuations. Furthermore, it could

also help to treat PD in a similar manner to diabetes, by using an injection pump that would administrate the proper doses of the medication according to the current needs. The detection will also help to assess the validity of new pharmacological treatments by measuring decreased time patients spend in OFF state, which are current indicators used in PD to evaluate new treatments.

PD patients also experience of sudden inability of moving legs or progress while turning or in the middle of walking. The situation is termed as Freezing of gait (FoG). FoG happens more frequently during OFF states although it may appear during ON states as well. During FoG, patients' feet seem to stick to the ground and they repeatedly try to move them. FoG episodes usually last from few seconds to more than half a minute. During them, patients often lose their balance while trying to walk and, consequently, they may experience sudden fall. Unfortunately, FoG does not respond well to medication. So early detection of FoG episodes are necessary in order to apply prevention strategies in proper time. The preventions strategies include sensory stimulation that helps to interrupt on FoG episode. The sensory stimulus could be rhythmic auditory signals, haptic (or electric) or visual cues [15][16].Using these techniques can help patients get out of FoG episode or reduce the risk of having it.

The relation between gait parameters and motor states has been widely analyzed in the treatment of PD. Abnormalities in gait are the most common symptoms of PD. Changes of step length, gait speed, posture, arm swing, direction of trunk and pelvis movement etc. are the most common parameters that are altered comparing ON and OFF states [14][17][18][19]. Murray et al. [20] identified some fluctuations in gait properties motor state by examining 44 PD patients, which are:

- Stride length is shortened and the speed is reduced with PD patients but the steps per minute are same between PD patients and healthy people. But Morris et al. [21] showed that to compensate the reduced stride length, some PD patients increase step frequencies.
- Stride width (the side-to-side distance between the lines of two feet) increases slightly.

- During walking, people in ON state rotate the trunk in the opposite direction of the pelvis. But during OFF state they twist the trunk in the same direction.
- The initial contact of the foot are close to flat foot (in which the patients place their entire foot on the ground at the same time) or sometimes they are even observed at the same time in advances stages of PD patients
- Schaafsam et al. [14] also showed that stride time variability increases during OFF state. This indicates that the PD patients also experience instability in gait during walking that affect rhythmic movements.
- Mazilu et al. [22] showed that PD patients go through a transition period (pre-state) before going into FoG episode from normal walking.

These are very important findings that made the researchers to concentrate on gait analysis for PD management. Monitoring step length in PD patients enable the assessment of gait disorders, the identification of patients' motor status (ON or OFF state) and the early prediction of FoG episodes. Prevention strategies such as audio cueing could be taken in this stage so that the patient would not go into a FoG episode. By these strategies, patients would be relived and protected from sudden fall.

Different clinical tools and techniques are used to measure gait parameters in the clinical setting. In some settings, gait is analyzed by motion analysis of a human body by using several high-speed video/infrared cameras to record the movements a human body walking on a treadmill or a walkway. Cameras are connected with a computer in which the recorded video are later analyzed for gait analysis. The system is very accurate but also too expensive and need an expert to analyze gait. Furthermore, monitoring is reduced to the laboratory setting. Electro-goniometers are also used to estimate step length by attaching them on the joints by continuous measuring joint's angle during gait. Electro-goniometers require a strain gauge or a potentiometer with cumbersome cabling, which is not practical for unobtrusive monitoring. Finally, walkways with pressure switches or force plates are other tools also used to estimate step length. This is, however, also expensive and also cannot be used during daily life activities [23].

Thus, many studies aim to develop a wearable device that is cheap and could be used during daily life for ambulatory monitoring of gait. These studies have employed MEMS (Micro-Electro-Mechanical Systems) sensors like accelerometers, gyroscopes and magnetometers. Their low cost and reduced weight and size make them suitable for use outside the clinical environment. Among these different sensors, accelerometers are found to be the most frequently used in research [3]. Accelerometer data are easy to interpret and the sensors are less prone to interference e.g. they barely show drifts due to temperature although offsets appear due to gravity [24]. Using these inertial sensors will help to monitor the patient online and provide proper strategies to handle with the disease [14][18][25]. This makes researchers to widely use accelerometers for continuous gait analysis.

1.2 Framework

The research was carried out at the Technical Research Center for Dependency Care and Autonomous Living (CETpD) of the Universitat Politècnica de Catalunya (UPC) and Interactive Systems of Alpen-Adria-Universität Klagenfurt. CETpD is a multidisciplinary research center in Vilanova i la Geltrú, Catalunya, Spain, working in different areas of research: soft computing, pervasive computing, and assistive technology for the elderly diseased people and human movement analysis among the others. The human movement analysis in CETpD is dedicated to study the movement of PD patients to develop improved technological solutions to assist them.

Since 2009, CETpD has undertaken several research projects within the scope of movement analysis based on wearable sensors of human being, for those suffering from Parkinson's disease:

- The first research project on PD was 'Monitoring the Mobility of Parkinson's Patients for Therapeutic Purposes' (MoMoPa, PI08/90756), started on 2009 and continued till mid-2011. In the project, movements of 35 PD patients were analyzed by means of inertial sensor attached on their body to develop intelligent

algorithms to detect symptoms related to PD like ON/OFF detection, freezing of gait, dyskinesia, gait parameters and falls.

- Another project started in the same year of MoMopa was 'Home-based Empowered Living Parkinson's Disease Patients' (HELP, AAL-2008-1-022). It began in mid-2009 and in March 2011. Gait parameters, involuntary movement, dyskinesia and other symptoms of PD are analyzed in this project. A system was developed to dynamically monitor by implementing real-time algorithm to detect symptoms, and treat PD through automatic drug-administration pump doses.

- Recently a new project 'Freezing in Parkinson's disease: Improving quality of life with an automatic control system' is being approved that is funded by La Marató of TV3 Foundation. The research is planned to develop a system to automatically detect FoG episodes and provide support to overcome from it.

- Finally, the fourth project is Personal Health Device for the Remote and Autonomous (REMPARK, EP7-ICT-2011-7-287677) funded by the European Community. The project started in late 2011 and planned to complete in 2015. REMPARK is developing a wearable monitoring system to identify the motor status of PD patients by analysis different symptoms that include gait parameter, FoG, Dyskinesia etc. It also plans to implement the monitoring system for long-term to improve the management of the disease. The work of this thesis is related to this project. All experiments with patients presented in this thesis are part of REMPARK project.

The **Interactive Systems** research group is working on different expects of user interfaces, smart homes control and interaction, design and modelling of information systems since 2000. The research activities are focussed on various aspects of "user friendliness" such as mobility and integration of computerized components into everyday artefacts/devices, accessibility of underserved population groups, digital divide, e-government and new interface paradigms for virtual reality and pervasive computing. One of the major research area of this group is smart home interaction. In a smart home,

it is possible to provide care for the elderly people, living independently by analysis their movements. The interactive systems is also investigating on the utility and usability of systems and devices of a smart home, to easily operated by the user and to reduce the high power consumption of the devices.

1.3 Motivation

To estimate step length, accelerometers are placed on different part of body i.e. upper trunk, waist, pelvis, shank, instep etc. Many studies show that valuable information for gait analysis is found by placing and accelerometer on the waist near the joint between 4th and 5th lumbar vertebrae in the spine (L4-L5) [26][27]. The position is considered close to center of mass (CoM) of human body. The cyclic sinusoidal pattern of CoM trajectory is used to model the locomotive movement of human.

However, this location is impractical while wearing a device during daily life because it is uncomfortable, may hurt the patient and could be damaged during sitting on a chair or lying on the bed. It is also hard for elderly people with motor complications, to properly place the device on this location. In consequence, a more user-friendly, comfortable and suitable sensor position is desired. To establish the most suitable position to locate the sensor on a PD patient to measure his or her movement, a study in the CETpD lab was carried out earlier to this thesis. The main goal of the study was to establish a single sensor position to detect different symptoms and motor states of PD patients. At the same time, the position should also enable patients to wear the sensor in a comfortable way without interrupting daily life activities. Ten PD patients were recruited for the study. They wore the movement sensors in 5(five) different position: above anterior superior iliac spine (ASIS), on both shanks and on insteps of both foot. Patients chose the location they felt more comfortable and less disturbing for the daily life. All patients chose the lower part of the iliac crest (ASIS), which is the upper border of the pelvis major bone, in a completely lateral position to the trunk, which is a user-friendly and comfortable position.

The ASIS point has some limitations compared to the lower back location since signals obtained from the lateral side greatly differ from those gathered from the lower back. If sensor is positioned on left lateral side, inertial signals from the left leg would be more prominent than those from the right leg and vice versa. As signals of left and right steps are not symmetrical, this new position poses new challenges since common step detection methods and step length estimators, developed considering the sensor on different parts of body including lower back of waist, cannot be used for the ASIS position. New step detection methods and step length estimators are needed for this purpose.

In this thesis, an accelerometer-based system is placed on the left lateral side of waist in order to estimate gait properties from PD patients. The device can be used during daily activities and has been shown capable of measuring other PD symptoms [18]. Several state-of-the art step detection and step length methods are tested and the most accurate step length estimators were then adapted to the new sensor position. A new step detector is developed that outperforms the existing ones. Finally, a new gait model for step length estimation is developed which shows more accuracy.

1.4 Objectives

The main objective of this thesis is to develop algorithms to detect steps and to estimate step length from the signals obtained from an accelerometer located on left lateral side of a PD patient's waist. By estimating step length, patient's quality of life could be improved since it would enable neurologists to improve the medication regimen or to anticipate FoG episodes. The focused group of this study consists in PD patients, although signals from healthy people are also analyzed. The following sub-objectives were set to achieve the mentioned ends:

- To study current algorithms for step detection, step length and gait speed estimation that were developed for the accelerometer signals from different part of body.

- To implement and evaluate current algorithms for the accelerometer signals obtained from left lateral side of waist of both PD patients and healthy people.

- To adapt current algorithms to the new sensor position and evaluate them for analyzing the accelerometer signals obtained from said location.

- To develop a new step detection method to efficiently detect steps from the lateral side accelerometer signals.

- Develop a new gait model specific to the new sensor position that provides step length estimation in PD patients based on the signals obtained from left lateral side of waist.

1.5 Main Contributions

The main contribution of this thesis is to develop efficient algorithms to detect step and to estimate step length of the patients suffering from Parkinson's disease using a triaxial accelerometer on lateral side of waist.

The contributions can be summarized as follows:

1) Existing step detection methods are implemented and evaluated for the accelerometer signals obtained from left lateral side of waist of healthy persons and PD patients.
2) A new step detection method - sliding window averaging technique (SWAT) is developed. Compared to current one, SWAT outperforming them by achieving overall accuracy of 99.24% for healthy person and 96.80% for PD patients.
3) Six existing step length estimators developed for different location of waist are implemented and evaluated for the left lateral signals of healthy person. The best ones are selected from them.
4) Adapted methods of the best ones are developed. Original and adapted methods are applied on the signals obtained from left lateral side of waist of 25 PD patients. The effects of calibrating the methods in each motor state are compared.

The best adapted method shows more accuracy than the original one by providing average error of 0.033m with standard deviation (SD) and root mean square error (RMSE) of 0.041 and 0.041 respectively. For the method, the calibration process is done in ON state. Given that, the patients would not need to attend without medication.

5) A new step length estimator, ICE-CETpD is developed based on a new gait model for the accelerometer signals obtained from left lateral side of waist. The method is evaluated by analyzing the signals obtained from 25 PD patients and compared with existing ones. The method estimates step length with higher accuracy by providing the lowest error of 0.021m.

1.6 Thesis Organization

The structure of the remainder of this is thesis is outlined below.

- Chapter 2 describes about Parkinson's disease, its symptoms and medication cycles.
- Chapter 3 describes the spatio-temporal parameters of gait. Parkinsonism gait is also described in this chapter.
- Chapter 4 describes the clinical tools and wearable devices used to estimate gait parameters. The sensor location is proposed in this chapter.
- Chapter 5 presents the state of art on step detection methods step length estimators. Limitations of the methods of using them on proposed sensor location are discussed here.
- Chapter 6 introduces the proposed step detection method and the adaptation methods of step length estimators for the proposed sensor location

- Chapter 7 describes the Experimental methods, protocol, data collection and data analysis with PD patients and healthy person for algorithm development and validation.

- Chapter 8 presents and compares the results step detection of existing ones and proposed one with healthy person and patients with PD.

- Chapter 9 presents the results from step length estimators for healthy person and patients with PD.

- Chapter 10 introduces the new gait model for step length estimation and their results of experiments

- Chapter 11 is the last chapter that is devoted to conclusions, author's contribution and future works.

Part I Background and state of the art

Chapter 2 Parkinson's disease

Parkinson's disease (PD) is a neurodegenerative disease that alters human movement. It can afflict persons of any age though it is very rare in persons under 30 years and common for about 3% of the population over the age of 65 years. According to World Health Organization(WHO) [28], around 5.2 million people suffer from PD in the world, where around 2 million people are from Europe and 1.2 million are from America. According to the European Parkinson's Disease Association (EPDA)[1], the disease affects around 6.3 million people in the world and 1.2 million people in Europe. Among them, approximately 0.26 million are from Germany, 0.2 million from Italy, 0.15 million from Spain and 0.12 million from UK. The mortality rate among diseased persons is also two to five times higher than the people in same age. Because of modern health care and medication, the ageing of population is progressive in Europe. With the increase of number of elderly people, the number of PD patients is also increased and creates a new social and economic challenge regarding their health care.

PD is caused by the progressive loss of dopamine-generating nerve cells in the basal ganglia region of the brain. The nerve cells sited in this region control the movements and coordination of human body. A special kind of neurotransmitter called dopamine is produced in this region and plays an important role in communication between neurons in basal ganglia and in supplementary motor area (SMA).When we want to move, the basal ganglia sends internal cue to the SMA for the well learned movement sequences via dopamine. After receiving the cue, SMA prepare the movement [29]. As the dopamine neurons gradually die in PD, they cause lack of dopamine production. The gradual fall of dopamine level disrupt the interaction between basal ganglia and SMA and patients consequently loss control over movements. The disruption leads to slowed movement or sometimes abnormal movements [30]. In the beginning of the disease, the loss of movement control is not visible accept tremor (involuntary movement) and bradykinesia

[1]http://www.epda.eu.com/en/parkinsons/life-with-parkinsons/part-1/prevalence-of-parkinsons-disease/

(slow movement). With the evolution of the disease, other symptoms become more prominent.

2.1 Parkinson's disease symptoms

The common motor symptoms of PD are Tremor [31], Bradykinesia [31], Freezing of gait (FoG) [32], Dyskinesia [31], reduced step length and gait speed [30]. Figure 2.1 shows the visible symptoms of PD that are the hallmark of the disease.

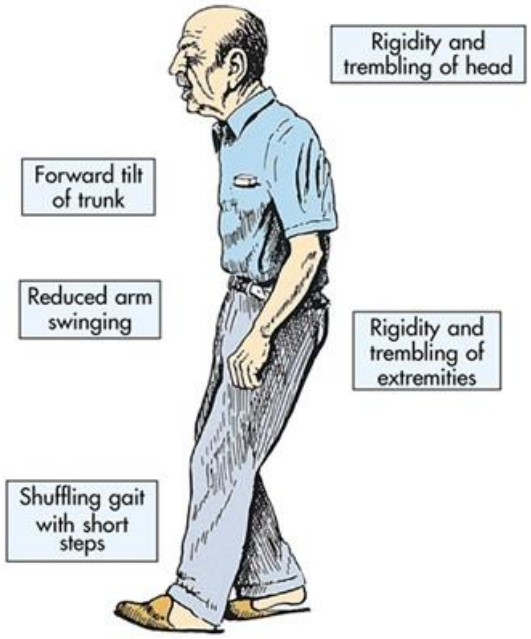


Figure 2.1: Visible symptoms of Parkinson's disease. (Source: http://parkinsons.ie/Professionals_What_Is_Parkinsons)

Tremor: The first noticeable symptom of PD is tremor. It is the involuntary movement like trembling or shaking of fingers, hands, arms, leg and feet of PD patients while the limb are in resting position. PD tremor is characterized to not being observed when the limb is voluntary moved. Most tremor occurs in the hands with finger flexion and/or wrist joint rotation and the frequency is about 4 to 6 Hz [31]. Tremor can also occur in

tongue, lips, face or jaw. In the early stage, tremor starts on one limb or one side of the body. The other side of the body is also included with progression of the disease.

Bradykinesia: The bradykinesia or slowness of movement is also one of the main symptoms of PD, noticeable in early stage of the disease. It is often suffered together with akinesia (loss of movements) and hypokinesia (reduced body movement). It is the typical symptom that people around PD patients can notice before patients. With bradykinesia, mobility is decreased, co-ordination is reduced and turning becomes more difficult. Patients have difficulties to move from resting position, for instance, rising from chair or turning over in bed. Performing daily activities that involve simultaneous or repetitive motor acts like brushing teeth, cutting food, writing on a paper, playing a musical instrument or buttoning a shirt become slower and harder. Patients voice also becomes lower and softer [31]. Moreover, with the disease progression, sense of balance is progressively lost and patients may experience sudden falls. When a PD patient falls, they may incur serious injury, as they are very slow to make attempt to catch themselves.

Freezing of Gait (FoG): FoG is the sudden involuntary and temporarily inability of moving legs in the middle of walking, during initiation or ending of walking and while turning. Fog may also appear while walking in narrow areas, corridors and doors and while turning to avoid an obstacle (furniture, animal, person etc.) in the trajectory. Patients feel that their feet are glued to the ground so they repeatedly try to move them. FoG lasts for some seconds to several minutes. FoG is one of the main symptoms in the patients with advanced PD (70%), but it also occurs to patients in the early stages who are not treated with any anti-PD medication [32]. FoG happens more frequently during OFF states although it appears during ON states as well [33]. FoG does not respond well to medication. Patients often lose their balance, while trying to walk during FoG episode, and experience sudden fall. There are other types of freezing that do not affect gait but instead affect speech, writing and eye blinking. Visual input, haptic (typically electric) or rhythmic audio cueing could be applied as an external sensory stimulus to unlock the freezing episode. Among the auditory cueing is not only effective to overcome the freezing attack but also to improve gait among PD patients [34].

Reduced Step length and gait speed: The step length is defined by the distance covered by one foot during walking and gait speed is the average distance covered in a unit time. A decreased step length and gait speed is a very common symptom on PD patients, which is commonly related to a lack of medication effect. Patients commonly walk with slow little steps and shuffling their steps close together while forward tilting their trunk (stooped posture) [30][35][36]. There is also strong relationship between FoG and reduced step length, as PD patients with FoG walk with shorter step length than patients without FoG [37]. Step length is also gradually reduced before occurrence of FoG during steady state walking [38].

Dyskinesia: This is not a symptom of Parkinson's disease but the side effect of overdosed or earlier dosed medication to treat PD. Dyskinesia are involuntary jerky, dance-like movements of arms, legs, torso and head. Dyskinesia occurs most often with excessive dose of medication but can also occur when the medication is wearing off (OFF state). Dyskinesia occurs in around 50% of PD patients treated for more than 5 year [31]. During dyskinesia, the movements of PD patients may be either choreic, dystonic or a combination. Choreic movements may be described as brief, rapid, restlessly involuntary dance-like movements of the limbs, face and trunk. Dystonic movements occur when opposing muscles are contracted simultaneously causing twisting movements and abnormal posture. ON-state dyskinesia is usually choreic, dystonic or both in nature while OFF-state dyskinesia is only dystonic [31]. Dyskinesia appear gradually and once established is hard to treat.

Rigidity, lack of facial expression, postural instability and impaired coordination, muscle pain or cramps are also common symptoms of PD. The patients also experience fatigue, mental disturbance, depression, visual and sensory motor impairments, loss of smell etc. because of PD. Reduced step length and gait speed and sudden inability of movements (FoG) has become a major concern for researchers, as these are the hallmark of the disease in every stage [39].

2.2 Medication cycle and ON and OFF motor states

PD symptoms result from lack of dopamine in brain cells. Unfortunately, the disease is not curable but relievable for some hours by increasing dopamine level in brain with proper medication. A combination of levodopa and carbidopa is the most commonly drug used for PD treatment. The brain converts levodopa into dopamine while carbidopa prevents levodopa to convert outside of the brain. While levodopa and carbidopa are dopamine agonists because they help to produce dopamine, antagonists such as bromocryptine and apomorphine, help to reduce those substances that remove dopamine. In human body, commonly we have a dual system based on facilitating, and inhibiting a substance. In dopamine, we have this kind of system; we have the substantia nigra that produces dopamine (facilitators) and some enzymes that remove the excess of dopamine (inhibitors). Dopamine agonists are facilitators (they help to produce dopamine), and dopamine antagonists are inhibitors (they help to reduce the enzymes that remove dopamine).

In the early stage of the disease, the effect of the medication may last 8 hours or more, the patient's conditions are significantly improved by the drugs and have stable response for a number of years. As, PD progresses, the effectiveness of the drug is shortened giving rise to the "wearing–off" or "end-of-dose" effect [31]. For this, patients gradually need higher dose or higher number of medication intake. From the fifth year of the treatment onward, phenomenon like tremor, bradykinesia, FoG and dyskinesia may emerge. Patients also fluctuate between ON and OFF states [31]. ON state is the state in which motor symptoms are almost invisible with the exception of dyskinesia and patients feel relatively clear and in control of their movements for some hours. When the effect of medication goes down, OFF state starts, and motor symptoms become more prominent. During OFF states, PD patients have less control of their movements, may fall in serious health risk and sometimes face sudden fall. On an average, patients in a moderate or severe stage of the disease may experience this clinical state fluctuation three to four times a day [18].

For optimal treatment of the disease, a smooth and steady level of drug in the blood is required. In the early stage of the disease, the first drug administration choice is the intake of pills every few hours. After some years of treatment, when ON/OFF and dyskinesia appear and are very cumbersome, the administration is changed. The idea is to have a constant level of dopamine; fluctuations are obtained because of them. So first, pills are fractioned into several parts and taken more often. Sometimes, a fast-acting agonist like apomorphine is administered subcutaneously to manage sudden or severe OFF state. Apomorphine is rapidly absorbed and sometimes act as rescue shot for the patients [31]. Apomorphine can be injected manually by the patients or caregiver or by a wearable and programmable infusion pump [12]. To ensure continuous drug administration over a 24 period, Levodopa/Carbidopa intestinal gel, (Duodopa) is pumped continuously into patient's gastrointestinal tract through an inner tube inserted through the abdominal wall by means of a wearable external pump attached to the end of the tube. Another dopamine agonist, rotigotin, is administered in the form of skin patch for continuous drug administration. The gastric pumps try to ensure a constant level of drug in the blood, as well as patch. In advanced stage, when some patients develop worsening symptoms and does not respond well with any medication, surgery is necessary. A surgical treatment named deep brain stimulation (DBS) is most commonly used in which the affected region of the brain is stimulated by providing electrical impulse from electrodes inserted into that region.

For a proper PD management, doses of drugs and their frequency of intake need to change time. For appropriate prescribed medication and its dosage, the detection of ON and OFF state and their fluctuations over time has to be determined accurately [18]. In clinical setting, neurologists assess the PD patients by observing the symptoms, by conducting a series of clinical tests and by rating their disabilities according to a scale, typically UPDRS (Unified Parkinson's disease rating scale). The main limitation of these tests is that they asses the disease only at a particular moment in time of the clinical condition and is not sufficient for better treatment. As long-term supervision is needed to determine the fluctuations over time, the process is not sufficient for the patients who are not hospitalized.

2.3 Conclusion

Reduced step length, lower gait speed and sudden inability of movement are the hallmark of the Parkinson disease in every stage. Monitoring step length in PD patients using a device will help to detect OFF states accurately and early predict FoG episodes and prevent FoG in the patients by applying cueing technique. This information will allow physicians to monitor their patients for long time, employ proper information of advancement of disease.

It will also open up the possibility of automated PD treatment by using drug-administration pump regulated by a PHS(Personal health care systems) [18]. For instance, in REMPARK project they proposed a subcutaneous injection pump that will automatically delivery a rescue dose if there is any un-expected OFF period and relieves the patients from sufferings and sometimes protect them from accident like sudden fall. The detection of ON and OFF period will also help to assess the validity of introducing new treatment by measuring the increased time of the patient spent in ON period, decreased time patients spend in OFF state or transition time between ON and OFF state.

