A Computational Model for Gait and Postural Sway for the Elderly

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Abstract

Maintaining a high standard of life, especially for the elderly, enables them to live their lives with minimum fear of sudden accidents. Falling is one of the most important problems that affect elderly lives. Falling causes injuries that may be fatal or decrease the functional ability and the quality of life. Predicting and preventing falls before they happen makes a critical difference, enabling optimal self-care for elderly people. While the main causes of falling are related to postural sway and walking, determining abnormalities in one or both of these activities can be informative in predicting the likelihood of having a fall. A need exists for a gait and postural sway analysis system that is easy to use, readily available, and inexpensive

This PhD thesis investigates using vision data, as an inexpensive option, to estimate gait and sway movements from video recordings. It also investigates measuring human gait and postural sway parameters from the estimated movements within acceptable accuracy when compared to the gold standard measurements, Vicon and force plate. Furthermore, based on analysing the measured gait and sway parameters for a different age groups, an increasing risk of having a fall is predicted.

Defining the changes in the pattern of gait and sway that are considered as signs for deterioration in an individual's health status is important for predicting the risk of a fall. Monitoring these changes, which are continuously occurring and are inevitable while a person is aging, allows early intervention to avoid possible fall accidents well before they happen. Seeking help and including proper exercises in the daily life are examples of appropriate intervention to avoid possible fall accidents.

First, a dataset of gait and sway activities is devised and recorded for two groups of people, elderly people over fifty years and younger healthy athletes. The dataset part for the healthy athletes group of people is considered as the ground truth part. Vision data is the main data type in the two parts. The ground truth part of the dataset contains centre of pressure displacements from a force plate as well as the joint movements in the three dimensional (3D) space from a Vicon motion capture system.

Second, a computational learning-based model to estimate the body's postural sway from vision data is proposed and validated. Another model to estimate human gait from vision data is also built and validated using the ground truth part of the dataset. The estimated gait and sway movements are used to

measure defined parameters that are used to analyse the gait and sway. The two computational models achieved high correlation between the estimated gait and sway signals from video recordings compared to their corresponding signals extracted from the force plate and the Vicon system.

Third, the gait and sway proposed models are used to estimate gait and sway movements for the group of elderly people, then the gait and the sway parameters are measured. Based on the measured sway parameters, each elderly subject is assigned to a *sway-age* group. Also, for the measured gait parameters, each elderly subject is assigned to a *gait-age* group. The chronological age of the subjects is compared with the estimated age from sway and gait movements toward analysing the fall risk.

From the presented work, vision data can be used to estimate humans' gait and postural sway with an acceptable accuracy that has reached 90% for the estimated postural sway and gait referenced to the measurements computed from the ground truth data. The proposed methods are then used on the elderly people data to estimate their sway and gait movements. Using these estimations, sway and gait parameters are measured. From these parameters, each elderly subject is clustered into *gait/sway age* group. Comparing subject's *gait/sway age* group with his/her *chronological age* group defines a likelihood risk of having a fall that gives the opportunity to intervene to improve maintaining the balance to avoid fall accidents.

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Publications

During the course of this study, the following peer-reviewed research papers were published:

- Hafsa Ismail; *Gait and Postural Sway, Multi-model*, Proceedings of the ACM on International Conference on Multimodal Interaction (ICMI), Doctoral Consortium, 629-633, 2015.
- Hafsa Ismail; *Fall Prediction by Analysing Gait and Postural Sway from Videos*, The IEEE International Conference on Automatic Face and Gesture Recognition (FG), Doctoral Consortium, 2017.
- Hafsa Ismail, Ibrahim Radwan, Hanna Suominen, Gordon Waddington, and Roland Goecke; *Human Postural Sway Estimation from Noisy Observations*, The IEEE International Conference on Automatic Face and Gesture Recognition (FG), 2017, 454-461
- Hafsa Ismail, Ibrahim Radwan, Hanna Suominen and Roland Goecke; *Gait Estimation and Analysis from Noisy Observations*, The International Engineering in Medicine and Biology Conference (EMBC), 2019.
- Hafsa Ismail, Ibrahim Radwan, Hanna Suominen, Gordon Waddington, and Roland Goecke; *Sway Risk Analysis Based on Age Group Classification*, The International Engineering in Medicine and Biology Conference (EMBC), 2019.
- Ibrahim Radwan, Akshay Asthana, Hafsa Ismail, Byron Keating, Roland Goecke; *Estimation of Missing Human Body Parts via Bidirectional LSTM*, IEEE International Conference on Automatic Face & Gesture Recognition (FG), 2019.

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Chapter 1

Introduction

Human gait and postural sway reflect an individual's health condition as they are easily affected by illness, weakness, and aging. Analysing human gait and postural sway has been initiated to detect pathological patterns from normal ones in clinical studies. Human gait and sway are receiving an increasing interest from different research areas, such as computer vision and sports science. Analysing human gait and sway have been used for human recognition/identification, rehabilitation, and fall detection as examples from different areas.