Chapter 3 Spatio-Temporal parameters of gait

Gait is "the method of a person's walking". It is the locomotive movement of human body resulted by the series of rhythmic, coordinate and alternative movements of trunk and limbs. Gait of PD patients is mostly analyzed in diagnosis, treatment and rehabilitation processes within the clinical environment. Next section first describes the common parameters of gait. Then, these parameters are described in the context of Parkinsonian's gait, which is presented in the second section of this chapter.

3.1 Gait cycle

Gait cycle is the time interlude between two successive and repetitive events of ipsilateral foot (on the same side of the body) [40]. The usual gait event used to define gait cycle is initial contact, the instant when one foot touches the ground. A gait cycle is considered to begin from the initial contact of one foot and to end with the initial contact of same foot. A gait cycle consists of two steps: left and right step. A person makes a step when he moves forward one of his leg. It begins from the initial contact of ipsilateral foot and ends with the initial contact of contralateral (other side of the body) foot. A left step could be defined as the interval between initial contact of right and left leg while a right step for the opposite. In consequence, a gait cycle could be redefined as a composition of both left and right steps. The sequence of the steps (left-right or right-left) depends on the person's first step in a gait cycle. Figure 3.1 shows the typical gait parameters in a gait cycle.

A gait cycle comprises two phases: the stance phase and the swing phase. To define phases of a gait cycle, two gait events, initial contact and terminals contact are usually used. Terminal contact is the instant in which a foot is lifted from the ground.

Stance phase

A gait cycle starts with stance phase. It is the part of gait cycle when either one or both feet are in contact with the ground and body passes through it. It begins with the initial contact of reference foot and concludes with terminal contact of ipsilateral foot. About 60-62% of the gait cycle of healthy person is made by stance phase [40].

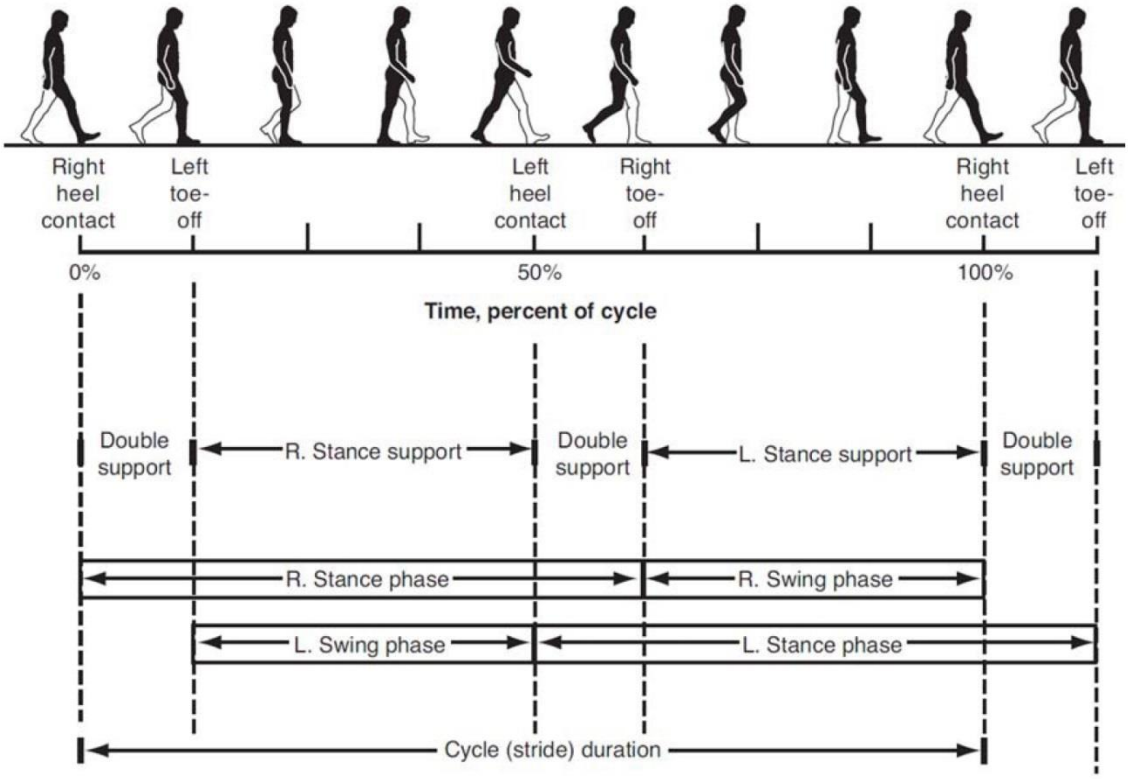


Figure 3.1: Spatiotemporal parameter of gait [41].

Swing phase

Swing phase starts immediately from the terminal contact of the reference foot and continues till initial contact of ipsilateral foot. In this part of gait cycle, the reference foot is not in contact with the ground and is in forward movement. In pathological gait, there are some cases where patients cannot lift their foot from the ground during walking. They drag their foot over the ground. In those cases, swing phase is defined by the forward

motion of all portion of the foot. This phase constitutes about 40% of the gait cycle of a healthy person [40].

Gait cycle may be further divided into the following sub phases [40]:

i) Loading response

It is the first part of stance phase. Loading response phase starts immediately after the initial contact of a foot and lasts till terminal contact of contralateral foot. During this phase, the weight of the body is transferred to the ipsilateral limb while forward progressing. The contralateral foot begins to go through to its swing phase.

ii) Mid stance

This sub-phase begins with the terminals contact of contralateral foot. In this phase, the forward progression of body is supported by ipsilateral foot bearing the whole weight. The phase continues until any part of ipsilateral foot leaves the ground. The contralateral foot is in swing phase in this phase.

iii) Terminal stance

This sub-phase starts when any part of ipsilateral foot (usually heel) is lifted off the ground and ends on initial contact of contralateral foot. The stance phase ends with terminal phase.

iv) Pre-swing

Pre-swing sub-phase is the interval between initial contacts of contralateral foot to terminal contact of ipsilateral foot. In this sub-phase, the last one corresponding to the stance phase, both feet are in contact with ground.

v) Initial swing

The swing phase begins with initial swing sub-phase, when the ipsilateral foot is lifted from the ground. The contralateral foot is in mid-stance during it. The ipsilateral leg swings forward and reaches to the opposite of the stance leg with maximum flexion of knee.

vi) Mid swing

This sub-phase starts when the ipsilateral knee reaches maximum flexing and continues until the tibia is in a vertical position. The contralateral foot is in its late mid stance phase. It starts immediately after the initial swing and continues until the swinging limb goes in front of the body.

vii) Terminal swing

It begins with the tibia vertical and ends the instant before the initial contact of ipsilateral foot ending the gait cycle also. The advancement of swinging leg is completed with this phase.

3.1.1 Key events in the gait cycle

There are four events in a gait cycle. These are:

Initial contact (IC)

It is the instance in which foot touches the ground. It is often called as heel contact or heel strike in normal gait as heel, among the other parts of foot, first touches the ground in normal gait. For a pathological gait it is possible that either the toe, side of a foot or even the whole foot first touches the ground rather than heel [40]. The terminology of initial contact (IC) is more accurate in this regards. The start and end of a gait cycle is defined as the IC of same foot.

Foot flat

It is the instant of foot contact when it is flat or all of its parts are in contact with the ground. It occurs after initial contact and second part of stance phase.

Heel off

The instant when any part of the reference foot is lifted off the ground.

Terminal contact (TC)

It is the instant of foot when it is lifted off the ground. Ideally (not always) toe is the last part of foot that leaves the ground. For this, it is often called as toe off event. For the cases when the last part of the foot that leaves the ground, is not toe, "terminal contact" is more appropriate. This represents the end of stance phase as well as beginning of swing phase.

3.1.2 Temporal parameters of gait

Temporal parameters of gait cycle are those related to time. A typical gait cycle consists of following temporal parameters:

Stride time [s]: The time required for two consecutive initial contact of ipsilateral foot, sometimes also referred as cycle time or simply gait cycle. For healthy person it is, in average, 1.03 sec and it remains same with aging [42].

Step time [s]: Step time is the duration between initial contact of ipsilateral foot and contralateral foot and vice versa. Sometimes step time is considered as half of stride time.

Cadence [steps/min]: Cadence is measured as the number of steps taken in certain time. Usually it is measured as the number of steps per minute. The cadence is inversely proportional to cycle time. Cadence of a healthy person remains intact with aging and it is 117 steps /minute in average [42]. Cadence is related to leg length. For a fixed gait speed, taller people take fewer steps as their step length is longer. In consequence, cadence is slower for taller people compared to the short people.

Gait speed [m/sec]: Gait speed is the average displacement of a person in unit time. The gait speed can be calculated as follows:

$$\text{Speed } \left(\frac{\text{m}}{\text{sec}}\right) = step\ length(\text{m}).1/60\ (\text{min}/\text{s}) \cdot \text{cadence (steps}/\text{min}) \qquad (3.1)$$

Gait speed of older individual is declined with their age. Compared with the average gait speed of 1.37 m/s in the young people, it is around 1.27 m/s in average in the older people [43].

Stance time [s]: Stance time is the elapsed time during the stance phase of the reference leg in a gait cycle. It is generally expressed in sec. The stance time remain stable with age and the average stance time of healthy person is 0.63 sec [42].

Double support time (DST) [s]: In stance phase during walking, double support time is the instance of stance time, when both feet are in contact with the ground. It occurs twice in the gait cycle, at the beginning and end of a stance phase, referred as, initial double support and terminal double support respectively. During double support, the ipsilateral foot is in the beginning and contralateral foot is in ending of their stance phase. It increases with age. In average, the double support time is 0.10 sec (9% of cycle time) in of young adults and 0.12 seconds (11% of cycle time) in healthy elderly people [42].

Single support time (SS) [s]: The period of time when only one foot is in contact with the ground. In walking, this is equal to the swing phase of the other limb. Single support time decreases with age. In average, the single support time of young adults and elderly people are 0.42 seconds 0.40 seconds respectively [42].

Swing time [s]: Swing time is the interval during swing phase, one foot is in contact with the ground while the other is swinging forward. Swing time of ipsilateral leg is same as the single support time of contralateral leg. In average, the duration of swing time of healthy person is 0.4 sec [42].

3.1.3 Spatial parameters of gait

A typical gait cycle consists of following spatial or distance parameters:

Stride length [m]: It is the linear distance between two consecutive initial contacts of same foot -sometimes referred as cycle length. The stride length consists of two step length i.e. left step length and right step length. For a normal gait, the stride lengths of both feet are generally equal for straight walking and changes during walking in a curve. The stride length depends on a person's sex, age, height, weight, type of dresses and footwear and condition of disease. Stride length decreases with age. The average stride length of young adults is 1.59 m. and 1.53 m. in healthy elderly people [42].

Step Length [m]: It is the linear distance between two successive IC of ipsilateral foot and contralateral foot during forward displacement. It has been observed that younger people take longer steps compared to elderly people. According to Murray et al. [42], there is significant difference in step length between younger people and healthy elderly people. The average step length of young people and healthy elderly people are 0.79 m and 0.76m respectively. It is common to have asymmetries between the steps of left and right feet and the difference is 0.05 m for healthy persons [44]. This difference affects other gait parameters.

Step width [m]: It is the distance between the ankle centers during foot strikes. The distance is measured side to side from the midpoint of the back of the heels between the lines of two feet. It is also known as walking base or base of support. According to Murray et al. [42], there is no significant effect of age on stride width though compared with different age group he showed that the stride width of mid aged people is comparatively longer than young and elderly people. The average stride width is 0.08 m for healthy person and is 0.07 m for healthy elderly people [42].

Toe out [degree]: Degree of toe out is the angle of a foot's position between the line of progression and midline of the foot. Healthy adults have greater degree of out toeing than the younger subjects and in average it ranges from 6.8^{o} to 9.5^{o} [42].

3.2 Parkinsonism gait

PD has noticeable effect on gait performance among the other voluntary movements. A PD patient may commonly walk during OFF states with slow little steps sometimes termed as *shuffling gait* while leaning their trunk slightly forward. The gait abnormality of a PD patient is often characterized by bradykinesia, reduced step length and gait speed, FoG and dyskinesia [39], which are mostly analyzed in diagnosis, treatment and rehabilitation process in the clinic.

Numerous studies have examined gait characteristics of PD patients compared to same aged elderly people as well as the effect of medication during ON and OFF states.

Earlier, Murray et al. [20] provided detail information on parameters of PD gait by examining 44 PD patients. Recent papers [14][36][45][46] investigate the effect of medication on PD patients and provided information whether gait parameters are improved by using medication. The following list illustrates the spatio-temporal parameters of PD gait and how they improve with medication:

1) **Balance and postural instability:** PD patients walk with stooped posture: head is bent forward, shoulders are dropped and pelvis is leaned forward. Movement of hip, knee and ankle are slower compared to the same aged healthy person. Arms swinging, trunk rotation, and lower limb joint excursion are significantly reduced. The direction of trunk movement is also changed i.e. healthy persons rotate their trunk in the opposite direction of the pelvis, though PD patients rotate their trunk together with pelvis in the same direction because of rigidity [39]. In advanced stage of the disease, the patients place their entire foot or most of the foot on the ground at the same time [20]. PD patients often experience difficulties on turning or changing direction. Typically, they take multiple small steps to accomplish this. The rigidity and abnormal posture sometimes leads to difficulties in controlling balance that may cause sudden fall [47].

2) **Gait speed:** Though older people walk slowly than young people, individuals with PD walk more slowly compared to same aged healthy persons. Significant differences were found in gait speed between PD patients and healthy elderly person. Azulay et al. [48] showed the average gait speed of a PD patient is 0.76 m/s, which is 1.5 times slower than the same aged healthy people (1.13 m/s). Gait speed of PD patients could be significantly improved using medication [36][45][46]. In a previous study [46], it is shown that the average gait speed of a PD patient could be significantly improved from 0.70 m/s (during OFF state) into 0.79 m/s with the help of medication (ON state).

3) **Cadence:** Cadence of PD patients are same [20] compared with healthy elderly people. It remains intact with the advancement of the disease. In a previous study [49] it is seen that, to increase the gait speed, sometimes PD patients may increase

their cadence to compensate the shortened step length but no significance were found. The average cadence of a PD patient is 102.42 steps/min during OFF state [46] and there is no significant improvement during ON states.

4) **Stride length:** As the cadence of PD patients remains unchanged, reduced gait speed is directly related with shortened stride lengths. PD patients walk with short stride length of 0.93 m in average compared to the stride length of same aged healthy elderly people which is 1.17 m in average [48]. Stride length continues to decreases with advancement of the disease. Significant improvement is achieved in stride length while a patient is following medication [36][45][46]. In average, stride length could be significantly increased from 0.82 m to 0.93 m from OFF state to ON state [46].

5) **Step width:** The stride width of PD patients increases slightly compared to same aged healthy adults. The average stride width of PD patients is 0.12 m while it is 0.1 m for the same aged healthy adult [48]. No study was found if there is any significant change of walking base between OFF and ON states.

6) Stride time: The stride time of PD patients is higher than the healthy adults. The stance time is prolonged though the swing time remains equal. The average stride time of PD patient is 1.24 sec while the average stance time is 0.78 sec (63% of gait cycle) and average swing time is 0.46 sec (37% of gait cycle). On the other hand, for the same aged healthy adult, the average stride time, stance time and swing time are 1.05 sec, 0.62 sec and 0.42 sec respectively. No significant difference in stride time was reported between ON and OFF state. Although the stance time is decreased and swing velocity is increased, these changes were not statistically significant [45].

7) Step-to-step variability:

The step-to-step variability of PD patient is increased compared to healthy adults. It is increased more in the patients with FoG compared to the patients without FoG [31]. This observed variability is included on both step length and step

duration. This indicates that there is walking instability on PD patients which effects the rhythmic movements also. Earlier it was reported that no significant improvement on step-to-step variability during ON state [45]. Recent studies showed that the step time variability could be significantly reduce in ON state compared to OFF state [14][46].

8) **Double support time (DST):** The double support time of PD patients is significantly increased with increased DST variability, compared to the healthy person. DST remain same in both OFF and ON states though the DS time variability could be reduced with medication [46].

9) **Gait deterioration before FoG:** FoG is the sudden inability of movement of a PD patient. Mazilu et al. [22] showed that PD patients does not go to a FoG episode directly from walking. A patient go through a transition period termed as pre_FoG, where the gait is deteriorated before going into FoG episode from normal walking. Significant differences in 3-axial accelerometer signals were found by the authors between normal walk and pre-FoG state. Another study observed that during three steps prior to freezing episode, the patients have an abnormal stride length and cadence [38].

3.3 Discussion

Gait is an important motor task that is being widely analyzed in the treatment of PD. Some of the gait parameters are significantly improved with medication. Table 3.1 shows summery of mean gait parameters during both ON and OFF state reported in [14][36][45][46]. Stride length and gait speed have shown to change significantly depending on the motor state. Stride length is shortened, which causes reduced gait speed during OFF state of PD patients with respect to ON states. The cadence and swing time remain unchanged in both motor states. Although DST is decreased, it is not statistically significant. Step-to-step variability are more prominent in OFF state than ON states [50]. These force to investigate more on step length than stride length. Significant differences were also found between left and right step length of PD patient [51]. Step length

estimation also fluctuates between normal and pre-FoG state, thus suggesting that it would be a good measure to early predict the appearance of a FoG episode. Therefore, monitoring step length in PD patients enables the assessment of gait disorders, the identification of patients' motor status (ON or OFF state) and the early prediction of FoG episodes.

Table 3.1: Mean (standard deviation) for gait parameters during OFF and ON state

Gait parameters	**OFF state**	**ON state**
Gait speed (m/sec) [46]	0.70 (0.23)	0.79 (0.18)
Cadence (steps/min) [46]	101.84 (12)	102.42 (11.72)
Stride length (m) [46]	0.82 (0.24)	0.93 (0.25)
Stride time (sec) [45]	1.28 (0.2)	1.24 (0.28)
DS (% of gait cycle) [36]	32.9 (5.6)	30.4 (3.8)
DST (sec) [45]	0.23 (0.08)	0.19 (0.06)
Swing time (sec)(NS) [45]	0.4 (0.08)	0.41 (0.08)
Stride time variability (CV %) [46]	6.12 (2.49)	4.43 (2.03)
Stride length variability(CV %) [14]	7.62 (5.45)	6.57 (2.53)

Chapter 4 Current technologies for estimating gait parameters

Gait analysis is important to diagnose and analyze the evolution of Parkinson's disease. In clinical settings, doctors could perform the gait analysis by observation through a series of clinical tests. Such analysis is very much subjective and time dependent, which is not sufficient to lead to a better treatment.

Relation between gait parameters and motor states has been widely analyzed in the treatment of PD. Reduced stride length and gait speed are common symptoms on PD patients that will be useful for the diagnose of the motor states [14][17][18][19]. In consequence, many different clinical tools have been analyzed in order to measure the gait parameters for PD like motion capture system, Infrared camera, pressure mats etc. Their main disadvantage is that they are not usable outside the laboratory. Recently, new systems using wearable devices have been developed based on Micro-Electro-Mechanical systems (MEMS) sensors like accelerometers, gyroscopes and magnetometers to measure the stride length and gait speed. MEMS devices are cheap, consume low energy and miniaturized that favors their use outside the clinical environment. Using MEMS based inertial sensors could help to monitor the patient online and provide proper strategies to handle with the disease [14][18][25].

In the first section of the chapter, the technologies for gait analysis are briefly discussed. In the second section, inertial sensors located on different part of body of PD patients are discussed and the best location to detects symptoms of PD. Last two sections discuss the sensor location and the sensor device used in this thesis.

4.1 Clinical tools/technologies for gait analysis

There are four basic types of instruments used in gait analysis: optical motion capture system, camera based, floor mat base and wearable sensor based.

4.1.1 Optical motion capture systems

Optical motion capture system is the most common and reliable systems in biomechanical laboratories among the others [3]. In this approach, a set of external markers (retroreflective or light-emitting diodes) are located on one or more body segments aligning them with human bony structure. Multiple high speed cameras connected with a computer are placed at different angles of a pathway or a treadmill. Real-time motions of the markers are captured by the cameras while walking through the pathway or the treadmill. The three dimensional (3-D) movements of the subject are analyzed from the trajectory of the markers based on a model [52] that maps the markers to the underlying bone. The instantaneous 3-D positions of the markers are used to compute spatio-temporal parameter of gait, joint angles, postural changes etc. Vicon MX system [2]and CODA[3]is the most common example of this kind of devices. Figure 4.1 shows a typical Vicon system in a biomechanics laboratory.

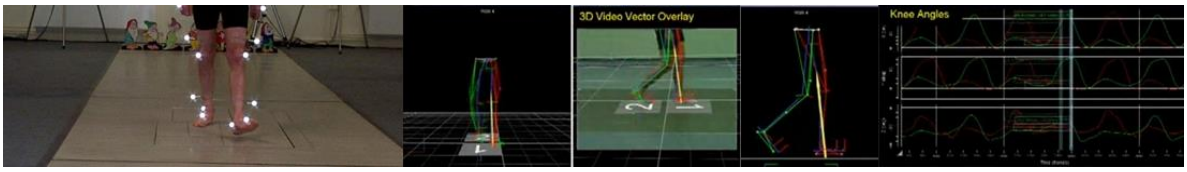


Figure 4.1 : Vicon Gait analysis System (Source www.vicon.com)

The system is reliable and highly accurate in estimating gait parameters and often used as a “golden standard’ in human gait analysis. As accuracy is crucially dependent on correct placement of the markers, the errors are found around 1mm [53].

[2]*http://www.vicon.com/applications/gait_analysis.html*

[3]http://about.brighton.ac.uk/sohp/research/resources/coda.php

The limitation of this system is that they are highly expensive and need highly trained and experienced personal to operate them. The setup process and calibration between the cameras and data processing are, moreover, complex. The space requirement for the system is too specific that it could only be used inside a laboratory with pre-setup of all the equipment's. It is also time consuming to prepare the subject for the trial and the subjects need to be almost necked. These are the reasons limiting the system to the laboratory setting.

4.1.2 Image processing

In this approach, the system typically consists of one or more cameras to record the movements of the body or, specifically, the trunk and legs during walking. Image processing and silhouette techniques are then used to extract the foreground images. These foreground silhouette images are then aligned and normalized to get the average motion energy (AME) in two-dimensional space to analyze the spatio-temporal gait as in Figure 4.2 [54][55]. Image processing method is more used in tracking and identify people with their gait pattern with an accuracy of 82.5% [56] in a specific area preferably in indoor settings. In a previous study [57], the method was used to gait of older adults the error rate was 4.2%, 5.4% and 6.6% in estimating gait speed, step time and step length. The only limitation is that it can only be used in an indoor setting i.e. patients home.

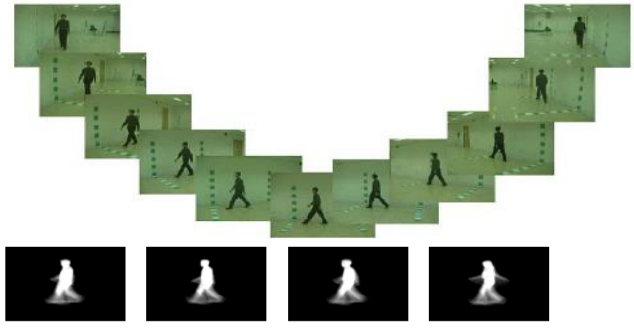


Figure 4.2: AME images extracted from a set of images (Source [55]).

4.1.3 Instrumented walkway system

An instrumented walkway system measures the foot's pressure on the floor during standing on or walking through them. It includes an electronic roll-up walkway of 4 to 7m length with encapsulated sensor pads within it. A sensor pad has an active area that is embedded with sensors (up to 4 sensors per cm^2) arranged in a grid pattern which enables to measure vertical and horizontal pressure of different zone of a foot. As foot's pressure varies between different gait phases (maximum during IC and minimum during TC), it could be used to quantify balance, gait events and other gait parameters [13][58]. Some examples of commercial instrumented walkways are:

Figure 4.3: GaitRite Walkway (Source: http://www.gaitrite.com/Downloads/GAITRite_Brochure.pdf)

- GaitRite walkway by CIR systems Inc,[4] (upto 90 x 700 cm)
- Zeno walkway by ProtoKinetics[5] (upto 10.16 x 81.28 cm)
- MatScan pressure mat system made by Tekscan[6] (43.6 x 36.9 cm)

[4]http://www.gaitrite.com/

[5]http://www.protokinetics.com/zenowalkway.html

[6]http://www.tekscan.com/medical/pressure-sensitive-mat.html

In a previous study [59], GaitRite system was compared with Vicon systems and showed that the maximum error on estimating individual step length is 0.038 m during preferred speed and 0.048m for the faster speed condition with errors in step times 0.05s and 0.04s respectively. The advantages of the instrumented walkway are that they are portable, easy to set up, need minimum training and can measure spatio-temporal parameter of gait. The limitations are in the fact that gait measurement is limited over a set distance (length of the mat) and could only be used in indoor.

4.1.4 MEMS based wearable sensors

The cost, skilled personal requirement and lack of ambulatory monitoring limit the use of optical motion capture system. Cameras or pressure sensitive mats can only be used in specific research laboratories or specialized clinics. They are not applicable for ambulatory monitoring, and routine checkups outside the laboratory settings. Thus, many studies aim to develop a wearable device that is cheap and could be used during daily life of patients for ambulatory monitoring of gait. These studies have employed MEMS (Micro-Electro-Mechanical Systems) sensors like accelerometers, gyroscopes, magnetometers, electrogoniometers, force sensors etc. to analyze gait without constraining the analysis of specific setting.

MEMS sensors are miniaturized mechanical and electro-mechanical devices and structures, made using microfabrication technique. The size of MEMS devices can vary from one micron to a millimeter. The size of the components inside MEMS can very form one to one hundred micrometers. A typical MEMS device consists of a central processing unit with micro sensors, micro actuators and microelectronics. The MEMS sensors can measure acceleration, angular movement, magnetic field, pressure, temperature etc. Their high performance, small size and weight, low power consumption and low cost favors their use increasingly in many consumer electronics like mobile phones, energy expenditure monitoring devices, automotive industry and medical services [60][61].

MEMS devices are also used to analyze human motion. The concept is to place a single or a multiple type of MEMS inertial sensors in a single or different part of body such as

feet, limb, thigh or waist to measure and to record the motion of the body [62]. This way, these sensors are also used to analyze the gait. Zhang et al. [3] showed that, in the field of health care application, single inertial sensors systems like accelerometer or inertial measurement units (IMU), which combine accelerometers, gyroscopes and sometimes magnetometers, are mostly used as wearable devices.

MEMS based inertial sensors are less expensive, small in size, low power required, convenient to use and efficient to provide adequate information for gait analysis. They are currently widely used in both clinical and biomechanical laboratory. This is the most flexible and low cost system that could be used to analyze gait during daily life activity [1][63][64][65]. In the next subsections, a brief overview of most commonly used MEMS sensors in research applications is presented.

4.1.4.1 Accelerometer

MEMS-based accelerometers are one of the most commonly used sensor to estimate step length and other gait parameters [66][67][68][69]. An accelerometer can measure the acceleration in one direction however, two or three-dimensional movement can be measured if two or three accelerometers are grouped together. The three dimensional measurement (tri axial accelerometer) helps to measure the 3D movement of human body by attaching them on different parts of the body.

According to their sensing principle, difference types of accelerometers are available, such as, capacitive, piezoelectric, piezoresistive, Hall effect, heat transfer etc. Among them, capacitive accelerometers are the most common type. In this thesis, capacitive type accelerometers are used [64]. A typical capacitive accelerometer is composed of a movable small proof of mass with plates, attached to a mechanical suspension system as shown in Figure 4.4. One or both of the plates are charged with electrical current. Under the influence of external acceleration, the proof mass is displaced from its neutral position. The displacement of the proof of mass changes the gap between the plates and, thus, changes the electrical capacity of the system. The change of capacitance produces an output voltage that is proportional to acceleration. As shown in Figure 4.4, the plates

are represented as capacitors. The capacitance is changed due to deflection of proof of mass.

The output voltage due to acceleration could be obtained as follows [61]

$$V_{out} = V_{in}\frac{C_2 - C_1}{C_2 + C_1} = \frac{x}{d}V_{in} \tag{4.1}$$

Where, x is the displacement of the mass M and d is the distance between the capacitors $C_1$and C_2. V_{out} *and* V_{in} are the output and input voltage respectively.

The acceleration due to displacement of the mass is directly proportional to output voltage and can be obtained following Newton's second law of motion ($F=m\cdot a$) and Hook's law for an ideal spring ($F=K.x$) [61] as follows

$$a = \frac{Kd}{MV_0}V_x \tag{4.2}$$

where K is the spring constant.

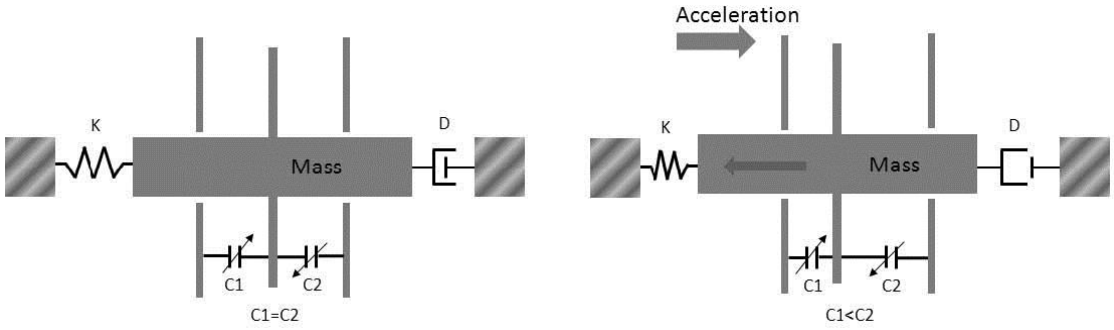


Figure 4.4: The operating principle of an accelerometer.[70]

Accelerometer data are easy to interpret and do not need excessive signal conditioning. The sensors are stable, less prone to noise and variation with temperature and less power dissipative. Although offsets appear due to gravity [24], they can be removed by proper calculation. These advantages justify the reason of using accelerometers in most of the

studies devoted to gait analysis, especially for detecting gait events and estimating step length and gait speed. In estimating step length using a single accelerometer, the lowest error obtained is -0.04±4.15 m [71]

4.1.4.2 Gyroscope

Gyroscope measures the angular velocity of motion of an object with respect to a reference frame based on the measurement of the Coriolis force that apparently deflects the path of that object [72]. The angular orientation could be calculated by detecting the linear motion from the Coriolis effect and then integrating the gyroscopic signals [62]. Current available gyroscopes are one axial, bi axial and tri axial gyroscopes.

Gyroscopes are used to perform gait analysis [73], to detect gait events [74], to determine human posture [72][75], heading information [76], temporal parameters of gait [77] and to estimate step length [1], by attaching them to different part of the body, specially to legs or feet [62], alone or together with an accelerometer [78][79].The gyroscope is prone to drift due to temperature changes over time. For long term monitoring using gyroscope, they need to be recalibrated. A more complex signal conditioning is then required.

4.1.4.3 Magnetometer

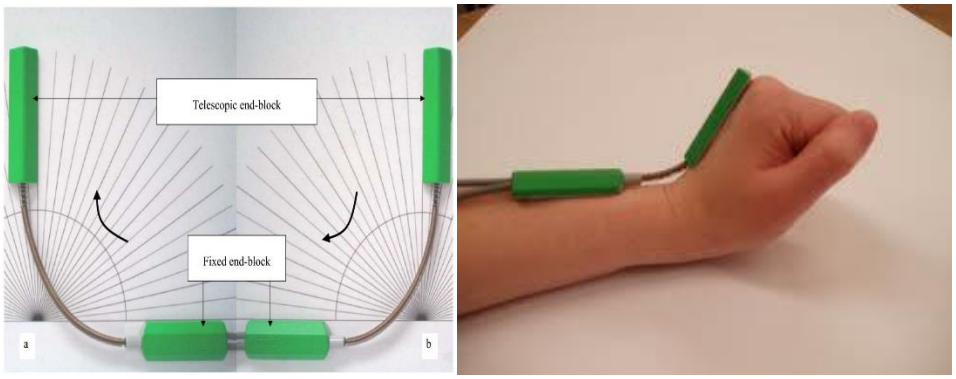
Magnetometer measures the magnetic strength or direction of magnetic field at a given point by measuring the magnetic flux density at the point of space [62]. It can be used to estimate the changes in orientation of body with respect to earth´s magnetic North but quite unreliably, as it is very much sensitive with the magnetic field and, therefore, metals and can provide variable error due to their magnetic field effect, which limits its use in indoor spaces.

Very limited work has been done using single magnetometers for gait analysis. While locating on the shank Based on locating of a single magnetometer, For step count, the error is around 5%,while locating it on the shank [80] and 0.94% while it is located on right foot [81]. No work is found for estimating step length and gait speed using this type of sensor.

4.1.4.4 Electrogoniometer

Electrogoniometer is used to continuously measure the angles of joints, i.e. ankles, knees hips etc. Optoelectronic, potentiometers and flexible strain gauges are three common types of electrogoniometers. Among them, strain gauges are the most popular ones. While located on two segments of a body spanning a joint, the strain gauge flexes with change of angle of the joint, as shown in Figure 4.5 (b). Its electrical resistance is changed and produces an output voltage proportionally to the flex angle. The output voltage is used to measure the angle of the joint. The strain gauges are light, flexible, portable and adapt well to different body segments. Electrogoniometer could be uniaxial or biaxial [82].

At present, commercial electrogoniometers are available to measure human posture, spinal motion and joint angle between body segment changes [58]. They also could be used to asses gait parameters [83]. The average error of the device is 0.5^0 for small change of angle (± 30°) and 2.4^0 for large change (± 100°) [84].These sensors are somehow obtrusive due to the cables needed.



(a) (b)

Figure 4.5: Flexible goniometer[7]

[7]http://www.freescale.com/webapp/sps/site/overview.jsp?code=784_LPBB_ELECGNIOMTR

4.1.4.5 Pressure sensors

This type of sensor measures force applied on it by converting it into an electrical signal. In gait analysis, force sensors are used to measure ground reaction forces (GRF) beneath a particular area of the foot. The most widely used force sensors are piezoresistive, capacitive and piezoelectric. Pressure sensors are widely used in gait analysis by integrating them into the insole of a shoes such as those developed in [85]. Figure 4.6 shows a typical force sensitive sensor with a schema of an insole of GaitShoe [85] with the pressure sensor inside.

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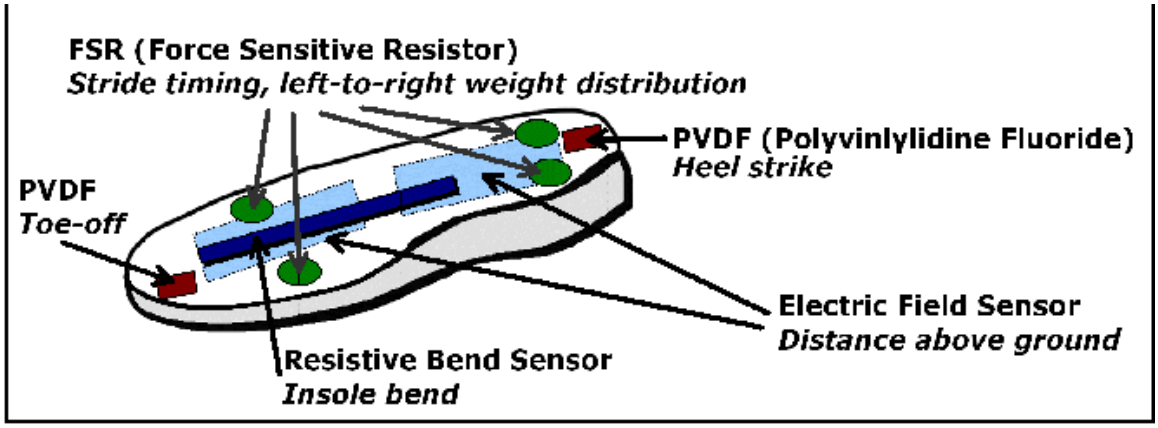

Figure 4.6: (a) Force sensitive sensor (FSR), (b) schema of GaitShoe insole with the FSR sensor inside mentioned as force sensitive resistor

4.1.5 Summary

Table 4.1 shows a comparison between the technologies presented for gait analysis. Non-wearable systems like optical motion capture systems, image processing and instrumented walkway are highly accurate and allow analyzing multiple gait parameters simultaneously. However, they are expensive, and have space limitation. They cannot be used to analyze real life gait outside the instrumented setup. In contrast, MEMS based

wearable sensors allow cost effective and non-intruding methods that could be used during daily life of human beings. The only limitation is that they are restricted to power consumption due to limited battery duration. With the evolution of technology, the power consumption of MEMS sensors is gradually decreased. For example, the sensor device used in this thesis could be used for 36 hours with a single fully charged battery [24]. In the field of medical application, it is seen that inertial sensors, specially accelerometers and gyroscopes, are mostly used for gait analysis [3].In next section, the application of inertial sensors in the context of PD is discussed.

Table 4.1: Comparison between existing gait analysis systems

Technology	**Application**	**Error [ref]**	**Cost**	**Ease of use**
Optical motion capture systems	Spatio-temporal parameter of gait, Postural transition, Joint angles etc.	Error around 1mm [53]	High	Complex, need expert personal, space limitation,
Image processing	Human tracking and identification. Gait speed, step time, step length	Average error is 4.2% in gait speed, 5.4% in step time and 6.6% in step length [57]	Medium to low	Complex analysis and algorithm. Only for indoor measurement.
Instrumented walkway systems	footfall, gait cycle, walk	0.038m to 0.048m in step length and 0.05s to 0.04s in step time	Medium	Portable and easy to use. Has space limitation and suitable only for indoor

		[59]		measurement.
Accelerometer	Posture detection Step detection Step length Gait speed	-0.04±4.15 m error in step length	Lowest	Wearable, light, flexible, portable and easy to locate on the body and to analyze the data.
Gyroscope	Stride time Stance time Swing time Step time Step length and Gait speed	3.03% [77] 10.5% [77] 29.55% [77] 11.4% [77] -0.08±0.66 (m) -0.04±0.38 (m/s) [86]	Lowest	Wearable, light, flexible, portable and easy to locate on the body and to analyze the data.
Magnetometer	Step count, orientation of body	5% error in step count	Lowes	Sensible to ferromagnetic materials
Goniometer	Joint angle Step detection	0.4^0 [84]	Low	Wearable, portable and easy to analyze the data. Limitation is that they are not connected, need absolute position of the body for compute the joint angle
Pressure sensor	GRF measurement Step detection	2.9% in detecting IC and 1.5% in	low	Easy to wear, simple algorithm but highly

	Gait phase detection	detecting TC [87]		nonlinear response

4.2 Inertial sensors in the context of PD

Gait analysis by means of inertial sensors may be performed based on one or more inertial sensors located on different part of body. Though gait is directly related to the lower extremities of human body, in a previous work [3] it is showed that sensors are not only placed on heels, ankles instep of foot, shanks, etc, but also on waist, chest, spine etc. and sometimes on head and ear also. In all these works, inertial sensors are used to measure either the spatio-temporal parameters of gait, gait balance, stability etc. during walking.

Inertial sensors are also used to monitor activities and symptoms of Parkinson's disease, such as tremor, bradykinesia or dyskinesia, by placing one or more sensors on different part of body. Table 4.2 shows some examples of sensor placement on different part of bodies for gait and activity analysis of PD patients. From the table, all the symptoms/parameters but tremor and hypokinesia, related to PD could be detected from lateral side of waist using a single triaxial accelerometer. To identify gait events, step length, gait speed and FoG, sensors are placed on lower part of body. Some researchers located sensors on each limbs or foot but they require more than one sensor. Waist is the location from where; the gait parameters and FoG could be identified using a single accelerometer. Dyskinesia and bradykinesia also could be detected using a single accelerometer worn on waist or multiple accelerometers on different part of body. Lateral side of waist is also applied to detect other parameters like postural transition, turning, body position and walking direction. Some researchers located sensors on arm to identify tremor and hypokinesia. As most tremors occur in the hand, it is the only location where sensor could be located to identify the symptom.

From the literature analysis of Table 4.2, we could conclude that locating a single accelerometer on lateral side of waist is enough to identify all the symptoms of PD except

tremor. From previous study [24], the location could also be used for long term monitoring of PD patients during daily life. Motor states could be assessed on a continuous basis for long time without disturbing the patient's daily life activities.

Table 4.2: Summary of sensor placement in the field of Parkinson's disease

Sympt./parameter	Location	Types of sensor	Ref.
Gait event	Lateral side of waist	One triaxial accelerometer	[66]
	Lower back of waist	One triaxial accelerometer	[88]
	Front center of waist	One triaxial accelerometer	[89]
	Each shank	two uniaxial gyroscopes	[1]
	Instep of Shoes	One triaxial accelerometer and gyroscope	[78]
	Shoes	One triaxial accelerometers, and biaxial gyroscopes, 4 force sensors, 2 bi-directional bend sensors, 2 dynamic pressure sensors, electric field height sensors	[85]
FoG	Lateral side of waist	One triaxial Accelerometer	[90]
	Ankle, thigh and lower back of Waist.	Five triaxial Accelerometer	[91]
	Ankle	2 IMU with triaxial accelerometer, gyroscope and magnetometer	[92]

	Ankle	2 MEMS device with triaxial accelerometer, gyroscope and magnetometer	[93]
Step length	Lateral side of waist	Triaxial accelerometer	[66]
	Each thigh and shank	4 uniaxial gyroscopes	[1]
	Instep of Shoes	three-axis accelerometer and gyroscope	[78]
	Shoes	3 axial accelerometers, and 2-axial gyroscopes, 4 force sensors, 2 bi-directional bend sensors, 2 dynamic pressure sensors, electric field height sensors	[85]
Gait speed	Lateral side of waist	Triaxial accelerometer	[66]
	Each thigh and shank	4 uniaxial gyroscopes	[1]
	Shoes	3 axial accelerometers, and 2-axial gyroscopes, 4 force sensors, 2 bi-directional bend sensors, 2 dynamic pressure sensors, electric field height sensors	[85]
	Instep of Shoes	three-axis accelerometer and gyroscope	[78]
	Arm	2 uniaxial accelerometer	[94]
	Chest and thigh	2 uniaxial accelerometer	[95]
	Both thigh, left wrist, both	6 accelerometers	[96]

	shoulders and chest		
Tremor	left and right forearm	Gyroscope	[97]
	Each forearm	2 MEMS device with 3D accelerometer, gyroscope and magnetometer	[93]
	Wrist	One 3 axial accelerometer	[98][99]
	Forearm, upper arm, thigh, shank (below knee)	8 accelerometer	[100]
	Both thigh, left wrist, both shoulders and chest	6 accelerometers	[96]
Dyskinesia	Lateral side of waist	3 axial Accelerometer	[18]
	Both upper limbs	2 gyroscope	[101]
	Accelerometers on ankle, wrist, chest, and front of waist. Gyroscope on chest and waist	6 accelerometers and 2 gyroscope	[102]
	Arm, leg and trunk	8 accelerometer	[103]
	Both thigh, left wrist, both shoulders and chest	6 accelerometers	[96]
	Forearm, upper	8 accelerometer	[100]

	arm, thigh, shank		
Bradykinesia	Each forearm	Gyroscope	[97]
	Arm	2 uniaxial accelerometer	[94]
	Both thigh, left wrist, both shoulders and chest	6 accelerometers	[96]
	Forearm, upper arm, thigh, shank	8 accelerometer	[100]
	left and right forearm	Gyroscope	[97]
	Lateral side of waist	Triaxial accelerometer	[104]
	chest and thigh	2 uniaxial accelerometer	[95]
	Ankle	2 MEMS device with triaxial accelerometer, gyroscope and magnetometer	[93]
Posture, gait direction, turning,	Lateral side of waist	Accelerometer	[105]
	Spine	MEMS device with triaxial accelerometer, gyroscope and magnetometer	[93]
	Chest and thigh	2 uniaxial accelerometer	[95]
	Shoes	three orthogonal accelerometers, and three orthogonal gyroscopes, four force	[85]

		sensors, two bi-directional bend sensors, two dynamic pressure sensors, as well as electric field height sensors	

4.3 Proposed sensor location

According to the literature, waist is considered the best position in terms of information to estimate gait parameters based on a single sensor [26][27][106]. Comparing fifty papers on gait analysis using wearable sensors in the field of healthcare applications Zhang et al. [3], also showed that the most used sensor location is pelvis and waist to analyze gait. Sensors used to measure pelvic movement and orientation are usually landmarked according to three easily located points: the iliac crest (ASIS) at each side of the hips, and the joint between the 4^{th} and 5^{th} lumbar vertebrae in the spine (L4-L5), as seen in Figure 4.7. These three points are useful in two ways; they are easily found with only a little practice, and they allow for a simple estimation of the geometric center of the pelvis – this being the point defined by the intersection between a line connecting the two lateral markers and the perpendicular line that passes through the L4-L5 point. This allows for relatively easy transference of sensor data to an extrapolated human model.

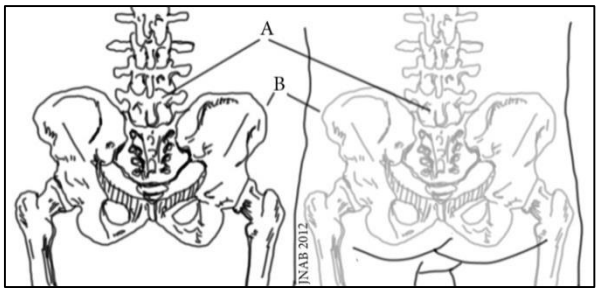

Figure 4.7: The L4-L5 joint (A) and the ASIS (B)

The L4-L5 joint is a point in the spine, so it is found in the horizontal middle of the back. More specifically, it is the joint where the spine starts to bend when the participant leans forward, deeply. To find the point, one can place a hand on the spine at the hip, and find a bony protuberance. This will be the crest of one of the vertebrae. Keeping their feet and

legs steady, and to bend slowly forward, the participant can trace the lowest crest that rises a lot. This is the 4th lumbar vertebra (L4) that rests above the 5th lumbar vertebra (L5), which can move only a very little compared to the pelvis.

Many studies show that valuable information for gait analysis is found by placing an accelerometer on the waist near the joint between the 4th and 5th lumbar vertebrae in the spine (L4-L5) [26][27]. However, this location is impractical while wearing a device during daily life because it is uncomfortable, may hurt the patient and could be damaged during sitting on a chair or lying on the bed. It is also hard for elderly people with motor complication, to properly place the device on this location by themselves. A more practical choice could be to locate it on any lateral side of waist, near Anterior Superior Iliac Spine (ASIS), which has been reported to be a more user-friendly and comfortable position by Mathie et al. [106]. The location is established from a study in the CETpD lab that was carried out earlier to this thesis. The main goal of the position was to detect different symptoms and motor states of PD patients. At the same time, the position should also enable to wear the sensor in a comfortable way without interrupting daily life activities. Ten PD patients were recruited for the study. They wore the movement sensors in 5 (five) different positions: above anterior superior iliac spine (ASIS), on both shanks and on insteps of both feet. Patients chose the location they felt more comfortable and less disturbing for the daily life. All patients chose the lower part of the iliac crest (ASIS), which is the upper border of the pelvis major bone, in a completely lateral position to the trunk.

The ASIS points are easily found by having the participant trace their fingers along the bony protrusion at either side of their hips. Once they have found the crest (high point) of the ilium bone (the big hipbone), one simply drops below the crest by 2-5 centimeters and aligns the sensor horizontally with that spot. Done properly, these measures affix the sensors so that they move with the pelvis, rather than with the surrounding soft tissues.

Locating an accelerometer on the lateral side of waist has been shown valuable in monitoring other symptoms or activities in Parkinson's disease patients (Table 4.2). For instance, in [90] a waist accelerometer was used to detect FoG. Regarding posture

transitions, the same sensor position used in this thesis was shown to be able to determine the posture of PD patients based on an accelerometer [105]. Similarly, this position enables a single sensor to determine the presence of most dopaminergic-induced dyskinesia, according to a previous study in 20 patients [18].

From the literature review and the given result of the study, the sensor position is established as the left lateral side of the waist. This position has been used to locate the inertial sensor in all the trails with healthy person and PD patients.

The ASIS point has some limitations compared to the lower back location since signals obtained from the lateral side greatly differ from those gathered from the lower back.Figure 4.8(a) and (b) shows the acceleration signal from lower back (around L4-L5) and left lateral side (near ASIS) of waist. We can see that the symmetry among left-right steps is lost in signals obtained from the lateral side. Signals from the left leg are more prominent than those from the right leg, which impose new restriction on step detection and step length estimation.

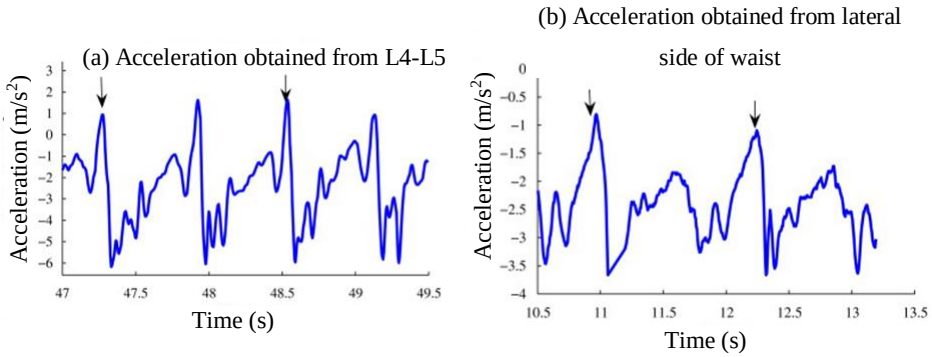

Figure 4.8: Acceleration signals obtained from (a) L4-L5 point of waist and (b) left lateral side of waist.

4.4 Sensor device

The sensor used here to obtain the acceleration measurements is an inertial system (9x2 version 6) developed by the CETpD laboratory of UPC, Spain. The prototype is composed of a 3-axis accelerometer (LIS3LV02DQ, ±6g range), a 3-axis gyroscope (IDG650+ISZ650, $\pm 20000^0$/s range) and a 3-axis magnetometer

(HMC6042+HMC1041Z, ±6Gauss range). The inertial sensors with CPU, µSD card and a 3.7V lithium-ion battery of 1130 mAh are encapsulated in a 77x37x21 mm white case. A Bluetooth device is also connected with the system for wireless communication. To optimize the energy consumption and control the battery there is also a system included and it interacts with user by two LEDs that indicate the battery level and the current state. The operational frequency of the device is 200Hz.

The device was affixed to a neoprene belt and placed on left lateral side of the waist near ASIS as shown in Figure 4.9. The position enables to match each axis of accelerometer with human body movement during straight-line walk i.e. X-axis (anterior or frontal acceleration), Y-axis (vertical acceleration) and Z-axis (lateral acceleration).

Figure 4.9: The inertial system prototype (9x2, Version 6) positioned in a neoprene belt

Though the device can be used to record acceleration, angular velocity and magnetic field, in this thesis only accelerometers are used. The triaxial accelerometer is used to measure acceleration up to 6 g (1 g = 9.81 m/s^2), with 2.94 mg sensitivity and 2% maximum nonlinearity on the full-scale range. The operating temperature of the accelerometer is from -40ºC to +85ºC and its sensitivity change vs. temperature is of 0.025%/º C. Assuming a change of 30º C, it would modify the acceleration measurements up to 0.75%, which is considered negligible, wearing the sensor for longer period of time.

The device is being used in the field of PD for gait analysis [66], symptoms identification [18][90][104], for posture identification [105], for motor state detection [18]. It is also used for long term monitoring and to enhance the treatment of PD [12][24][107].

4.5 Conclusion

MEMS based wearable sensors are cheap, small in size, low power, convenient to use and efficient to provide adequate information for gait analysis. They are now widely used in both clinical and biomechanical laboratories. These are the most flexible and low cost systems that could be used to analyze gait during daily life activities. In the studies with PD, accelerometers are commonly used for long term monitoring, identifying symptoms and motor state to optimize treatment of the patients [12][18][66][90][99][104][105]. It is also found that a triaxial accelerometer locating on the lateral side of waist could be used to measure the gait parameters for detecting motor status. The location is also suitable to measure the other symptoms of Parkinson's disease.

Chapter 5 State of the art on step detection methods and step length estimators based on inertial sensors

5.1 Step detection methods

Step is identified as the instant when the reference leg first touches the ground. For most of the step length estimators, detection of step events is required. It is also required in order to estimate the gait speed. Wearable sensors, especially accelerometers, are the most frequently used sensors to detect steps by locating them in different parts of human body. In this chapter, step detection methods from the literature are described in the following subsections. They are applied to the proposed sensor location (lateral side of waist) and their performances are compared. The results are discussed in chapter 8 and chapter 9.

5.1.1 Peak-detection and template-matching methods

The peak detection methods consider that the local maxima (peaks) of the inertial signal correlate to the ICs of a foot. A local maximum is the point where the magnitude of the signal is higher than proceeding and following points.

- **Pan-Tompkins method**: The Pan-Tompkins method is originally used in electrocardiography (ECG) signal to detect QRS complexes. This method is used to detect steps in accelerometer signals from a left foot mounted accelerometer [108]. The anterior-posterior signal is preprocessed by means of a band pass filter to reduce the noise. The slope of a peak is obtained using a differentiator. The peaks are then intensified by means of a squaring

operation and an integration process. Finally, an adaptive threshold is used to search the peaks that correspond to the steps. Figure 5.1 shows the schematic diagram of the method.

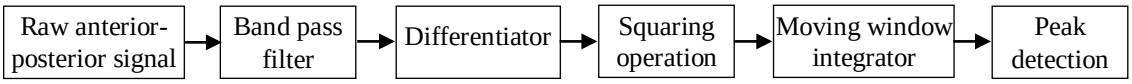

Figure 5.1: Block diagram of a Pan-Tomkins method [108]

- **Template-matching method:** Ying et al. [108] proposed this method by locating an accelerometer on the left foot to detect steps. In this method, the accelerometer single is first split into several data blocks of 10 seconds. They are then filtered by a low pass filter with cutoff frequency of 20 Hz. Steps are detected as peaks by comparing adaptive templates in the signals.

- **Dual-axis peak-detection method:** This method recognizes the steps as the negative peak when both anterior-posterior and vertical acceleration signals coincide. The signals are preprocessed by a series of filters as shown as a schematic diagram in Figure 5.2.The method was proposed by Ying et al. [108] placing the accelerometer on the left foot of the subjects.

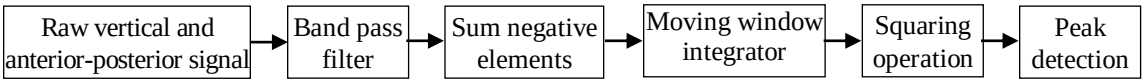

Figure 5.2: Block diagram of a Pan-Tomkins method [108]

- **Autocorrelation process:** The autocorrelation process is proposed by Moe-Nilssen et al. [109] locating an accelerometer on lower back of waist. The autocorrelation coefficient can be calculated by Eq. (5.1).

$$AC(m) = \frac{1}{N + |m|} \sum_{i=1}^{N-|m|} a_i a_{i+m} \tag{5.1}$$

where a_i(i=1,2,…,N) is the is the acceleration data, N is the amount of samples and m is the time lag phase shift parameter (m=-N, -N+1,….0,1,2,…N).

A peak is found in *AC(m)*, when the time lag m is equal to the periodicity of the acceleration a_i. Figure 5.3 shows an example of an autocorrelation obtained from verticalacceleration measured at laterals side of waist. Peaks are detected after every zero phase shift.

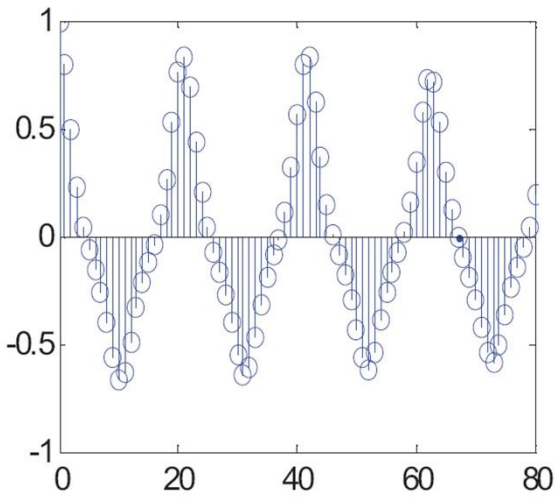

Figure 5.3: Example of autocorrelation obtained from the signal from left lateral side of waist [110].

5.1.2 Jiménez's algorithm

Jiménez et al. [81] detected step locating the accelerometer on the right foot. To detect steps, the magnitude of acceleration a_i is first calculated and, then, the local mean acceleration $\bar{a}_i$ is computed by using the following equations

$$a_i = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2} \tag{5.2}$$

$$\bar{a}_i = \frac{1}{2w+1} \sum_{j=i-w}^{i+w} a_j \tag{5.3}$$

where a_x, a_y and a_z are the acceleration values at time i towards horizontal, vertical and lateral direction and w is the averaging window of size 15 samples.

The local acceleration variance σ_i are then computed from local mean acceleration ($\bar{a}_i$) to highlight the foot activity and to remove gravity using Eq. (5.4)

$$\sigma_i^2 = \frac{1}{2w+1} \sum_{j=i-w}^{i+w} (a_j - \bar{a}_j)^2 \tag{5.4}$$

Two threshold points were empirically defined. Swing phase were then detected when local acceleration variance is greater than the first threshold (2m/s^2) and stance phase were detected when it is smaller than the second threshold (1 m/s^2). They proposed to detect the steps at the end of swing phase and beginning of stance phase. The percentage error in detecting steps is 0.1%.

5.1.3 Orientation Free Adaptive Step Detection (OFASD)

The OFASD method is proposed by Huang et al. [111] that uses triaxial acceleration signal from an accelerometer located on five different location close to body (left and right shorts pocket, breast pocket, in a bag over right shoulder and in a rucksack across back. In this method the magnitude of acceleration a_i is first computed using Eq.(5.2). Noise is reduced from a_i by using a derivative function DM_i as Eq.(5.5). The absolute value of derivative magnitude DM_i, AM_i is then obtained as follows:

$$DM_i = a_{i+1} - a_i \tag{5.5}$$

$$AM_i = abs(DM_i) \tag{5.6}$$

Steps were detected by detecting the peaks in AM. To avoid false positives and false negatives, an empirically defined adaptive threshold values are also used.

5.1.4 Sliding window summing technique (SWST)

Shin et al. [112] proposed a method that employs a sliding window summation and acceleration differentials to detect steps from an accelerometer located on lateral side of

waist. The magnitude of acceleration a_i is first calculated using Eq. (5.2). Sliding window summation technique (SWST) is then implemented using following equation:

$$SWST = \sum_{t=i-w+1}^{i} a_t \tag{5.7}$$

where w is the window size fixed to 0.2s interval. In the experiment, size of w is set 40 as the operating frequency is 200Hz. Noise and effect of gravity were reduced using an acceleration differential technique that is

$$a(k) = SWST(k+w) - SWST(k) \tag{5.8}$$

Step was detected from the zero crossing points of the jerk signal.

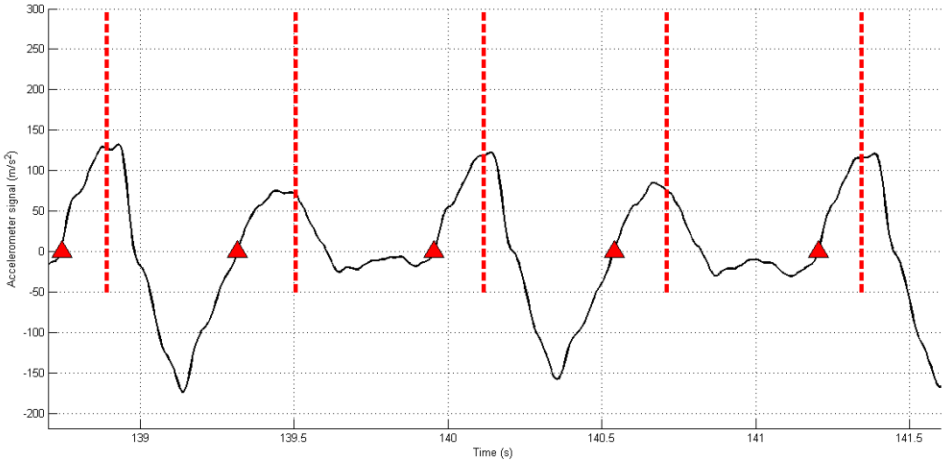

Figure 5.4: Step detected using sliding window summing technique. The red triangles are five detected steps and the dotted lines are the actual steps (based on a previously synchronized video-labeling).

5.1.5 Threshold based approach (CETpD)

This method is developed in CETpD lab [17]. Signals from a belt worn accelerometer located on left lateral side of waist are used to detect steps. In this case, the forward

acceleration is filtered by 2nd-order low-pass Butterworth filter with 15 Hz cut off frequency and the lateral acceleration is filtered by 4th order low pass Butterworth filter with 0.8 Hz cut of frequency.

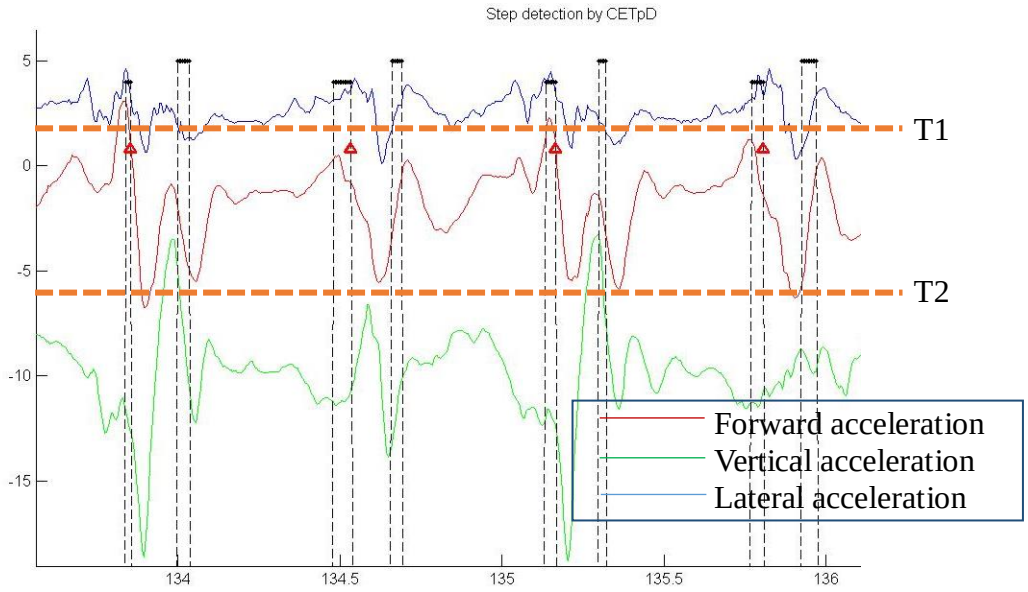

Figure 5.5: Step detection using Threshold based approach (CETpD). The red triangles are the detected steps and the dotted lines are the actual steps (based on a previously synchronized video-labeling).

Mean acceleration $\bar{a}_x$ and standard deviation σ_x are then calculated from the forward acceleration (X). Using $\bar{a}_x$ and σ_x, three thresholds T1, T2 and T3 are set as follows

$$T1 = \bar{a}_x + 0.7 * \sigma_x \tag{5.9}$$

$$T2 = \bar{a}_x - 0.7 * \sigma_x \tag{5.10}$$

$$T3 = 10.15 \tag{5.11}$$

Peaks are detected from the forward acceleration by finding the local maxima values. For each peak greater than T1, local minimum values of lateral acceleration are detected. Steps

are identified to start from a local minima of forward acceleration smaller than T2 until another one, while between them the mean magnitude acceleration should be greater than T3.

5.2 Step length estimation methods

Step length is defined as the traverse distance between two successive initial contacts of lower extremities. Step length is varied between people based on their age, weight, height, muscle strength etc. There may also differences between left and right step lengths of same person. Wearable sensors, especially accelerometers, are a practical and the most frequently used option to estimate step lengths in daily life. Step lengths are estimated by locating a single or multiple sensor in different part of the body [3]. As in this thesis, the sensor location is being fixed on lateral side of waist (Section 4.3), this section explains six step length estimators that are used to estimate step length by locating an accelerometer at waist. First 4 methods presented were developed considering the sensor position near L4-L5 position, close to the center of mass (CoM) of human body [113]. The 5th method used the sensors of mobile phone locating it in the pocket of users' trouser. In method 6, the sensor was placed on the lateral side of waist, same as our proposed position

The first two methods are based on a biomechanical model. The trajectory of the body's center of mass (CoM) is expressed by means of an inverted pendulum model to demonstrate the displacement of lower trunk during walking [113] considering user's leg as an inverted pendulum. The center of mass is the imagery point where the mass of a geometrical shape is concentrated. For a regular geometrical shape it is determined at the geometric center of it. But the shape of human body is irregular and changing. Their CoM is also varying because of their weight, height and physical structure. Due to all of the parameters, it needs direct measurement to find the CoM of a human body. Whittle [39] stated that the approximate position of CoM is just in front of the lumbosacral joint while standing, which moves with the movement of the body. By mentioning the CoM, Zijlstra and Hof [113] suggested the lumbosacral point from where significant rotation of upper and lower trunk can be observed. So, instead of mentioning this point as CoM, center of rotation (CoR) would be more appropriate here.

The remaining methods are a kind of parametric methods as they use variation of accelerometer data, gait speed, walking frequency or other parameters to estimate step length.

5.2.1 Zijlstra's method

The most common approach to measure the average step length is by considering human gait as an inverted pendulum model. Zijlstra et al. [113] expressed the vertical excursion of CoR of human body during walking by means of a simple inverted pendulum model while considering the stance leg as a rigid body fixed to the ground as showing in Figure 5.6. They assumed that there is a fixed relationship between the step length and the vertical displacement of the CoR. Locating an accelerometer around L4-L5 (close to CoR), Zijlstra et al. [71] provided mathematical relation between the step length and the vertical displacement of the CoR of human body as follows:

$$SL_{Zijlstra} = 2K\sqrt{2hL - h^2} \tag{5.12}$$

where, *K* is the individual correction factor, *L* is the leg length of individual from sensor position to heel and *h* is the vertical displacement of CoR during each step. Value of *h* can be computed as the range of double integrating vertical accelerations between the instants of two consecutive initial contacts of leg.

$$h = \iint_{1}^{n} a_n dtdt \tag{5.13}$$

where a_n is the vertical acceleration of the CoR during forward movement and *n* is the number of acceleration samples.

Before the integration process, vertical acceleration was first low pass filtered by a fourth-order zero lag Butterworth filter with 20Hzof cut-off frequency, to remove jittery noise. Then the double integration of vertical acceleration between the instants of two consecutive ICs were performed to estimate the vertical position of the waist during this period. Vertical position was then high pass filtered by a fourth-order zero lag

Butterworth filter with cut-off frequency of 0.1 Hz to avoid drift error induced by integration. Finally *h* was computed as the difference between the maximum and minimum of CoR positions.

K is obtained from a training session of each individual based on the ratio of mean reference ($SL_{reference}$) and mean estimated step length ($SL_{estimated}$) of a course of reference.

$$K = \frac{mean(SL_{reference})}{mean(SL_{estimated})} \tag{5.14}$$

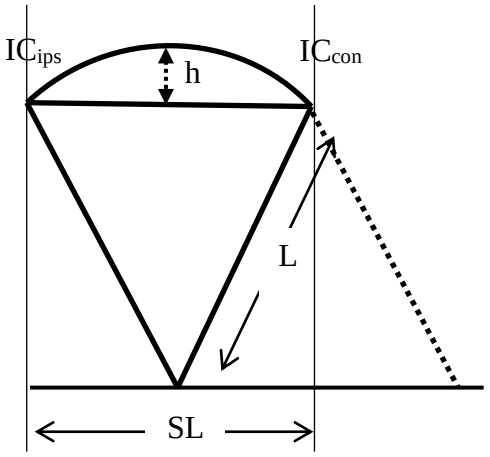

Figure 5.6: The trajectory of CoR according to the inverted pendulum model. IC_{ips} and IC_{con} stands for ipsilateral and contralateral initial contact (IC) of foot respectively, SL stands for step length between these ICs. *L* and *h* are the leg length and vertical displacement during one step.

The advantage of this method is that it could be personalized by including the leg length and individual correction factors, although the correction factor needs a training session. Zijlstra also proposed a generic correction factor of 1.25 to use instead of individual correction factor to avoid time consuming training sessions [114].

5.2.2 Gonzalez's method

Gonzalez et al. [115] modified the previously described inverted pendulum into a more complex model as shown in figure 5.7. They considered the forward displacement of the

CoR as related to the foot size of the person during double support phase (DSP) and an inverted pendulum during single support phase (SSP). So the total step length was considered to be the sum of the displacement in both stages as follows:

$$SL_{Gonzalez} = SL_{ssp} + SL_{dsp} = 2\sqrt{2h_{ssp}L - {h_{ssp}}^2} + Cl_{foot} \quad (5.15)$$

where SL_{ssp} and SL_{dsp} are the step length during the swing phase (SSP) and the double support phase (DSP) respectively. h_{ssp} is the vertical displacement of CoR during single support phase, L is the leg length of individual from sensor position to heel, l_{foot} is the length of individual´s foot and C is a fixed proportional constant.

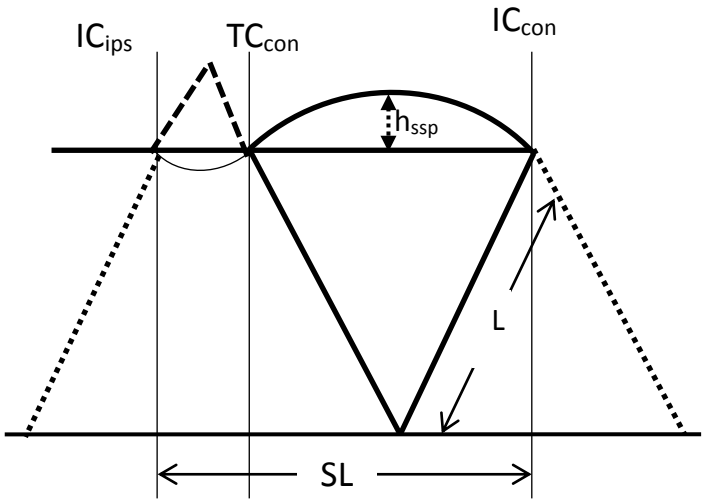

Figure 5.7: Modified pendulum model. The trajectory of CoR according to the modified inverted pendulum model. TC_{con} is the terminal contact of contralateral foot. h_{ssp} is the vertical displacement during single support phase.

C was determined by considering that the forward displacement during double stance is proportional to the foot length l_{foot}. C has been fixed as 0.83 by Han et al. [116] and 0.67 by Schmid et al. [117]. The vertical displacement (h_{ssp}) of CoR is computed as the range

of double integrating vertical acceleration between the instance of terminal contact (TC) and initial contact (IC) of reference foot (single support phase) following Eq.(5.13).

The advantage of this method is that it does not need any complex calibration constant. So, no previous training session is needed. The displacement during double stance is dependent on the predefined constant which needs to be identified carefully.

5.2.3 Weinberg's method

Weinberg [118] considered step length as a function of the difference between maximum and minimum vertical acceleration of waist during one step. They proposed to estimate step length using the following equation:

$$SL_{Weinberg} = K \sqrt[4]{\max(a_y) - \min(a_y)} \tag{5.16}$$

where, max(a_y)and min(a_y) are the maximum and minimum values of vertical acceleration, respectively, during each step and *K* is the correction factor.

The value of *K* is measured for each individual based on the ratio between average reference and anticipated step length of a course of reference during training phase, as in Eq. (5.14). In this method, acceleration signals are obtained from a 3-axial accelerometer located on the back part of waist near CoR. Steps are defined using the IC time events. The vertical acceleration is low pass filtered by a fourth-order Butterworth filter with 3Hz cut-off frequency. Finally, step lengths are estimated using the given equation. The error of estimating step length is ±8% between subjects with different leg length [118].

This method again needs the calibration constant *K* following the same process as Zijlstra's method, but does not need any integration and, thus, avoids drift errors.

5.2.4 Martin's method

Martin et al. [119] proposed a method to estimate average gait speed by means of wavelet transform average step length is estimated from the typical relationship between step length and gait speed (Eq. (3.1)). In their work, they applied the continuous wavelet transform to the acceleration signals obtained from an accelerometers located on waist

near L4-L5 region. They analyzed the relationship between the kinetic energy of different walking patterns of human and the energies of the wavelet transform detail coefficient to infer the speed.

Steps were recognized by means of two consecutive negative-to-positive transitions of the resultant signals from the wavelet analysis. Four novel formulations were proposed, which are presented as $Speed_1$, $Speed_2$, $Speed_3$ and $Speed_4$.

$$Speed_1 = \frac{1}{2}\sqrt{\sum_{i=1}^{5}\frac{WE_{di}}{i}} \tag{5.17}$$

$$Speed_2 = \frac{1}{2}\sqrt{\sum_{i=2}^{5}\frac{WE_{di}}{i}} \tag{5.18}$$

$$Speed_3 = \frac{1}{2}\sqrt{\sum_{i=1}^{5}\frac{WE_{di}}{i} + WE_{d6}} \tag{5.19}$$

$$Speed_4 = \frac{1}{2}\sqrt{\sum_{i=2}^{5}\frac{WE_{di}}{i} + WE_{d6}} \tag{5.20}$$

where, WE_{di} is the weighted energy of the wavelet transform detailed coefficients at level i from J decomposition levels of wavelet transform with n number coefficient:

$$WE_{d_i} = \begin{cases} \frac{E_{di}}{\sqrt{2}(J-i)} & i = 1, 2. \ldots J-1 \\ \frac{E_{di}}{\sqrt{2}} & i = J \end{cases} \tag{5.21}$$

Finally, they measured the step length as:

$$SL_{Martin\ (n)} = \frac{Speed_n}{Step\ Frequencies} \tag{5.22}$$

The benefit of using this method is that it does not need any biomechanical model and could be used in different walking speeds and patterns. In their study, the authors showed that on estimating average step length in different walking patterns, the average error of $Speed_1$, $Speed_2$,$Speed_3$and $Speed_4$ are10.9%, 12.0%, 11.6% and 10.3% respectively.

5.2.5 Bylemans' method

Bylemans et al. [120] developed an empirical solution to estimate the step length using the accelerometers of mobile phone placed in the user´s right trouser pocket. The advantage of this method is that it is orientation free. However, the method is complex. The step length estimation method is as follows:

$$SL_{Bylemans} = 0.1^{2.7}\sqrt{a_{av}\sqrt{\frac{K}{\sqrt{\Delta t * a_{peak-diff}}}}} \tag{5.23}$$

where, a_{av} is the average vertical acceleration between initial contact of ipsilateral foot and contralateral foot, Δt is the duration of the step in ms and $a_{peak\text{-}diff}$ is the range of vertical acceleration during Δt. K is a calibration constant that is set for individual subject with the following equation:

$$K_{individual} = (K_{default})^{\frac{Mean(SL_{real})}{Mean(SL_{estimated})}} \tag{5.24}$$

Following several trials, the authors mentioned that the value of $K_{default}$ was set to 750 for men and 630 for women.

5.2.6 Shin's method

Shin and colleagues [112] proposed a method to estimate the step lengths using optimal parameters based on a linear combination of walking frequency and the variance of the accelerometer signals during one step. The advantage of this method is that it uses a

regression model and they could be used in real time. The sensor was placed on lateral side of waist.

For each detected step the walking frequency f and local acceleration variance σ^2 are calculated using the following equations

$$f = \frac{1}{t_k - t_{k-1}} \tag{5.25}$$

$$\sigma_k^2 = \frac{1}{n-1}\sum_{k=1}^{n}(a_k - \bar{a})^2 \tag{5.26}$$

where, $\bar{a}$ is the mean acceleration during one step, n is the number of steps and t_{k-1} and t_k are the time of the detected steps. The step length were then calculated as

$$\mathrm{SL}_{Shin} = \propto.\mathrm{f} + \beta.\sigma^2 + \gamma \tag{5.27}$$

where α, β are the regression walking parameters and γ is a constant that are learned in a training phase.

5.3 Gait speed estimation methods

Gait speed is the walking pace of a person. It is defined as the traverse distance in a unit time. Gait speed of a person varies with the change of their step length or walking frequency or both. It also differs due to age, muscle strength and other health related parameters. As accelerometers are more frequently used to detect steps and to estimate step length, they are also used in estimating gait speed in daily life.

In order to estimate gait speed, after detecting each step, step duration is also measured. Gait speed is then estimated in the same way by all methods described in previous section, except for Martin's method. The majority of these methods estimate walking speed as the obtained step length divided by step duration as follows:

$$speed = \frac{SL_{estimated}}{step\ duration} \tag{5.28}$$

This way, among the six step length estimation methods described in previous section (section 5.2), only Martin's method [119] is used to directly estimate gait speed by applying continuous wavelet transform. The four novel formulations (*Speed$_1$, Speed$_2$, Speed$_3$ and Speed$_4$)* proposed by Martin et. al. [119] are described in section 5.2.4.The performance of the four formulations varies between walking patterns. On average, the error on estimating gait speed is 8%. In their study, the authors showed that to estimate gait speed, *Speed$_1$* is provides lower error for only medium speed with short step lengths (-1.1%) and slow speed with long step lengths (-2.4% error). The error of *Speed$_2$* are lower in fast speed with long (6.3%) and short (4.1%) step length. *Speed$_3$* shows error of -1.6% , -2.5% and -6.5% respectively in fast speed with normal step length medium speed with long and normal step length. Finally, *Speed$_4$* has lower error in only medium speed with short step length (-0.9%). For slow speed with normal and short step length no one is found appropriate, though the lowest error is shown by *Speed$_1$* for short step length (-20.7%) and by *Speed$_2$* for normal step length (-15.3%) they are not sufficient to employ them in this two walking pattern.

5.4 Discussion

In this section, existing step detection methods that employ a single accelerometer located on different part of body are discussed. Existing step length and gait speed estimators developed for the signals obtained from a single waist mounted accelerometer are also discussed. In the following subsections, limitations of step detection methods, step length and gait speed estimators are presented.

5.4.1 Limitation of existing step detection methods

The Pan-Tompkins method and dual-axis peak-detection method were implemented in a previous study [121] with the accelerometer signals from waist of both healthy and mobility impaired persons and the error rate was 30% and 28% respectively for Pan-Tompkins method and 10% and 62.1% respectively dual-axis peak-detection method.

They were also implemented to apply on the signals from left lateral side of waist of three healthy person. Because of variable speed and walking pattern during normal walking, there was more than one peak during a single step, which made harder to detect them. So the Pan-Tompkins method overestimates the steps with an error rate of 39.3% while it is 18% for dual-axis peak-detection method. Because of the high error rates, both of these methods are not found suitable to be applied for step detection.

Template-matching method is tried to implement with the signals from the said location of three healthy persons. As, there is no symmetry among left-right steps in signals obtained from this location (Fig. 4.8), and people does not have constant walking speed and patterns during normal walking, no template could be identified for detecting steps and could not be put in a list for further analysis.

In a previous study [110], the autocorrelation process was implemented with the signals from lateral side of waist. Data was collected from 5(five) healthy users and the method achieved 82% of accuracy for the 5 user.

The peak detection methods described above may perform very well while the accelerometer is located on leg but does not perform well while it is on left lateral side of waist. The gait behavior is clearer on the acceleration signals obtained from leg than waist. For these reasons, the methods are not selected for further analysis.

Jimnez's algorithm was implemented with the acceleration signal found from the left lateral side of waist. As the gait speed is not constant and the signals found from the lateral side of the waist are affected by the movement of both upper and lower parts of the body, there are more false detection of stance and swing phase and thus could not be used for step detection.

The authors [111] placed the mobile phones on user's left shorts pocket, right shorts pocket, breast pocket, in a bag over right shoulder and in a rucksack across back and reported that the error on detecting steps are 13%, 9%, 14.5%, 16% and 14.7% respectively. This method was implemented with the acceleration signals received from lateral side of waist. The signals were filtered with 2nd order low pass Butterworth filter

with 10 Hz cut off frequency. Still it was found that, there were more peaks between two steps, which made hard to separate into steps using an adaptive threshold.

SWST and CETpD methods were implemented and found to be good candidates for step detection using the lateral side of waist. The limitation of SWST is that it is eligible to detect the initial contacts (IC) only. Terminal contacts (TC) could not be detected from SWST signals. Infect no method mentioned above could detect TC. The CETpD method could be used to detect TC by introducing thresholds but the method is sometimes found to overestimate the steps. So a new step detection method is required which could detect initial contacts with high accuracy. The new method should also detect TC.

5.4.2 Limitation of existing step length estimation methods

Zijlstra's and Gonzalez's methods are both prone to drift error over time because of the double integration. Given that the drift error could be avoided by limiting the integration period, Zijlstra et al. [114] proposed to reset the integration periodically at the point of the step where the vertical velocity of CoR is approximately zero, which coincides during flat foot.

The next limitation of Zijlstra's methods is that it has a tendency to underestimate step lengths in all subjects and at all speeds [114]. The error of Gonzalez's method on step length estimation differs between gait speed [115]. The estimation ranged from 94.5% to 106.07% and at high speed, it tends to underestimate the step length.

Weinberg easy to implement as it does not need any integration and, thus avoids drift error. According to Weinberg [118], The step length estimation varies ±8% between subjects with different leg lengths.

Martin's methods were tested for different gait speed(fast, medium and slow) and different walking patterns (long, normal and short step length) [119]. They reported that the step length might be estimated with an error below 5%. The main limitation of this method is to select best method among the four to estimate gait speed for step length estimation. As the older people and PD patients walk slowly with normal and(or) short steps, it would be preferable to select the one that could be used in slow speed with

normal or short steps. From the authors study, only *Speed*$_1$ has lowest error in these situations. The method 20.7% underestimates the step length while the users walk with slow speed and short step lengths. The underestimation is reduced to 15.3% while they walk with slow speed and normal step lengths. These errors are higher than the other methods with other gait speed and walking patterns [119].

Bylemans' method is much more complex. They need two different type of calibration constant that are very time consuming. In estimating step length, the average error is reported by the author as from 0.06 to 0.03 meters.

Shin's method needs a training session to estimate the regression parameters. To optimize them, they need a long set of training session which is very hard to do with elderly people. The authors also tested their method on only one person and reported that the error on estimating step length increased with gait speed. At the worst case, the estimation error was 3.7% during walking and 4.8% during running [112].

5.4.3 Limitation of existing gait speed estimation methods

As gait speed is directly related to step length and step duration, its accuracy depends on the accuracy of step length estimators as well as the step detection methods. For example, the under estimation tendency of Zijlstra's and Gonzalez's method on estimating step length also causes to underestimate the gait speed. The gait speed estimation using the estimated step length by Weinberg's method range from 92% to 108%. Though the gait speed estimation error using Martin's method is below 5%, the error varies on different walking pattern. During slow gait speed with normal or short step length, all of the gait speed variants underestimate gait speed. The lowest error during slow speed with normal step length and slow speed with short step length was -15.3% by *Speed*$_2$ and -20.7% by *Speed*$_1$ respectively, which are very high. The complexity on calculating tow calibration constant of Bylemans' method also limits their usability on estimating gait speed. Shin's methods need longer training session with different walking speed to train the method. According to the author, the error during normal waking is 3.7% that increases with gait speed.

5.5 Conclusion

This chapter has presented current methods for detecting steps and estimating step lengths from inertial sensor located on waist. Biomechanical models are employed on first two methods. The step detection methods vary according to sensor position. It is found that the step detection methods developed considering the sensor located on the foot are not possible to be used with the signals from the sensors located in the lower limbs or the hip given the different behavior of the signals. For this reason, only SWST methods and CETpD methods are considered to be implemented with the signals from a sensor located on left lateral side of waist of healthy person and PD patients. The comparison among them and a proposed step detection method is presented in Chapter 8.

The step length estimators and the gait speed methods considered in this chapter are all developed for the sensor located on either back of waist or lateral side. In consequence, all of them are implemented in order to evaluate with the signals from left lateral side of waist of healthy persons and compare them to select the best methods. The comparison is described in Chapter 9. The selected methods are then employed with the signals from PD patients, which is also described in Chapter 9.

Part II Estimating step length from Parkinson's disease patients through a new step detection method and adapted estimators

Chapter 6 Proposed step detection method and adapted methods for step length estimation

In this chapter, a newly developed step detection method –Sliding Window Averaging Technique (SWAT) – is described. This chapter also presents the modification of the step length estimators in order to adapt them to the proposed sensor position by considering four different correction factors. Each correction factor is obtained for individual patients, which are described in the second part of this chapter.

6.1 Sliding window averaging technique (SWAT) for step detection

In this thesis, an accelerometer-based system is placed on the lateral side of waist in order to estimate gait properties from PD patients. As discussed earlier signals, from the lateral side differ from those from the lower back of waist. A new step detection method–Sliding Window Averaging Technique (SWAT) is developed for the proposed location. The step detection methods stated before are able to detect only the initial contacts (IC) of the step. But for some step length estimators, detection of terminal contact (TC) is also required. Using SWAT technique, the events of ICs and TCs are detected. It can also distinguish left and right steps. From the experimental study described in Chapter 8, we could see that, it could detect steps more accurately than the others.

The basic idea is very similar to that of SWST technique. But instead of sum up the acceleration values in a window size, the average acceleration is considered here. The

orientation of the accelerometer is same as described in Chapter 4, i.e. positive X value corresponds to frontal acceleration, positive Y values to vertical acceleration and positive and negative Z values to the acceleration to the left and right side, respectively. The implementation of the algorithm is simple. First, the magnitude of the triaxial accelerometer signal a_t following Eq. (5.2). The local mean $\bar{a}_i$ of acceleration magnitude is then computed following an overlapped sliding window technique as described by Eq. (6.1).

$$\bar{a}_t = \frac{1}{w}\sum_{j=1}^{w} a_j. \tag{6.1}$$

where w is the averaging window size fixed to 40 samples, equivalent to 0.2s following the same rule as [112].

During the experiment, the participants were asked to stand still for at least 10 seconds before starting their walk. The mean acceleration ($\bar{a}_{(stand)}$) during this period was calculated and subtracted from $\bar{a}_t$ as follows to remove gravity and offsets from the accelerometer signals.

$$SWAT_t = \bar{a}_t - \bar{a}_{(stand)} \tag{6.2}$$

The resulting signal is used to identify left and right initial contacts (IC) and terminal contacts (TC) events. The instant when heel of the foot touches the ground is called as IC and, when the foot leaves, it is called as terminal contact (TC). The initial contact and terminal contact events of left and right legs are represented here as LIC, LTC, RIC and RTC respectively.

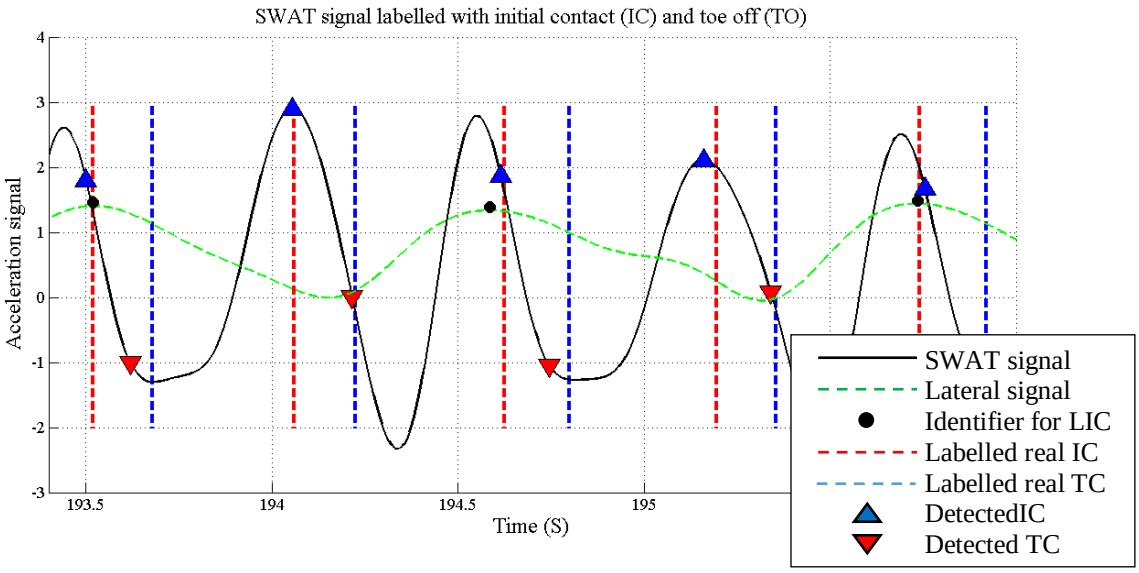

Figure 6.1*:* Five Initial contact (IC) and terminal contact (TC)are detected using SWAT. Lateral signal that is used to discriminate between left and right is also shown. The red and blue dotted lines are the actual ICs and TCs (based on a previously synchronized video-labeling) respectively.

The proposed method must discriminate between left and right ICs. According to Zijlstra et al. [114], the waist moves from left to right and right to left during walking and reaches maximum lateral position during ICs.

- **LIC:** As sensor was placed on left lateral side, the local maximum lateral signal can be used to identify incident of LICs immediately before or after it. For each local maximum in SWAT signal, if there is a local maxima in lateral signal immediately before or after it, the mid-point from local maximum to zero in SWAT signal is considered as LIC.

- **RIC:** For each local maximum in SWAT signal, if there is no local maximum in lateral signal immediately before or after it, itis considered as RIC.

- **LTC:** For each detected RIC, the next zero crossing point was considered as LTC.

- **RTC:** For each LIC, mid-point of next zero to local minimum are searched and considered as RTC.

Figure 6.1shows the step detection from a PD patient using the described algorithm. The dotted green line is the lateral signal where the local maxima is marked as black circles denoted as LIC identifier. ICs and TCs are denoted as blue and red triangles. The vertical red and blue lines are the labeled real ICs and TCs. The method is evaluated with the experiments described in chapter 7, whose results are in chapter 8 and 9.

6.2 Adaptation of step length estimators to new sensor location

The step length estimators presented in Chapter 5 were developed considering the sensor position near CoR of human body. Thus, they need to be adapted to our system located on left lateral side of waist. Since the new position imposes new restrictions (Figure 4.8)that were not considered in the original methods, they must be taken into account by modifying the original methods. To adapt them to the new sensor position, we proposed four adaptations to each presented method based on different correction factors. It should be noted that all correction factors are applied to the three estimation methods, so the influence of each one of them in approximating the step length is analyzed:

- Correction factor 1 corrects the estimation based on the multiplication factor employed by Zijlstra's and Weinberg's method, i.e. Eq. (5.12)and (5.16), in order to evaluate its effect in Gonzalez's method.

- Correction factor 2, which consists of an addition rectification, is the adapted correction factor from Gonzalez's method, i.e. Eq. (5.15) which is also applied to Zijlstra's and Weinberg's method.

- Regarding the remaining two factors, they are conceived based on the asymmetries in the acceleration signal among left and right steps (Figure 4.8) because of sensor's position on left lateral side. Correction factors 3 and 4 update the estimations in order to include these differences: factors for left and right step

lengths are obtained separately from estimated left and right step length. Left correction factors are applied to left estimated step lengths and, separately, right correction factors are applied to right estimated step lengths. Correction factor 3 employs a multiplication correction while correction factor 4 uses an addition rectification.

Finally, it should be noted that those correction factors trained during OFF state of the patient and tested during ON state are mentioned as $K_{i.OFF}$ and, those trained in the opposite way, they are mentioned as $K_{i.ON}$.

Figure 6.2 shows a schematic diagram of step length estimation process during a patient's OFF state. Signals are obtained from a PD patient during both their ON and OFF state. During training session (here ON state), steps are detected using a step detection method. Signals are preprocessed according to the step length estimators and for each detected step, step lengths are estimated without any correction factor. The correction factors are then obtained based on the estimated and real average step lengths. During the test session, step detection is performed, signals are preprocessed and then step lengths are estimated by employing the correction factors previously obtained. Opposite process is followed to estimate step length during ON states.

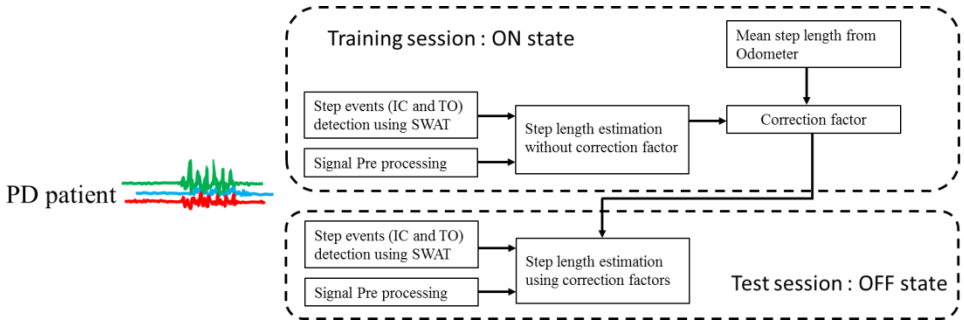

Figure 6.2: Schematic diagram of step length estimation during OFF state. The training session here is during a patient's ON state

6.2.1 Correction factor 1: Multiplication

This individual correction factor is obtained based on the ratio of real and anticipated step lengths of a course of reference, i.e. in a training phase. Here $K_{1.OFF}$denotes the correction

factor obtained from a PD patient in OFF state and that is applied to measure step length during ON state. On the other hand, $K_{1.ON}$ denotes the factor obtained during ON state and tested with OFF state signals.

$$K_{1.\{OFF,ON\}} = \frac{mean(SL_{real})}{mean(SL_{estimated})} \quad (6.3)$$

6.2.2 Correction factor 2: Summation

This individual correction factor is calculated by finding the difference between real and anticipated step length during training session. This factor will be then summed up with the estimated step length during test session.

$$K_{2.\{OFF,ON\}} = mean(SL_{real}) - mean(SL_{estimated}) \quad (6.4)$$

where, $K_{2.OFF}$is the summation correction factor obtained during OFF state of a PD patient and is used to measure step length during ON state. In the opposite way, $K_{2.ON}$is found during ON state and tested with OFF state signals.

6.2.3 Correction factor 3: Multiplication considering left and right step individually

For this correction factor, $K_{3.OFF}$ and $K_{3.ON}$ are measured for each individual in respect of both left and right step length separately based on a course of reference. This correction factor will be employed into testing signals by multiplying estimated left and right step lengths separately. $K_{3.OFF}$ from training data during OFF state and tested during ON state and vice versa.

$$K_{3.\{OFF,ON\}} = \frac{mean(SL_{real})}{mean(SL_{estimated(left\ or\ right)})} \quad (6.5)$$

6.2.4 Correction factor 4: Summation considering left and right step individually

Here $K_{4.OFF}$ and $K_{4.ON}$areobtained for each individual in respect of left and right step lengths separately based on training signals. This factor is applied onto testing signals summing it up to the estimated left and right step lengths. $K_{4.OFF}$and $K_{4.ON}$are measured from train data during OFF and ON state.

$$K_{4.\{OFF,ON\}} = mean(SL_{real}) - mean(SL_{estimated(left\ or\ right)}) \quad (6.6)$$

The multiplication factors (1 and 3) are applied to the three methods as follows

$$SL_{M1} = 2 \times K_{i.\{Off,On\}} \sqrt{2hl - h^2} \quad (6.7)$$

$$SL_{M2} = 2 \times K_{i.\{Off,On\}} \sqrt{2h_{sp}l - {h_{sp}}^2} \quad (6.8)$$

$$SL_{M3} = K_{i.\{Off,On\}} \times \sqrt[4]{\max(a_y) - \min(a_y)} \quad (6.9)$$

The summation factors (2 and 4) are applied to the three methods as follows

$$SL_{M1} = 2 \times \sqrt{2hl - h^2} + K_{i.\{Off,On\}} \quad (6.10)$$

$$SL_{M2} = 2 \times \sqrt{2h_{sp}l - {h_{sp}}^2} + K_{i.\{Off,On\}} \quad (6.11)$$

$$SL_{M3} = \sqrt[4]{\max(a_y) - \min(a_y)} + K_{i.\{Off,On\}} \quad (6.12)$$

6.3 Conclusion

In this chapter, a newly developed step detection algorithm – SWAT is presented and discussed. SWAT is developed considering the sensor location on left lateral side. It can detect both LICs and RICs. It also can detect LTC and RTC, which is the major advantage among the other techniques, as no other methods described before could do this. From Fig. 6.1 we can also see that the detected ICs and TCs are very close to the actual ICs and TCs, that indicate their better performance. The step detection method is implemented with the signals from 25 PD patients and compared with existing step detection methods SWAT and CETpD, described in Chapter 9.

Furthermore, four adaptations for those length estimators that employ calibration factors are also described in this chapter. The four types of correction factors are used on PD patients in both of their motor status The Correction factors trained during OFF states are mentioned as $K_{i.OFF}$ and during ON states are mentioned as $K_{i.ON}$. Correction factor $K_{1.OFF(ON)}$ are the original correction factors used in Zijlstra's and Weinberg's method. $K_{2.OFF(ON)}$ are the adapted correction factor for Gonzalez's method. $K_{3.OFF(ON)}$ and $K_{4.OFF(ON)}$ are the correction factors used to discriminate taking into account, separately, the differences between left and right step lengths.

The errors are calculated from the reference data and are compared among the different correction factors. The expectation is to find the best methods with a specific correction factor. As all three step length estimators need a training session, it is also checked if the step length estimators with correction factors obtained during ON state have higher or atleast similar performance compared with the same during OFF state. The target is to relieve the patients not to attend without medication in order to train the methods. After selecting the best method with specific correction factor, a generic correction factor is also estimated to avoid time consuming individual calibration. The results are discussed in Chapter 9.

Chapter 7 Experiments

Throughout the presented work of this thesis, experiments have been performed to verify the implemented algorithm for step detection and step length estimation. Two databases were employed, where the first database belongs to healthy people that is developed as part of the thesis. The second one is the REMPARK database that belongs to the patients with PD. In both cases, the data collection was performed using the 9x2 v6 IMU described in section 4.4 located on the left lateral side of the body near the anterior superior iliac spine (ASIS).

The first experiment was conducted to compare the performance of existing step detection methods with the newly developed step detection methods SWAT. In this experiment, all step length estimators described before are implemented and evaluated. The best ones are selected according to the results obtained, which are presented in the next chapter.

7.1 Data collection from healthy persons

In first phase of the experiment, signals were collected from three healthy adult male neither of whom reported difficulties on walking normally. The age of the participants was between 27 and 32 years and height was between 1.65 meters and 1.80 meters.

The task that the 3 volunteers performed consisted of a straight walk along a 26m long flat corridor. The participants were asked to stand still for several seconds before starting and then were cued to start. The walk was at the participant's own "comfortable pace". When the participant reached the end, he or she was asked to hold still for a few seconds.

The signals during these steady periods (before start and end of the walk) were used later to identify the start and end of walking. A Casio Exlim high speed video camera is used to record the gait events at 200fps. Following the same methodology as of Samá et al [122], the video recording and the movement signals were synchronized by using a fall event of the inertial sensor at the beginning and at the end of each video recording.

The recorded video is analyzed by an open-source sport technical analysis software KINOVEA [123] to measure accurate step length, gait speed and travelled distance. Before starting the test and video recording, a sticky paper of 0.16m length was pasted below the knee on the volunteer's trouser as a reference length. The video was recorded following the subject from left lateral side parallel to the waist covering the sticky paper and both of the subject's leg with ground. From video analysis, using KINOVEA, initial contacts (IC) of a foot are identified to the point where it initially touches the ground and marked as blue circles as shown in Figure 7.1.For each pair of ICs, a line is drawn over the video between the two point (the blue circles) and at the same time, another line is drawn over the sticky paper attached on the volunteer's trouser. The length of the line on the paper is measured and calibrated with the known length (0.016m) using KINOVEA. Step length is then estimated by measuring the length of the line drawn between the two ICs. The length of the paper acts as a measure of reference here that allows KINOVEA obtaining the step length distance based on the estimated reference. However, since video is recorded perpendicular to the forward displacement, measuring length by drawing line between two initial contacts maybe biased by step width. In order to reduce the accuracy error, grid lines are used to find the point of two initial contacts in a line. Measurements are obtained through the line between these two points. As the subject and the camera are both moving during the video recording, it is hard to fix the position of the camera with the moving body. Therefore, the measurements are needed be calibrated for every step to get more accurate results. For this reason, a new line is also drawn along the sticky paper in the video to measure the length of it. As the length is already known (0.16m), it is used to calibrate the measurement of every step length. Figure 7.1 shows the process to measure one step length with calibration.

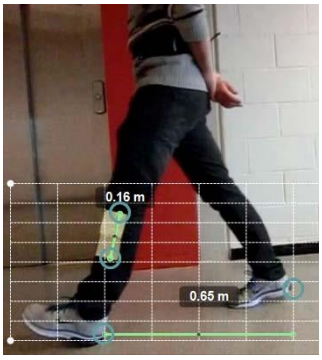

Figure 7.1: Measuring step length using KINOVEA

7.2 Data collection from PD patients

In the second phase, signals from 25 PD (19 male and 6 female) patients who were in ON and OFF motor states were collected. The age of the PD patients range from 47 to 80 years and duration of illness from 4 to 24 years. The inclusion criteria were to have a clinical diagnosis of Idiopathic PD according to the UK Parkinson's Disease Society Brain Bank [124] and moderate-severe phase (Hoehn and Yahr greater or equal to 2.5) with motor fluctuations with Bradykinesia, FoG and/or Dyskinesia [125]. The exclusion criterion consisted of suffering other health problems different from PD that hamper gait: rheumatologic, neuromuscular, diabetes, orthopedic, respiratory, or cardiologic problems or significant pain. All patients signed an informed consent. The data collection was part of a bigger database that was constructed for REMPARK project [122].

The experimental phase started early in the morning at patient's home. The morning medication was delayed to find the patients in an OFF state. Once a patient was in a clear OFF state, the gait test was performed. To do so, the patients were asked to walk from 5 to 28 meters on a flat and clear path. Walk length and indoor/outdoor placement varied based on patient's health condition and weather conditions. Before starting the walk, patients were asked to stand still for several seconds and then cued to begin their walk at

their own “comfortable pace”. An odometer T592[8]was used to measure the distance walked, which accuracy was 1 cm.

For each walk, a camera was placed behind the patient so that his/her feet appear in the frame from the beginning to the end of the walk. Walks were video recorded using the camera. The video was used as the basis to validate step counts and, by using the odometer measurements, the average step length considered as reference step length, was obtained. After walking in OFF state, patients took their medication. Once the Patient turned into a complete ON state (confirmed by an expert), the same gait test was done.

The advantages of this data collection is that, data was collected in the natural environment in both motor sates and non-laboratory conditions, which allows us to measure gait alterations not commonly observed at the clinical site. The movement signals of PD patients in an uncontrolled environment (home and/or outdoor)to monitor their free natural daily life activities.

7.3 Signal conditioning

An application developed under REMPARK project [122] is used to synchronize the video and the movement signals gathered and to label initial contact and foot-off events on the signals. The program enables the labeling of left /right IC and TC events manually on the signal with the support of high-speed video recordings as shown in Figure 7.2. For every pair of dotted lines, the first one is the initial contact of ipsilateral foot and second one is foot-off of contralateral foot event. Instead of selecting one single point of initial contact and foot-off, periods of start and end time of initial contact and terminal contactare labeled and the events are considered in between this periods. During analysis, the first and last 2 steps from each test are discarded as it is found from the video analysis that the gait is not steady at that time.

[8]https://www.pce-instruments.com/english/measuring-instruments/meters/measuring-wheel-gottlieb-nestle-gmbh-measuring-wheel-t592-det_61459.htm

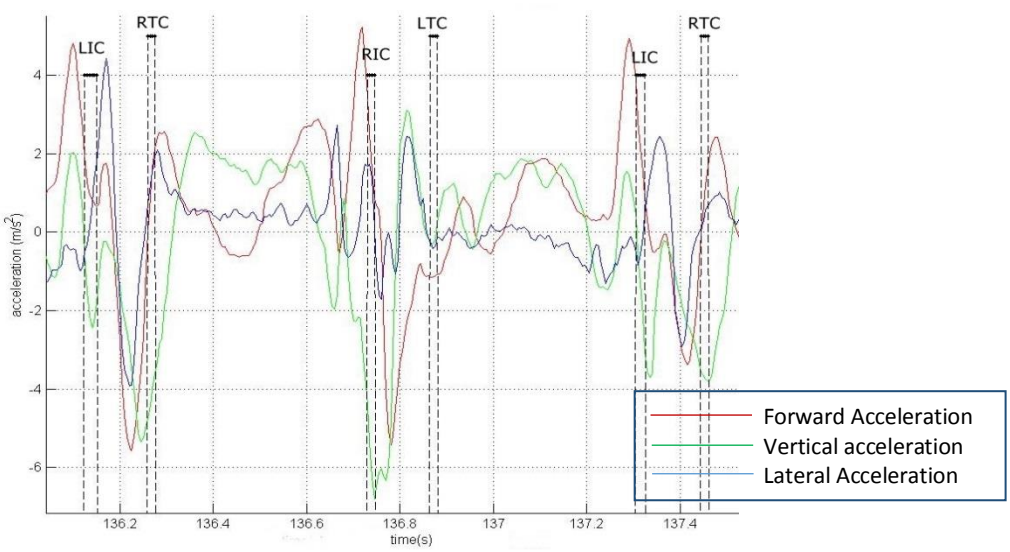

Figure 7.2: Labeled gait event of acceleration signal. LIC and RIC are the left and right initial contact and LTC and RTC are the left and right terminal contact events.

Before applying the movement signals, to estimate the step length, they are filtered with zero-lag fourth order low pass Butterworth filter with a cut-off frequency of 30Hz to reduce the noise for all the methods accept method 4 (Martin's method).

Lateral signals are filtered through a 2nd order zero-lag Butterworth low pass filter with 0.8Hz cut-off frequency to remove the jittery noise. For all the 25 PD patients, the gait initiation (when the first foot leaves the ground) part of the gait signal are closely observed and found that the minimum acceleration of 0.4m/sec^2 is needed to initiate gait. A threshold of 0.4m/sec^{2}was empirically defined and all the peaks below this threshold values are discarded as candidate for ICs. The minimum step duration from the 25 PD patients is found as 0.49 sec so after each step detection, peaks within next 0.4 seconds are also discarded in SWAT.

7.4 Data Analysis

The accuracy on detecting steps with healthy person and PD patients are obtained for sliding window summing technique (SWST), Threshold based approach (CETpD) and

Sliding window averaging technique (SWAT). Moreover, step length and gait speed estimations are analyzed as well.

The accuracy metric for step detection used is defined in Eq.(7.1). The observed steps are the actual number of steps, obtained from the video, and the estimated steps are the result of each step detection method. The missed step and overestimated steps are considered as error.

$$Accuracy = \left(1 - \frac{|Estimated\ steps - Observed\ Steps|}{Observed\ Steps}\right) \times 100 \qquad (7.1)$$

Regarding the step length estimation, its average reference is considered to be the distance measured through the odometer divided by the step count from the recorded video.

The average reference of gait speed is then calculated using Eq. **Error! Reference source not found.**).Step lengths of each patient are estimated using the step length estimators mentioned before based on step detections performed by the SWAT algorithm. The average step lengths estimated by the step length estimators and the average step duration measured by SWAT are then used to estimate the average gait speed following Eq. (5.28). Since for all four step length estimators considered need a training session to obtain a correction factor, they are trained with the signals of the patients during their OFF state and tested during ON state and vice versa.

The reference and estimated average step lengths and gait speed are tested by performing Shapiro-Wilk test to find if they are normally distributed. Parametric tests are applied since the test confirmed that the data is normally distributed. To determine average performance of the step length estimators, mean absolute error, standard deviation (SD) and root mean square error (RMSE) of each approach is calculated. RMSE is calculated using Eq. **Error! Reference source not found.**.

$$RMSE = \sqrt{\frac{\sum_{number\ of\ samples}(estimated - reference)^2}{number\ of\ samples}} \quad (7.2)$$

7.5 Conclusion

In this chapter, the data collection process from healthy person and PD patients are discussed. Signal conditioning, synchronization process and labeling processes are also discussed. Finally, data analysis used in the experiments is presented. In the next two chapters, step detection and step length estimation results from healthy person and PD patients are presented. All the experiments conducted in next two chapters follow the same data analysis described in this chapter.

Chapter 8 Step detection, step length estimation and gait speed results with healthy users

In this chapter, results of the existing step detection methods and the proposed SWAT method are presented. In the second section step length and gait speed of each healthy person are estimated by each method described before. In this case, the labeled real steps are used to estimate the step lengths to avoid introducing errors from the step detection methods.

8.1 Result of step detection with healthy users

In this section, results from three step detection methods SWST, CETpD and SWAT are presented. The signals are collected from three healthy volunteers (V1, V2 and V3). Among them, the number of detected steps is correct in only one person, by SWST, and 2 persons, by SWAT. One step is missed by SWST and CETpD in one person and also one step is over estimated by SWST and SWAT in one person. Table 8.1shows the comparison the exact results from these three step detection methods based on accuracy. Both missed and overestimated steps are counted as an error here and presented as NMOS in the table.

Besides the accuracy on step detection, time error was calculated by comparing the time of real initial contacts of the healthy persons and those obtained by each step detection method. Their results are presented in Table 8.2.

From Table 8.1 and Table 8.2, we can see that the overall performance of SWAT is better than the others. The accuracy of SWAT and SWST is very close, though SWAT has higher accuracy, which is 99.24% for healthy person. The mean absolute error is always lower for SWAT(0.04 sec) than SWST (0.05 sec), as well as their standard deviation which are 0.035 sec and 0.077 respectively

Table 8.1: Overall step detection performance for 3 volunteers

	#observed Steps (r)	SWST		CETPD		SWAT	
		#NMOS	Accuracy (%)	#NMOS	Accuracy(%)	#NMOS	Accuracy (%)
V1	42	1	97.62	1	97.62	0	100
V2	42	1	97.62	2	95.24	0	100
V3	48	0	100	4	91.67	1	97.92
Total	132	2	98.48	7	94.70	1	99.24

Table 8.2: Error comparisons between 3 methods

Method	Mean absolute error (sec)	SD (sec)
SWST	0.05	0.077
CETPD	0.36	0.340
SWAT	0.04	0.035

8.2 Step length and gait speed estimation

Among the six step length estimators described in Chapter 5, the first 4 methods were developed considering the sensor position near CoR of human body. In Bylamans'

method, they used a smart phone located in the pocket of the user's trousers near waist that is close to our proposed location. The sensor location for Shin is the lateral side of waist similar to the location used in this thesis. A small study is conducted, and published in [126], to implement all these six methods using acceleration signals from left lateral side of waist of 3 healthy persons (V1, V2 and V3).

For Zijlstra's method and Weinberg's method, we adapted the correction factor for each individual for left step and right step length separately as follows and then estimated the step length which are presented as estimator $SL_{Zijlstra(A)}$ and $SL_{Weinberg(A)}$ while the results from original methods are presented as $SL_{Zijlstra(O)}$ and $SL_{Weinberg(O)}$ respectively.

Gonzalez's method uses a constant *C* for DSP displacement. The value of *C* has been fixed as 0.83 by Han et al. [116] and 0.67 by Schmid et al. [117] and are presented as $SL_{Gonzalez(O1)}$ and $SL_{Gonzalez(O2)}$ in this study. Instead of a fixed value for C, we propose to measure it for each individual from a training phase based on the same original variables used during swing phase mentioning as C_a. $C_a$could be calculated using the following equation

$$C_a = \frac{mean(SL_{reference}) - mean(SL_{ssp})}{l_{foot}} \tag{8.1}$$

The reference step length ($SL_{reference}$) are obtained from video analysis and SL_{ssp} are obtained during swing phase. By using Eq. (44), we can avoid using foot length and rewrite Eq.(5.15) as follows

$$SL_{Gonzalez(a)} = 2\sqrt{2hL - h^2} + K_C \tag{8.2}$$

withK_C = $mean(SL_{reference})$ - $mean(SL_{ssp})$. In the result, the method is presented as $SL_{Gonzalez(a)}$

Shin's method estimate step length by calculating optimal parameters. The parameters could be calculated from multiple training session with longer walk with different speed. In their experiment, Shin et al. [112] had to conducted 30 trials with one subject with a trajectory of 70 m for each trial. As in this work, these much training session was out of

scope, we considered the best case where, the optimal parameters are considered as 1 and the measurement errors as 0.5.

Table 8.3: Reference and anticipated average step length during test phase

	V 1		V 2		V 3	
Methods	**SL (m)**	**RMSE(SD) (m)**	**Test (m)**	**RMSE(SD) (m)**	**Test (m)**	**RMSE(SD) (m)**
Reference	0.64		0.53		0.62	
$SL_{Zijlstra(O)}$	0.70	0.085 (0.058)	0.58	0.071(0.052)	0.68	0.062(0.028)
$SL_{Zijlstra(A)}$	0.70	0.072 (0.044)	0.58	0.064(0.043)	0.68	0.062 (0.023)
$SL_{Gonzalez(O1)}$	0.64	0.097 (0.133)	0.73	0.303 (0.228)	0.50	0.140 (0.077)
$SL_{Gonzalez(O1)}$	0.59	0.108 (0.097)	0.68	0.273 (0.228)	0.45	0.183 (0.077)
$SL_{Gonzalez(a)}$	0.67	0.096 (0.098)	0.48	0.0226 (0.286)	0.65	0.083 (0.233)
$SL_{Weinberg(O)}$	0.67	0.049 (0.041)	0.57	0.088 (0.078)	0.63	0.026 (0.024)
$SL_{Weinberg(A)}$	0.67	0.047 (0.039)	0.56	0.050(0.034)	0.63	0.0231 (0.022)
$SL_{Martin(1)}$	0.60	-	0.80	-	0.63	-
$SL_{Martin(2)}$	0.60	-	0.80	-	0.63	-
$SL_{Martin(3)}$	2.18	-	1.95	-	2.57	-
$SL_{Martin(4)}$	2.18	-	1.95	-	2.57	-
$SL_{Bylemans(O)}$	0.85	0.232(0.102)	0.79	0.266(0.045)	0.92	0.314 (0.084)
$SL_{Bylemans(O)}$	0.85	0.219 (0.079)	0.79	0.267 (0.028)	0.92	0.307(0.067)
SL_{Shin}	0.62	0.030 (0.024)	0.57	0.050 (0.033)	0.63	0.023 (0.021)

For each step length estimators, gait speed is also estimated using Eq. (5.28)after estimating step lengths. Table 8.3 and **Error! Not a valid bookmark self-reference.** show comparison between real and anticipated average step length and gait speed respectively, measured by means of the estimators during the test phase. The real step

lengths and gait speeds are measured from the video using KINOVEA as described in Section 7.1. Standard error of each method for each volunteer is also calculated using root mean square error (RMSE) and standard deviation (SD), which are showed together as RMSE(SD) in the tables. Martin's method first measure the average gait speed after each trial of each person. Average step lengths are then estimated from the average gait speed. So RMSE and SD for each person considering each step length could not be calculated for $SL_{\text{Martin(n)}}$.

Table 8.4: Reference and anticipated average gait speed during test phase

	V 1		V 2		V 3	
Methods	**SL (m)**	**RMSE(SD) (m)**	**Test (m)**	**RMSE(SD) (m)**	**Test (m)**	**RMSE(SD) (m)**
Reference	1.10		0.87		1.21	
$SL_{\text{Zijlstra(O)}}$	1.21	0.141 (0.095)	0.95	0.117(0.084)	1.33	0.123 (0.055)
$SL_{\text{Zijlstra(A)}}$	1.20	0.121 (0.072)	0.95	0.105 (0.070)	1.32	0.122 (0.047)
$SL_{\text{Gonzalez(O1)}}$	1.10	0.169(0.171)	1.20	0.501 (0.377)	0.98	0.275 (0.148)
$SL_{\text{Gonzalez(O1)}}$	1.02	0.186(0.169)	1.12	0.451 (0.377)	0.89	0.358 (0.149)
$SL_{\text{Gonzalez(a)}}$	1.16	0.172(0.230)	0.78	0.370 (0.464)	1.28	0.159 (0.452)
$SL_{\text{Weinberg(O)}}$	1.15	0.082(0.069)	0.93	0.144(0.128)	1.23	0.051 (0.047)
$SL_{\text{Weinberg(A)}}$	1.14	0.079(0.066)	0.93	0.085 (0.054)	1.23	0.045 (0.042)
$SL_{\text{Martin(1)}}$	1.01	-	1.26	-	1.21	-
$SL_{\text{Martin(2)}}$	1.01	-	1.26	-	1.21	-
$SL_{\text{Martin(3)}}$	3.66	-	3.09	-	4.95	-
$SL_{\text{Martin(4)}}$	3.66	-	3.09	-	4.95	-
$SL_{\text{Bylemans(O)}}$	1.46	0.406 (0.186)	1.30	0.436 (0.049)	1.80	0.617 (0.169)
$SL_{\text{Bylemans(O)}}$	1.45	0.383 (0.146)	1.30	0.436 (0.030)	1.80	0.604 (0.137)
SL_{Shin}	1.07	0.051 (0.041)	0.93	0.081 (0.053)	1.23	0.043 (0.040)

Results show that most of the methods have a tendency to over-estimate the step length as well as the gait speed. Only Shin's method underestimates the step length and gait

speed. Martin's method and Byleman's methods provides the highest error. $SL_{Gonzalez(O1)}$ and $SL_{Gonzalez(O2)}$ provides inconsistent results i.e overestimate for one subject and under-estimate for the others. $SL_{Gonzalez(a)}$ provides consistent result with better performance than its original methods ($SL_{Gonzalez(O1)}$ and $SL_{Gonzalez(O2)}$). The reason is that in the original method, a fixed proportional constant *C* was considered. In our case, method $SL_{Gonzalez(a)}$, *C* is replaced by K_c which is calculated for every subject with the proposed adaptation method and, thus, the performance is improved.

Though the performance of Shin's method is higher than the others, it needs a longer training session with multiple set of data for same person. In this experiment, best case was considered for the optimal parameter, which is not always true. As the main concentration of this thesis is to estimate step length with PD patients multiple set of training data is hard to be collected. This is the reason for this method to be excludedfrombeing implemented with the signals from PD patients in next chapters.

8.3 Conclusion

In this study, 3 different methods for step detection are selected to check their performance in the new sensor location consisting in the lateral side of the waist. Among them, SWAT method performed better than the others. These three methods are further analyzed with the movement signal database gathered from PD patients in Chapter 9.

Six different methods for step length and gait speed estimation are also selected from literature to adapt them to the new sensor location. The original and the adapted methods are compared with real preliminary data. Zijlstra's method, Gonzalez's method and Weinberg's method show better performance than the others do. The performance of the adapted methods of these estimators is shown to be higher than the original ones by providing both lower SD and RMSE. In Chapter 9, these original and adapted methods are further analyzed with the mentioned movement signal database of PD patients.

Chapter 9 Step detection, step length estimation and gait speed results with PD patients

In this chapter, the three step detection methods selected in the previous chapter are evaluated with signals from patients with PD. The best method is selected to be implemented with three step length estimation methods. These three methods were selected among a total of 6 state-of-the-art step length estimators in previous chapter. In Chapter 8, these 6 methods are tested on healthy people with the sensor placed on proposed location and their performance on measuring step length and gait speed are compared. Zijlstra's method [113], Gonzalez's [115] and Weinberg´s algorithm [118] performed better than the other showing less than 5% error in average step length and gait speed estimation. Their lower Root means square (RMSE) and Standard deviation(SD) values also showed a good significance of their accuracy. Based on these benchmarks, these three methods are selected to explore further with Parkinson disease patients in this chapter. As the original methods were developed considering the sensor position near CoR of human body, they are modified to adapt them to the proposed sensor position by considering different correction factors. Their results in a database of signals gathered from 25 PD patients [13] are presented.

Since all three step length estimators considered need a training session to obtain a correction factor, they are trained with the signals of the patients during their OFF state and tested during ON state and vice versa. The correction factors $K_{1.OFF}$, $K_{2.OFF}$, $K_{3.OFF}$

and $K_{4.OFF}$ are calibrated during OFF states and tested during ON states. The opposite are done, which corresponds to correction factors $K_{1.ON}$, $K_{2.ON}$, $K_{3.ON}$ and $K_{4.ON}$.SD and RMSE are then calculated from the errors of each method and correction factor.

A generic correction factor for all PD patients is estimated from the one that performs better than the others. In this case, the correction factor that has a central tendency is considered to be the generic correction factor. This factor is also tested with the best performance method. SD and RMSE are then calculated as before.

9.1 Step detection results with PD patients

The three step detection methods are applied to the signals from lateral side of waist of 25 PD patients during their OFF and On states. Among the 25 PD patients, the number of detected steps during their OFF and ON state, noted in this paragraph as (*number OFF, number ON*), is correct in *(5, 8)* patients by CETpD's method, (*6, 8*) patients by SWST and (*12, 15*) patients by SWAT. Among the remaining patients, one step is missed by CETpD's method in (*2, 4*) patients, in the case of SWST it is missed in (*2, 3*) patients while SWAT misses it in (*10, 6*) patients. No overestimation is performed by SWAT. On the other hand, overestimation is obtained in (*4, 2*) patients by CETpD's method and in (*16, 13*) patients by SWST.

Table 9.1: Overall step detection performance with PD patients.

Methods	**OFF state [a]**			**ON state [b]**			**OFF and ON state**		
	NMOS	**MA (%)**	**IQR (%)**	**NMOS**	**MA (%)**	**IQR (%)**	**NMOS**	**MA (%)**	**IQR (%)**
SWST	38	95.03	91.67- 98.08	27	96.33	93.62-100.00	65	95.67	93.48- 100.00
CETpD	108	85.86	83.00- 94.00	93	87.36	80.00-100.00	201	86.60	80.63- 98.94
SWAT	26	**96.60**	**95.00-100.00**	**22**	**97.01**	**96.67-100.00**	**48**	**96.80**	**95.23- 100.00**

[a]Total number of observed steps during OFF state was 764

[b]Total number of observed steps during ON state was 736

NMOS = Number of missed and over-estimated steps

IQR = Inter quartile range

MA = Mean accuracy

The comparison of the results obtained by the step detection methods applied to the signals obtained from 25 patients during both OFF and ON states are presented in Table 9.1 based on the number of missed and over-counted steps (NMOS), mean percentage accuracy and their interquartile range among patients (IQR). Here both missed and overestimated steps are counted as error. Since the IQR is the range of the accuracy among patients, they are presented as percentage. From Table 9.1, we can see that SWAT method detects steps with more accuracy than the others (96.60% accuracy during OFF state and 97.01% accuracy during ON state). The NMOS and IQR are also lower than the others. The IQR of SWAT method during OFF state shows that the estimation is more accurate than the other 2 methods. Though the ICCs are all above 0.90 Table 9.3, the error of CETpD's method is significantly different than the others ($p<0.05$). The errors of SWST and SWAT are significantly different during OFF states but not during ON state.

Table 9.2: Agreement of step detection methods with observed steps. Intraclass coefficient and 95% confidence interval are presented as ICC (95% CI)

Method	**OFF state**	**ON state**	**OFF and ON state**
SWST	0.984 (0.965 - 0.993)	0.993 (0.984 - 0.997)	0.989 (0.982 - 0.994)
CETpD	0.905 (0.799 - 0.956)	0.951 (0.894 - 0.978)	0.932 (0.884 - 0.960)
SWAT	**0.988 (0.973 - 0.995)**	**0.997 (0.992 - 0.998)**	**0.993 (0.988 - 0.996)**

In consequence, SWAT is used as the basis to detect steps with the different step length estimation methods. During step detection process, SWAT does not overestimate the steps though it misses few steps. After inspecting the detected steps with labeled signals it is found that the missed steps are either the first or final steps or both made by the patients. This is probably caused by low movement from standing position to start of walk (first step) or from walk to standing position (final step). Consequently, first and last steps are excluded from the analysis.

9.2 Step length and gait speed estimation with PD patients

From the odometer measurements obtained from 25 PD patients, the mean step length was 0.42 m (95% CI is 0.37 – 0.48) during OFF state and 0.48m (95% CI is 0.44-0.53) during ON state. The mean gait speed was 0.67 m/sec (95% CI is 0.61 – 0.79) during OFF state and 0.80 m/sec (95% CI is 0.58-0.94) during ON state.

All three step length estimation methods are tested using 4 different type of correction factors for each patient during their OFF and ON states. The correction factors trained during OFF states are mentioned as $K_{i.OFF}$ and during ON states are mentioned as $K_{i.ON}$. Correction factor $K_{1.OFF(ON)}$ are the original correction factors used in Zijlstra's and Weinberg's method. $K_{2.OFF(ON)}$ are the adapted correction factor for Gonzalez's method. $K_{3.OFF(ON)}$ and $K_{4.OFF(ON)}$ are the correction factors used to discriminate taking into account, separately, the differences between left and right step lengths. The ICC with 95% confidence interval of all correction factors with reference step length are shown in Table 9.3. Standard deviation (SD) and root mean square error (RMSE) for each method are shown together as (SD) RMSE in Table 9.4.

Table 9.3: Agreement of adapted step length estimators. Interclass coefficient and 95% confidence interval are presented as ICC (95% CI)

	Zijlstra	**Gonzalez**	**Weinberg**
$K_{1.OFF}$	**0.924 (0.841 - 0.965)**	0.862 (0.720 - 0.935)	0.810 (0.625 - 0.909)
$K_{1.ON}$	**0.951 (0.897 - 0.977)**	0.898 (0.792 - 0.952)	0.873 (0.744 - 0.939)
$K_{2.OFF}$	**0.936 (0.864 - 0.970)**	0.883 (0.759 - 0.945)	0.766 (0.549 - 0.886)
$K_{2.ON}$	**0.953 (0.900 - 0.978)**	**0.906 (0.807 - 0.955**)	0.870 (0.738 - 0.937)
$K_{3.OFF}$	**0.918 (0.828 - 0.962)**	0.855 (0.708 - 0.931)	0.808 (0.623 - 0.908)
$K_{3.ON}$	**0.957 (0.909 - 0.980)**	0.899 (0.794 - 0.952)	0.871 (0.740 - 0.938)
$K_{4.OFF}$	**0.936 (0.865 - 0.970)**	0.882 (0.759 - 0.945)	0.765 (0.547 - 0.885)
$K_{4.ON}$	**0.953(0.901 - 0.978)**	**0.905 (0.805 - 0.955)**	0.869 (0.737 - 0.937)

A significant difference between Zijlstra method and the others is found ($p<0.05$) on estimating step length, though there is no significant difference between the different

correction factors applied to Zijlstra's method. Table 9.3 shows that the ICC's are high (>0.9) for all of the correction factors of Zijlstra's method and for only $K_{2.ON}$ and $K_{4.ON}$ of Gonzalez's method. From Table 9.4we could see that Zijlstra's method provides the closest step length estimations in respect of the reference values (RMSE=0.04 m.). Among all of the correction factors, the least error (0.033 m) with lowest (SD)RMSE is obtained by Zijlstra's method with correction factor $K_{3.ON}$

Table 9.4: Error comparison on step length between adaptation methods

	Zijlstra		**Gonzalez**		**Weinberg**	
	Average Error (m)	**(SD) RMSE (m)**	**Average Error (m)**	**(SD) RMSE (m)**	**Average Error (m)**	**(SD) RMSE (m)**
$K_{1.OFF}$	0.038	(0.048) 0.048	0.059	(0.052) 0.066	0.064	(0.075) 0.084
$K_{1.ON}$	0.034	(0.043) 0.044	0.058	(0.065) 0.067	0.062	(0.070) 0.080
$K_{2.OFF}$	0.034	(0.044) 0.044	0.053	(0.048) 0.062	0.061	(0.081) 0.081
$K_{2.ON}$	0.034	(0.044) 0.044	0.056	(0.066) 0.066	0.060	(0.081) 0.081
$K_{3.OFF}$	0.038	(0.050) 0.050	0.060	(0.052) 0.067	0.065	(0.075) 0.085
$K_{3.ON}$	**0.033**	**(0.041) 0.041**	0.059	(0.065) 0.067	0.062	(0.070) 0.081
$K_{4.OFF}$	0.034	(0.043) 0.044	0.053	(0.048) 0.063	0.062	(0.081) 0.081
$K_{4.ON}$	0.034	(0.044) 0.044	0.056	(0.066) 0.067	0.061	(0.081) 0.081

After detecting steps and estimating the step length by each estimator, gait speed is calculated using Eq. (5.28). The ICC with 95% confidence interval of all correction factors with reference gait speed are shown in Table 9.5. The mean error and (SD) RMSE are presented in Table 9.6.

On estimating gait speed, significant difference ($p<0.05$) between Zijlstra's method and the others is found. No significant difference are found between the correction factors of Zijlstra's method. From Table 9.5we could see that, for all of the correction factors of Zijlstra's method, for $K_{1.OFF}$,$K_{2.ON}$,$K_{2.OFF}$ and $K_{4.ON}$of Gonzalez's method and only $K_{4.OFF}$ of Weinberg's method, the ICCs are high (>0.9).

Table 9.5: Agreement of gait speed estimation by using adapted step length estimators. Interclass coefficient and 95% confidence interval are presented as ICC (95% CI)

	Zijlstra	**Gonzalez**	**Weinberg**
$K_{1.OFF}$	**0.953 (0.896 – 0.979)**	**0.902 (0.791 – 0.956)**	0.853 (0.696 – 0.933)
$K_{1.ON}$	**0.962 (0.915 – 0.983)**	0.788 (0.575 – 0.901)	0.857 (0.702 – 0.934)
$K_{2.OFF}$	**0.955 (0.900 – 0.980)**	0.692 (0.416 – 0.852)	0.802 (0.600 – 0.907)
$K_{2.ON}$	**0.952 (0.915 – 0.983)**	**0.902 (0.791 – 0.956)**	0.921 (0.828 – 0.964)
$K_{3.OFF}$	**0.952 (0.894 – 0.979)**	**0.920 (0.827 – 0.964)**	0.852 (0.692 – 0.932)
$K_{3.ON}$	**0.962 (0.916 – 0.983)**	0.866 (0.719 – 0.938)	0.856 (0.701 – 0.934)
$K_{4.OFF}$	**0.955 (0.901 – 0.980)**	0.798 (0.593 – 0.905)	0.799 (0.596 – 0.906)
$K_{4.ON}$	**0.953 (0.896 – 0.974)**	**0.936 (0.861 – 0.971)**	**0.919 (0.826 – 0.964)**

Table 9.6: Error comparison on gait speed between adaptation methods

	Zijlstra		**Gonzalez**		**Weinberg**	
	Average Error (m/s)	**(SD) RMSE (m/s)**	**Average Error (m/s)**	**(SD) RMSE (m/s)**	**Average Error (m/s)**	**(SD) RMSE (m/s)**
$K_{1.OFF}$	0.078	(0.053) 0.094	0.116	(0.067) 0.129	0.114	(0.147) 0.147
$K_{1.ON}$	0.077	(0.043) 0.088	0.114	(0.120) 0.143	0.139	(0.117) 0.172
$K_{2.OFF}$	0.095	(0.061) 0.112	0.095	(0.138) 0.202	0.137	(0.166) 0.186
$K_{2.ON}$	0.069	(0.046) 0.082	0.109	(0.072) 0.130	0.121	(0.157) 0.167
$K_{3.OFF}$	0.080	(0.054) 0.096	0.121	(0.056) 0.101	0.114	(0.148) 0.148
$K_{3.ON}$	**0.068**	**(0.041) 0.088**	0.116	(0.121) 0.146	0.140	(0.118) 0.172
$K_{4.OFF}$	0.094	(0.060) 0.111	0.096	(0.109) 0.159	0.137	(0.167) 0.187
$K_{4.ON}$	0.077	(0.046) 0.081	0.106	(0.072) 0.127	0.120	(0.156) 0.166

Table 9.6 shows that gait speed calculated with the average step length estimated by Zijlstra's method has less error than the others. The correction factors obtained during ON states ($K_{i.ON}$) applied to Zijlstra's method provide more or similar accurate results than those obtained during OFF states. Consequently, since calibration is in ON state, in a real application of the method, patients would not need be required to skip medication intakes given that OFF state data are not necessary. In respect to the reference value, the

closest gait speed estimation is obtained by Zijlstra's method with correction factor $K_{3.ON}$ showing least error of 0.068 m/s with (SD)RMSE of (0.041)0.088 m/s.

Table 9.4 and Table 9.6 show that, among all correction factors, Zijlstra's method has the lowest RMSE and standard deviation with $K_{3.ON}$. Hence, separately multiplication correction factors for left and right steps and for each individual provide the best approach. Zijlstra's method with correction factor $K_{3.ON}$ has the same mean than the remaining correction factors with Zijlstra's method and for $K_{2.OFF}$ and $K_{4.OFF}$with Gonzalez's method ($p<0.05$).

The usage of a generic correction factor for all individuals and for both left and right legs have also been tested. From all 25 patients, considering both their OFF and ON states, we found the correction factors that have more central tendencies as 0.7938 for left SL and 0.8127 for right SL. This generic constant provides an RMSE (±SD)of 0.060 m. (± 0.058)during OFF state and 0.053 m. (± 0.051)during ON state. Figure 9.1 shows a box plot using reference step length, $K_{3.ON}$ and generic factor during both OFF and ON state. From each group, it is shown that step length during ON states are bigger than OFF states which is an indication to determine whether the patient are in OFF state or ON state.

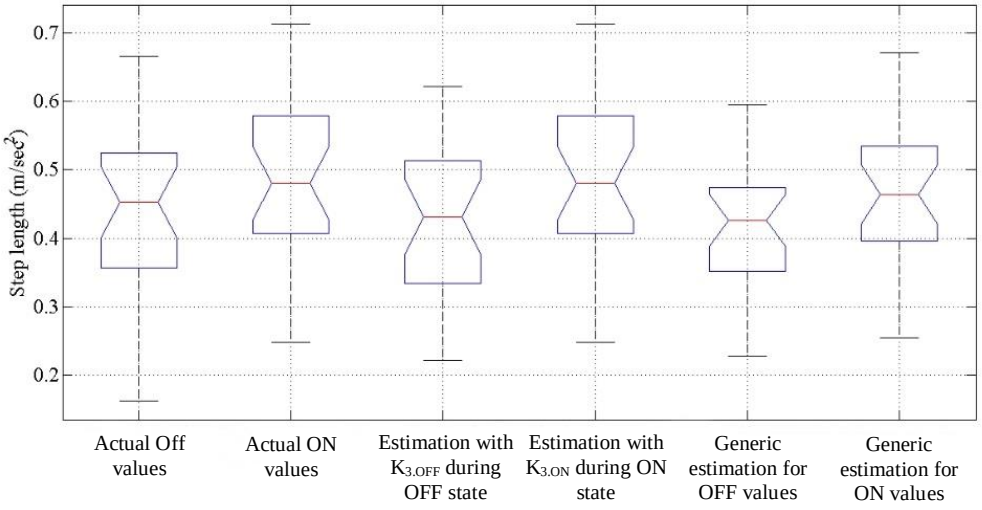

Figure 9.1: Average Step length grouped by reference values, K_3 and generic factors during both OFF and ON state

In summary, results show that the best methodology to estimate the average step length in PD patients based on the proposed sensor location consists of combining SWAT step detection method and Zijlstra's method with correction factor $K_{3.ON}$. SWAT accuracy rate shown is 96.76% on average (96.53% during OFF state and 97.00% during ON state). On the other hand, the best step length estimation method, Zijlstra's method with correction factor $K_{3.ON}$, shows the lowest average error (0.033 m.) with lower SD and RMSE (0.041m and 0.041m, respectively) for estimating step length. It also has lowest error (0.078 m/s) with lower SD and RMSE (0.0090 m/s and 0.106 m/s, respectively). As this correction factor and the generic correction factor are estimated during ON state, the patients would not need to skip medication.

Zijlstra's adapted method $K_{3.ON}$ and SWAT step detection algorithm could be implemented in the movement sensor of REMPARK's wearable system [107]. This wearable system aims to monitor both motor and non-motor symptoms of PD patients and it is composed of three devices: a movement sensor, a wireless headset and a smart phone. The movement sensor continuously monitors patient's movement and determines the presence of dyskinesia, bradykinesia and FoG. It sends the collected information to the smart phone, which controls the wireless headset providing audio cues to the patients in order to overcome FoG or improve their gait. Given that the movement sensor is worn in the location presented in this paper, the proposed step length estimation algorithm could be integrated with the existing methods in order to complement the monitoring of motor symptoms. From prior literature [29], it is seen that the mean step length of PD patients during their ON state is 0.66m (95% CI is 0.615 – 0.695) where it is 0.48m (0.475-0.486) during OFF state. But from the current data base of 25 PD patients, the difference of mean step length between ON and OFF state is very low. The average step length of 25 PD patients is 0.48 m (95% CI is 0.44-0.53) during their ON state and 0.42 m (95% CI is 0.37 – 0.48) during their OFF state.

9.3 Conclusion

In this experiment, gait properties are extracted from PD patients using an accelerometer located in left lateral side of waist. A newly developed step detection algorithm and four

adaptations of three step length estimators (discussed in chapter 7)are implemented with the signals obtained from 25 PD patients. Results on 25 PD patients show that the step detection method detects steps with the highest accuracy and lowest RMSE.

The four types of correction factors are used on PD patients in both of their motor status with the SWAT method. The errors are calculated from the reference data and are compared among the different correction factors. The inverted pendulum model proposed by Zijlstra et al. [114] provides the most accurate estimations. It is also found that the training sessions to calculate the correction factors done with patients in ON state provide more accurate results than in OFF state. Specially, training with $K_{3.ON}$ during ON state provides the lowest error. Given that training is in ON state, the advantage of this approach is that patients would not need to attend without medication in order to train the method. Finally, a generic multiplication factor for left and right legs is also tested in this study and found that its performance, though lower, is close to $K_{3.ON}$. The advantage of using generic correction factor will help to avoid time consuming individual calibration.

Part III: Estimating step length from Parkinson's patients through a new gait model

Chapter 10 ICE-CETpD: A new step length estimator for patients with Parkinson's disease

In this chapter a new step length estimation method ICE-CETpD is introduced. The estimator is based on an adapted inverted pendulum (IP) model. Previously described step detection method SWAT is used combined with ICE-CETpD to estimate the step lengths and gait speed more accurately from left lateral side of waist.

10.1 ICE-CETpD:

Zijlstra et al. [113] considered the vertical displacement of COM as an inverted pendulum (IP) for a step cycle. From signal obtained from left lateral side IP model is a good approach to describe displacement of right step but not left step. Gonzalez et al. [115] extended the model by considering the vertical displacement of COM during single support phase (SSP) as an IP model and a constant during double support phase (DSP). This could be used to describe displacement of only left step. An adapted model would be useful to describe both left and right steps and to estimate their lengths.

The first figure (the upper one) of Figure 10.1 shows five (5) detected ICs and TOs on SWAT signal from a PD patient. The second figure (the bottom one) of Figure 10.1shows the detected ICs and TOs on vertical displacement along with the vertical acceleration from same patient. From the figure, we can see that the forward displacement during

right step (LIC to RIC) can be represented using an inverted pendulum (IP) model. The left step can be described as a standard pendulum model during DSP and an IP model during SSP.

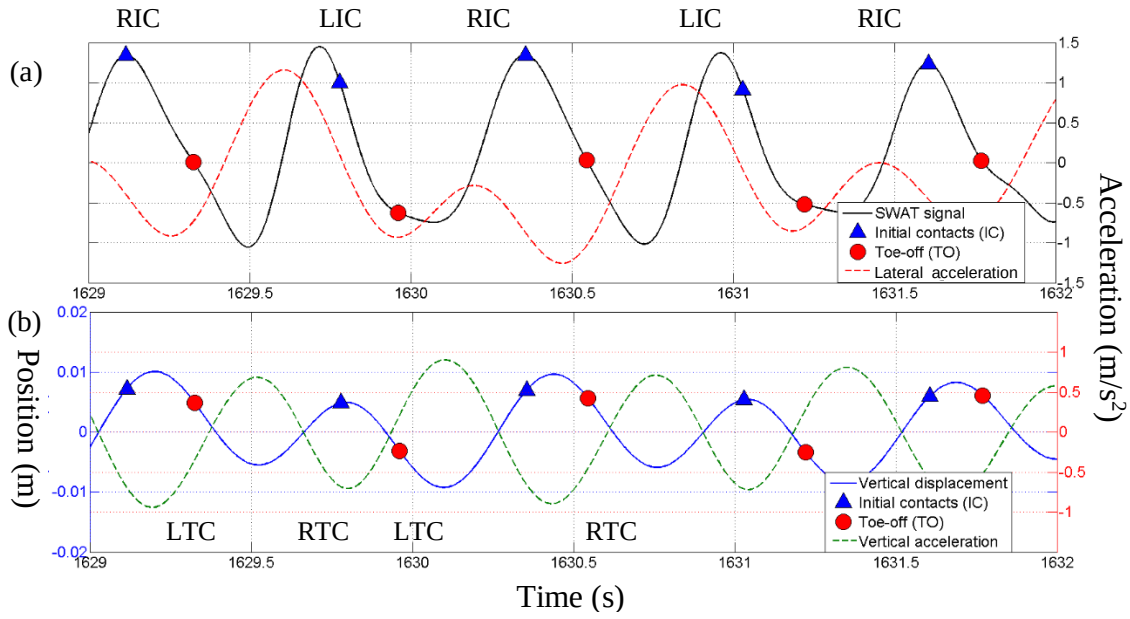

Figure 10.1: Five initial contact (IC) and terminal contact (TC) events are detected using SWAT (a) on SWAT lateral signal with lateral signal (b) on vertical displacement with vertical signal.

Figure 10.2 shows the proposed gait model where the right step and SSP of left step is represented by two inverted pendulum. The radius of the inverted pendulums are same as leg length L. h_r and h_l are the vertical displacement of waist during right step and SSP of left step respectively. The DSP of left step is represented as a standard pendulum with unknown radius As the duration of DSP is only around 18% of a single step of a PD patient [29]. So, they could be ignored in estimating left step length and the displacement during left step can be estimated using only inverted pendulum model. As the DSP is ignored, left step length is underestimated that can be corrected by using an individual correction factor with respect to left step length.

Forward displacement during right step (SL_{right}) can be computed from the vertical displacement of the waist (h_r) and the leg length (L), rewriting Eq. (5.13) employed by Zijlstra et. al. in section5.2.1as follows.

$$SL_{right} = 2 \times K_r \sqrt{2h_r L - {h_r}^2} \tag{10.1}$$

where, h_r can be computed as the range of the signal obtained by double integrating vertical accelerations between the instants of initial contacts of left to right leg.

The measurement is corrected by an individual correction factor K_r that is measured in respect to right step length using Eq.(10.2):

$$K_r = \frac{mean(SL_{real})}{mean(SL_{right(estimated)})} \tag{10.2}$$

K_r is obtained from training data of a PD patient during ON state and tested during OFF state and vice versa.

Forward displacement during left step (SL_{left}) can also be computed from the vertical displacement of the waist (h_l) and the leg length (L) according to:

$$SL_{left} = 2 \times K_l \sqrt{2h_l L - {h_r}^2} \tag{10.3}$$

where, h_l can be computed as the range of the signal obtained double integrating vertical accelerations between the instants of TC and Initial contact of left leg.

The left step length is underestimated as it considers the displacement during single support ignoring the small displacement during double support. The underestimation is corrected using an individual correction factor K_l which is measured in respect to left step length using Eq. (10.4).

$$K_l = \frac{mean(SL_{real})}{mean(SL_{left(estimated)})} \tag{10.4}$$

K_l is also obtained from training data of a PD patient during ON state and tested during OFF state and vice versa.

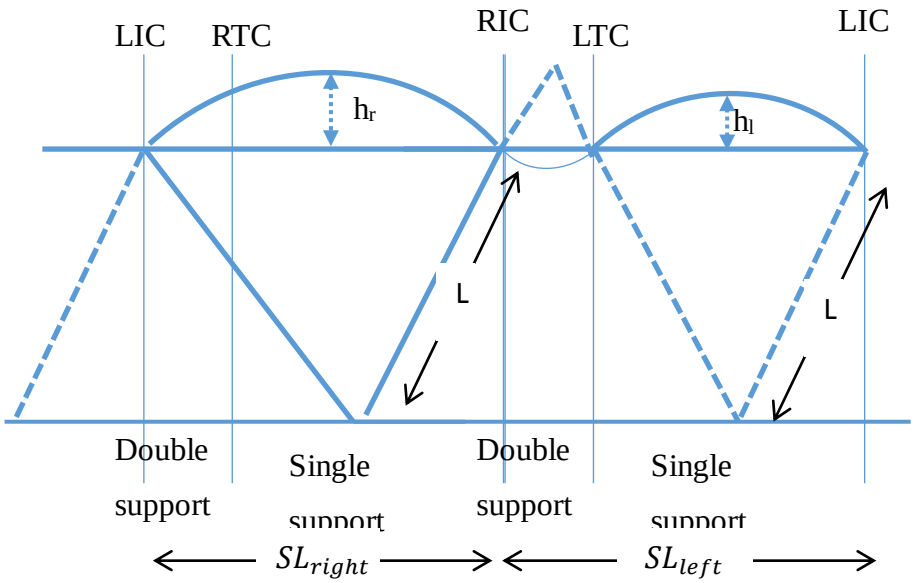

Figure 10.2: The forward displacement of left waist during right step is modeled as an inverted pendulum and during left step as a pendulum during double support and an inverted pendulum during single support

10.2 Discussion

Zijlstra et al. [114] approximated the step length by the vertical displacement of CoR during a step. Gonzalez et al. [115] modified this model by extending the step length as sum of forward displacement during double and single stance phase. After closely observing the vertical displacement with detected steps from left lateral side of a PD patient (Figure 10.1), we observed that both of these models do not completely explain the behavior of signals for left and right steps. The newly proposed method ICE-CETpD overcomes this limitation by providing a mixed model for left/right step length. This would help to explain the slow and short stepped walking behavior of a PD patient. As it explains the walking behavior of signals for both left and right steps, it can estimate each step length more accurately and thus will help to identify the gait variability during OFF state and pre-FoG state.

Chapter 11 Evaluation of the new gait model

In this chapter, the ICE-CETpD gait model is evaluated and the results in a database of signals gathered from 25 PD patients [127] are presented. Reliability, consistency and estimation error of this method are compared with three selected step length estimators discussed before. Experimental results show that the intra-class correlation with reference step length are above 0.9 for the ICE-CETpD during both motor states while this holds for Zijlstra's method only during OFF state. ICE-CETpD estimates step length with more accuracy providing lower mean error ± SD (RMSE) of 0.029 ± 0.027 (0.038) m during ON state and 0.021 ± 0.020 (0.029) m during OFF state.

11.1 Data analysis

The reference and estimated average step lengths are tested by performing a Shapiro-Wilk test to find if they are normally distributed. Parametric tests are applied since the test confirmed that the data is normally distributed. Relative reliability or consistency between estimated and reference step length is described with single measures, two-way mixed intraclass correlation coefficient (ICC) with absolute agreement definition and related 95% confidence intervals (CI). The agreement is considered 'fair' when ICC is above 0.7, 'good' when they are between 0.8 and 0.9 and 'excellent' when they are above 0.9. Pearson correlation coefficients (r) are also used to describe the association of step lengths between estimated and reference values. Bland-Altman plots [128] for each step length estimators to compare the estimated step length obtained by each with the

reference step length are generated. Associated mean differences and the 95% upper and lower limit of agreement (LoA) to the mean value calculated from reference step length and each step length estimations are shown in the plots.

11.2 Result with step length estimation and gait speed

All 25 patients performed trials during their OFF and ON states. The trials were performed either in an outdoor street, an indoor hallway or inside patients' homes based on weather condition. The length of the path varied also from 28 m to 5m based on the patients' physical conditions and whether an indoor or outdoor pathway. From the odometer measurements, the mean step length was 0.42 m (95% CI is 0.37 – 0.48 m) during OFF state and 0.48m (95% CI is 0.44-0.53 m) during ON state. The mean gait speed was 0.7 m/sec (95% CI is 0.6 – 0.8 m/s) during OFF state and 0.82 m/s (95% CI is 0.72-0.92 m/s) during ON state

Pearson correlation coefficient between mean reference step length (gait speed)and step length estimators during OFF and ON states are presented in Table 11.1.and Table 10.2. Agreement between step length estimators and the reference step length are also presented in the same table by the interclass correlation coefficient (ICC) with 95% confidence interval (CI) and the range of limits of agreements (LoA). The average errors are calculated from the absolute differences between estimated and reference step length. The standard deviation and RMSE of each method are obtained from these absolute mean differences and are also presented in Table 11.1. and Table 10.2

From them, it can be observed that the correlation between reference step length and ICE-CETpD are excellent ($r > 0.9$) during both motor states although, for Zijlstra's method, it is true only during OFF state. On the other hand, the agreement between reference and ICE-CETpD are also "excellent" in both states. The lower range of 95% CI and LoA of the ICE-CETpD also show an increased reliability and consistency of the proposed method in both motor states with respect to the others. The error (Mean ± SD and RMSE) of Zijlstra's method and ICE-CETpD are also lower in both states though ICE-CETpD exhibits the lowest values.

Table 11.1: Correlation, agreement and error of the step length estimators with reference step length during OFF and ON states. ("winner" values are in bold face)

Motor state	Method	Pearson Correlation coefficient (r)	ICC single measurement (95% CI)	LoA (m)	Error	
					Mean ±SD (m)	RMSE (m)
OFF (Training session is during ON state)	Zijlstra's	0.930 (p<0.0001)	0.929 (0.847 to 0.968)	-0.0826 to 0.1026	0.038 ± 0.029	0.036
	Gonzalez's	0.883 (P<0.0001)	0.860 (0.669 to 0.801)	-0.0841 to 0.1431	0.054 ± 0.036	0.064
	Weinberg's	0.862 (P<0.0001)	0.801 (0.401 to 0.924)	-0.0757 to 0.1733	0.061 ± 0.051	0.079
	ICE-CETpD	**0.973 (P<0.0001)**	**0.971 (0.934 to 0.966)**	**-0.0492 to 0.0643**	**0.021 ± 0.020**	**0.029**
ON (Training session is during OFF state)	Zijlstra's	0.896 (P<0.0001)	0.897 (0.782 to 0.953)	-0.1118 to 0.094	0.041 ± 0.033	0.049
	Gonzalez's	0.788 (P<0.0001)	0.788 (0.578 to 0.900)	-0.1661 to 0.1407	0.058 ± 0.053	0.076
	Weinberg's	0.693 (P=0.0002)	0.667 (0.377 to 0.838)	-0.2226 to 0.1490	0.076 ± 0.067	0.097
	ICE-CETpD	**0.946 (P<0.0001)**	**0.944 (0.878 to 0.975)**	**-0.0864 to 0.0664**	**0.029 ± 0.027**	**0.038**

Table 11.2: Correlation, agreement and error of the gait speed with reference step length during OFF and ON states. ("winner" values are in bold face)

Motor state	Method	Pearson Correlation coefficient (r)	ICC single measurement (95% CI)	LoA (s)	Error	
					Mean ±SD (s)	RMSE (m)
OFF (Training session is during ON state)	Zijlstra's	0.954	0.944 (0.877 to 0.975)	-0.11847 to 0.214547	0.75±0.062	0.096
	Gonzalez's	0.967	0.936 (0.860 to 0.971)	-0.09441 to 0.247399	0.065±0.663	0.115
	Weinberg's	0.923	0.914 (0.815 to 0.961)	-0.09216 to 0.316912	0.118±0.097	0.152

	ICE-CETpD	**0.974**	**0.971 (0.935 to 0.987)**	**0.07096 to 0.1625**	**0.058±0.048**	**0.074**
ON (Training session is during OFF state)	Zijlstra's	0.902	0.900 (0.786-0.955)	-0.177 to 0.277	0.083±0.094	0.124
	Gonzalez's	0.860	0.860 (0.708-0.936)	-0.235 to 0.281	0.097±0.091	0.131
	Weinberg's	0.769	0.768 (0.542-0.891)	-0.347 to 0.303	0.118±0.117	0.164
	ICE-CETpD	**0.963**	**0.963 (0.918-0.983)**	**-0.104 to 0.167**	**0.062±0.042**	**0.075**

* Correlation is significant at the 0.01 level

The Bland-Altman plots of mean difference (MD) and 95 percent limit of agreement (LOA) between estimated and reference step length during OFF and ON states by each method are presented in Figure 11.1. The MDs between each estimators and reference step length are close to zero during ON and OFF state. The difference between adapted IP model and reference step length is lower (based on 95% LoA) in both motor state.

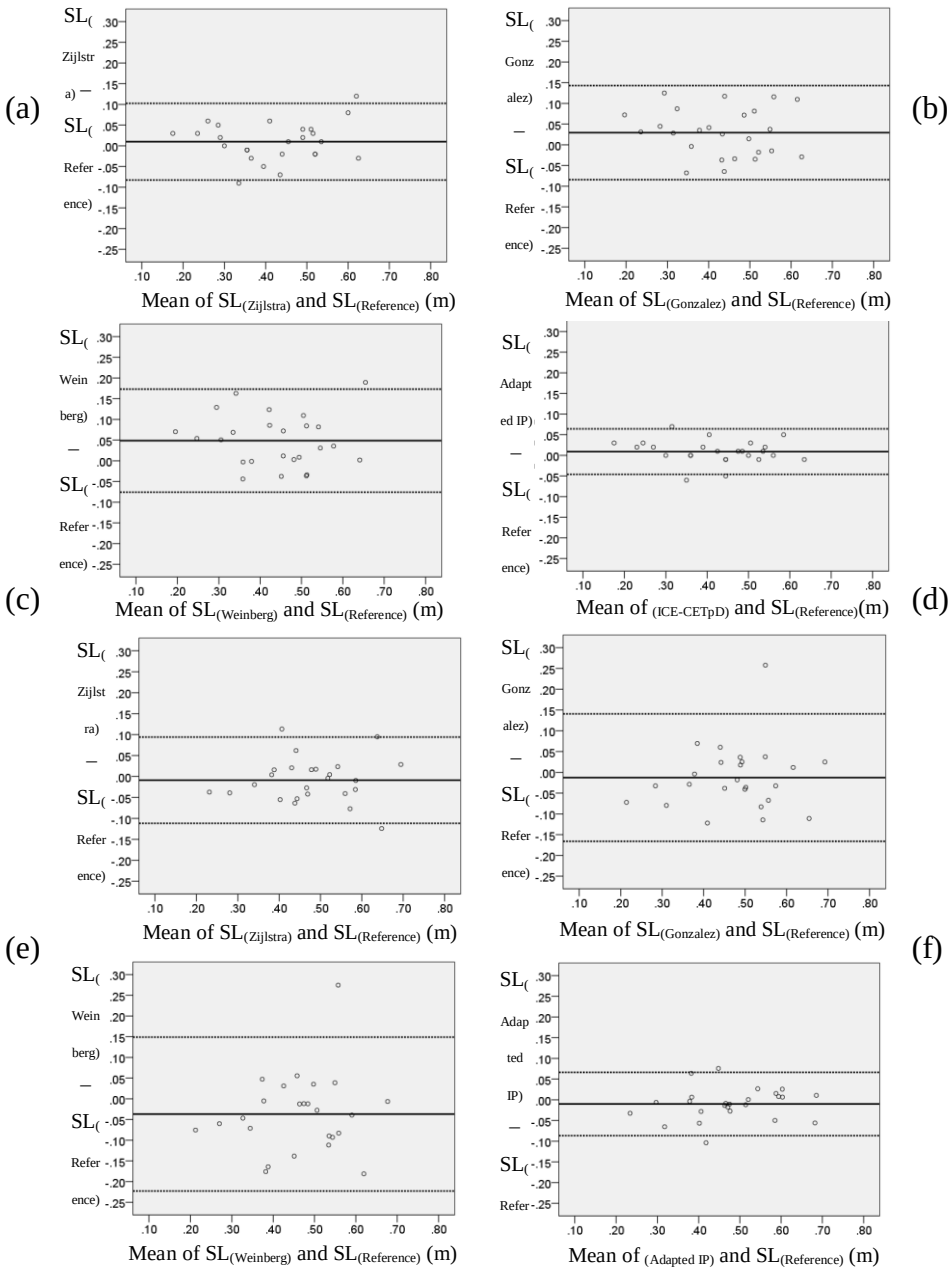

Figure 11.1: Bland-Altman plots for mean step length of each estimators during the patients' OFF state (a-d) and ON state (e-h). Solid horizontal lines represent mean difference and dashed lines represent 95% limit of agreement.

The Bland-Altman plots of mean difference (MD) and 95 percent limit of agreement (LOA) between estimated and reference step length during OFF and ON states by each method are presented in Figure 11.2 and 11.3 respectively. The MDs between each estimators and reference step length are close to zero during ON and OFF state. The difference between adapted IP model and reference step length is lower (based on 95% LoA) in both motor state.

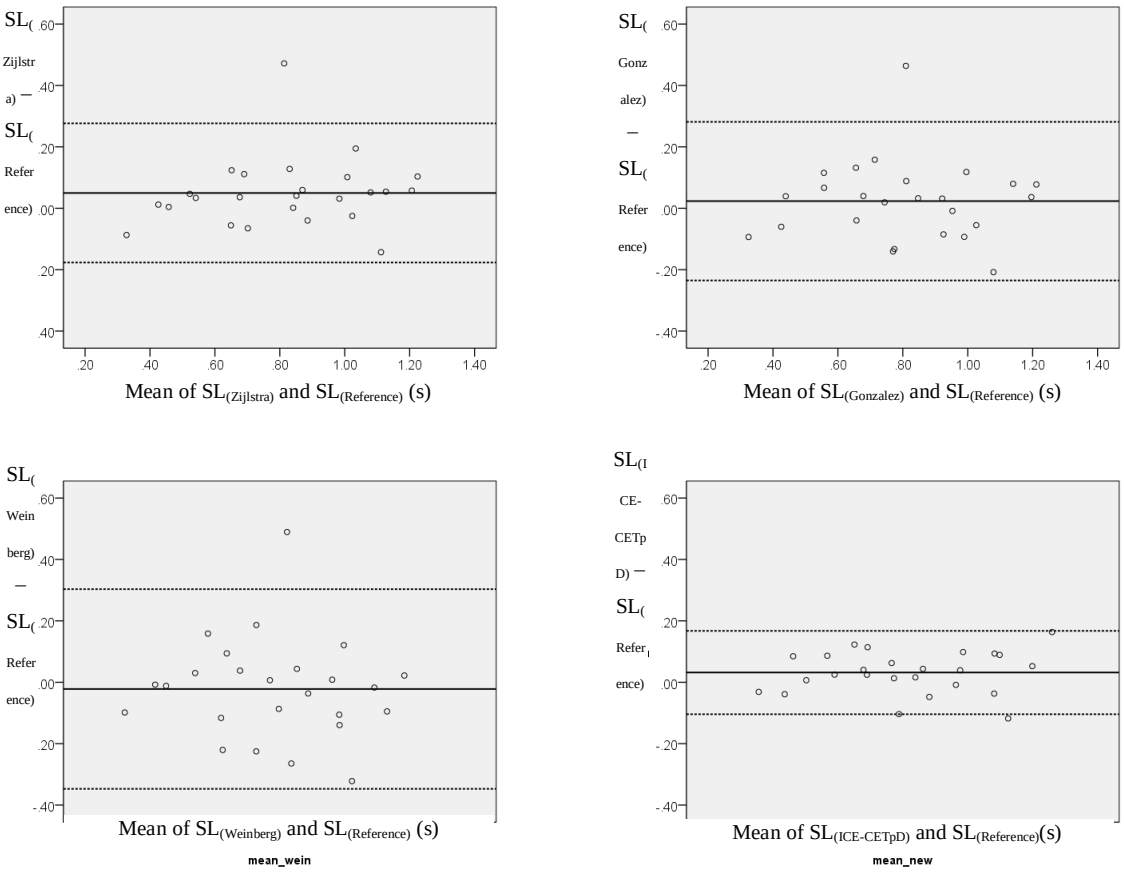

Figure 11.2: Bland-Altman plots for gait speed of each estimators during the patients' ON state. Solid horizontal lines represent mean difference and dashed lines represent 95% limit of agreement.

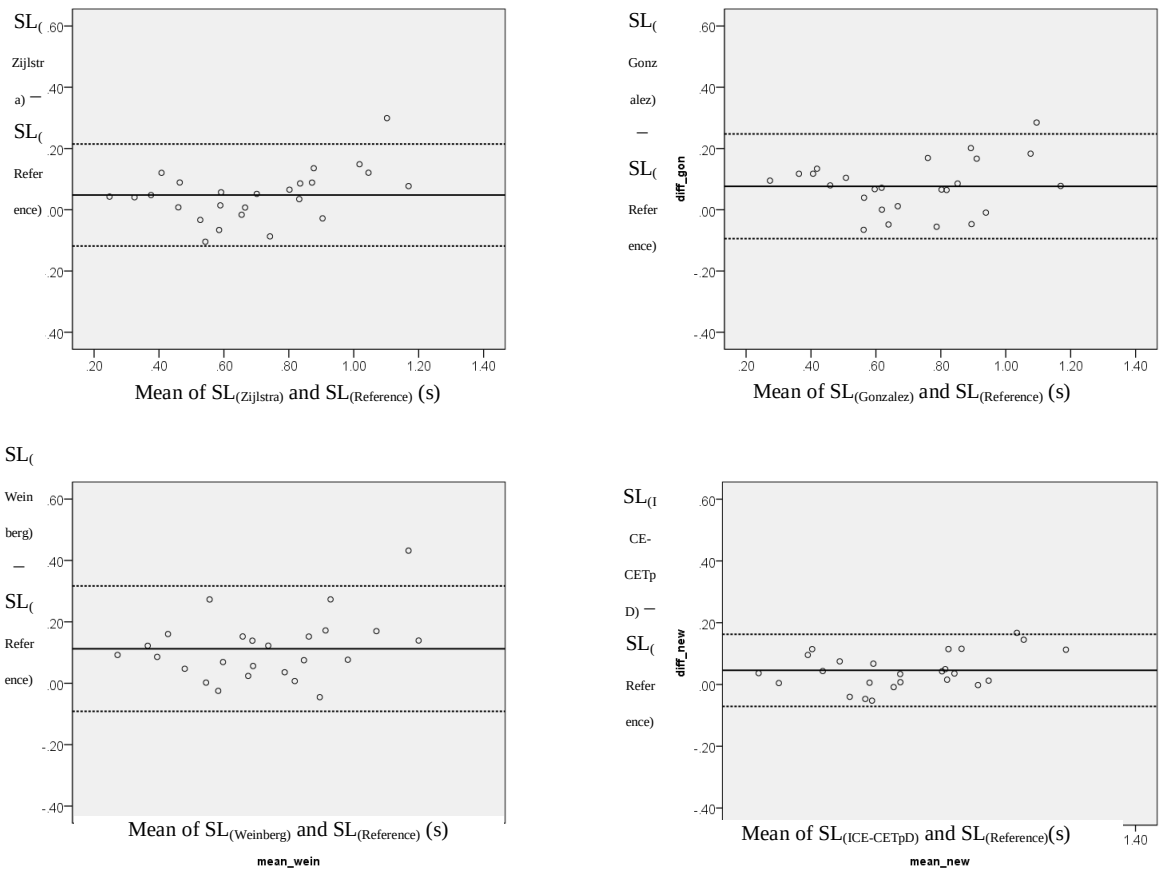

Figure 11.3: Bland-Altman plots for gait speed of each estimators during the patients' OFF state. Solid horizontal lines represent mean difference and dashed lines represent 95% limit of agreement.

11.3 Conclusion

In this chapter, an adapted IP model for step length estimation of PD patients is proposed and discussed. Agreement and consistency of the adapted IP model and existing three step length estimators with reference step length is reported. Comparing the group mean, excellent agreements are reached with reference step length withICE-CETpD and Zijsltra's method OFF state, but only for ICE-CETpD during ON state. To obtain the individual correction factor, the test session during OFF state, provide results with more accuracy than ON state. Given that training is in ON state, the advantage of this approach is that patients would not need to attend without medication in order to train the method.

Part IV: Final remarks

Chapter 12 Conclusions

12.1 Author's Contributions

The aim of this thesis is to contribute in developing algorithms for step detection, step length and gait speed estimation of PD patients in their daily life and during both of their motor states, using a single accelerometer located on a user-friendly position. In this regards, the most relevant contributions are summarized below:

- **Sensor location**

  In this thesis, a tri axial accelerometer is located on the lateral side of the waist, above the ASIS. The position is user-friendly and comfortable. The location is also suitable to measure the common symptoms of PD accept tremor.

- **Step detection**

  A new method for step detection SWAT has been developed for the signals obtained from an accelerometer on said location. Compared to current state-of-the-art methods, SWAT outperforms the existing ones for both healthy person and patients with PD. For healthy persons, SWAT achieved accuracy of 99.24%. For PD patients, despite variable gait speed, the accuracy is 97.01% with IQR of 96.67-100% during ON state and 96.60% with IQR of 95-100% during OFF state. The overall accuracy is 96.75% and the IQR is 95.23-100%. The method is used to detect steps for step length estimations.

- **Step length estimation**

To estimate step length, first existing step length estimators are modified to adapt them to the new sensor location. The adapted methods outperform the original ones. The best method is with an individual correction factor. The correction factor is a multiplying factor that considers left and right step separately. The average error of the best method, on estimating step length of PD patients is 0.033m with (SD)RMSE is (0.041)0.041m. To avoid individual calibration process, a generic multiplying correction factor for both left and right legs is also proposed. The average error is 0.046 m with (SD)RMSE of (0.058)0.060m is during OFF state. During ON state, the error is 0.036m with (SD)RMSE of (0.051)0.053m during ON state.

Finally a new step length estimator, ICE-CETpD based on an adapted inverted pendulum model is proposed. In this model, the vertical displacement of waist is considered as an inverted pendulum during right step. During single support phase of left step, the vertical displacement is considered as an inverted pendulum model and during double support phase, it is considered as a standard pendulum. From the experiment results from 25 PD patients, it is seen that the accuracy of ICE-CETpD on estimating step length is higher than current state-of-the-art estimators. The mean error is 0.021m during OFF state and 0.029m during ON state. The standard deviation and RMSE shown as (SD)RMSE during OFF state and ON states are (0.02)0.029m and (0.027)0.038m respectively. During both motor state, the ICC is above 0.9, showing their reliability on estimating step length. The correction factors obtained during ON state provide more accurate results than in OFF state. Given that the training session is ON state, the patients would not need to go to OFF state to train the method.

- **Gait Speed**

The gait speed estimation is directly related to the performance of step detection and step length estimation. Gait speed is estimated with the cadence estimated by SWAT and step length estimated from the adapted methods. The average error of the best method, on estimating gait speed of PD patients is 0.078m/s with

(SD)RMSE is (0.090)0.106 m/s. The performance of gait speed is improved for the step length estimated from ICE-CETpD. The average error is 0.058 m/s during OFF state and 0.062 m/s during ON state. The (SD)RMSE during OFF state and ON states are (0.048)0.074 m/sand (0.042)0.075 m/s respectively.

12.2 Future Work

There is still room for improvement in the works presented in this thesis. First, the algorithms will be updated to remove their limitations and, second, they will be implemented for real-time analysis.

12.2.1 Algorithmic enhancement

The limitation of step detection method is that it sometimes misses the first and/or final step made by the PD patient during walking. In future, SWAT will be updated to identify these events. By improving these events, it will improve gait detection, average step length and gait speed estimation.

12.2.2 Real-time deployment

The step detection algorithm SWAT along with the step length estimator ICE-CETpD developed in this thesis will be updated in future to deploy them in real-time. As there are other algorithms developed in REMPARK to detect symptoms of PD, the real-time deployment along with these algorithms will enhance the performance of overall detection. This will not only identify symptoms of the disease, but also will detect the ON or OFF motor state online.

12.3 Publications

Journal paper

- T. Sayeed, A. Samà, A. Català, A. Rodríguez-Molinero, and J. Cabestany, "Adapted step length estimators for patients with Parkinson's disease using a lateral belt worn accelerometer.," *Technol. Health Care*, Dec. 2014.

Conference papers

- T. Sayeed, A. Samà, A. Català, and J. Cabestany, "Comparison and adaptation of step length and gait speed estimators from single belt worn accelerometer positioned on lateral side of the body," in *8th IEEE International Symposium on Intelligent Signal Processing*, 2013.
- T. Sayeed, A. Samà, A. Catala, and J. Cabestany, "Comparative and adaptation of step detection and step length estimators to a lateral belt worn accelerometer," in *e-Health Networking, Applications Services (Healthcom), 2013 IEEE 15th International Conference on*, 2013, pp. 105–109.

Submitted journal papers

- T. Sayeed, A. Samà, A. Rodríguez-Molinero, M. Hitz and J. Cabestany, "ICE-CETpD: A new step length estimator, its validity and reliability for patients with Parkinson's disease using a lateral belt worn accelerometer," *IEEE Journal of Biomedical and Health Informatics.*

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