Multiple parameters have been defined to measure human gait and postural sway using different techniques and devices. Some measuring devices require special installation, a special environment, and/or the presence of operator (observer), such as force plate and motion capture systems. These devices are expensive and not applicable for frequent, daily use by individuals, and continuing follow up. Nowadays, more practical devices could be used for capturing human body movements, such as wearable sensors. These devices are portable, however, they still have to be attached to the body to collect body's movements data, which may lead to a feeling of discomfort when using. Due to the wide spread use and availability of cameras, as well as the vast development in vision-based learning techniques, there is a high demand for using these technologies in estimating the human gait and sway parameters from video only. In this thesis, this problem is studied toward proposing solutions to estimating the likelihood risk of a fall for elderly people based on the changes occurring in their gait and sway patterns over time from their recorded videos only.

1.1 Motivation and Aim

This PhD thesis investigates analysing human gait and postural sway movements from video recording towards predicting the hllikelihood risk of having a fall, specially in elderly people. Predicting the likelihood risk of having a fall enables the appropriate intervention to avoid serious fall accidents. Such an intervention could take the form of an exercise regime to counter that deterioration.

The research is innovative in that, to the best of my knowledge, there is no current vision-based method of evaluating gait and sway pattern changes over time that can be applied at the individual level. Current assessment of sway, in particular the medial-lateral sway, which is particularly relevant to falls, relies on the use of force/pressure platforms. While these have become less expensive in recent years, it is unlikely that these will be omnipresent in homes any time soon. The cost is still in the tens of thousands, plus they are heavy and cumbersome. On the other hand, capturing accurate body movement during gait requires motion capture system, such as Vicon. Motion capture systems require a lab environment with special system and operator. Therefore, an inexpensive, easy to install and use system is needed to fit in the daily life of people to measure and assess gait and sway movements as well as monitor the changes that are occurring to gait and sway.

The proposed methodology is based on a multi-modal approach to link vision data, motion capture (Vicon), and force plate data altogether and to explore the correlation between them. Validating the accuracy of the estimated human gait and postural movements from video can be utilized in improving a system that uses these movements to measure, analyse, and assess human gait and postural sway. Therefore, monitoring an individual's gait and sway movement changes over time can be obtained using vision data. A focus of this research will be on measuring gait and sway parameters from vision data and quantifying the differences in these parameters in a different age groups towards predicting the likelihood risk of having a fall.

1.2 Research Questions

Changes in sway and gait patterns are a normal sign of aging, but these are generally slow changes over a long period of time. These changes usually represent the normal deterioration in the different human sensory systems and their connections, which cause in reduction of the control of the body balance that then may lead to a fall. The frequent measuring of gait and sway to identify and assess these changes requires special equipment in special environment and therefore is expensive. Finding an inexpensive and easy-to-use tool for measuring gait and sway movements in the daily environments, such as home and aged care facilities, allows observing the occurred changes and assessing them. Therefore, an intervention well before a serious fall accident happens would be possible.

From the literature, different methods and techniques have been proposed to measure gait and sway movements and parameters using special equipment, such as force plates and motion capture systems, in special laboratory set-ups. Wearable sensors have been invented to be used in a daily life but these sensors are requiring to be worn most of the time to collect the movements data. That is hard, especially speaking about elderly people, who may forget wearing them as a simple example of the downside points about wearable sensors. Measuring gait and sway have been differently used by different research disciplines, such as rehabilitation in clinical research and human recognition and identification in computer vision research. Detecting falls – when happening – is one point that utilizes gait and sway movements.

The main interest in this work is quantifying and analysing human gait and sway between different age groups and over time for an individual, in particular where they reach a point that significantly increases the likelihood of a fall occurring, using only vision data. This leads to the main research question:

Question – Risk Analysis: Can a risk analysis be performed to detect a relative fall risk group based on the measured gait and postural sway parameters from vision data alone?

To investigate this question, two other questions head to be asked:

Question – Postural: Can computer vision algorithms and techniques be used to estimate human body postural sway from a video recording with an acceptable accuracy compared to measurements from gold standard devices, such as a force plate?

Question – Gait: Using vision data, can human gait movements be estimated and measured with an acceptable accuracy compared to the gold standard system for motion capture, such as a Vicon system?

To validate the proposed algorithms for measuring gait and sway from vision, simultaneously collected data from the gold standard devices need to be available. Existing datasets do not contain the three sources of the data, vision, force plate, and motion capture systems. Moreover, existing datasets that contain data for elderly people are usually confidential and not publicly available. Moreover, the combinations of gait and sway data for elderly people using video cameras are not available. Thus, a dataset related to the research questions is needed.

Question – Ground Truth Data: Can a dataset that contains different types of collected data for gait and sway be provided?

Question – Elderly Data: Can a dataset that contains elderly data for gait and sway be provided?

1.3 Contributions

This PhD thesis makes the following four key contributions:

First contribution – Dataset:

To provide a dataset that contains gait and sway activities that are recorded from the three data sources, a video, force plate, and motion capture system, as well as data for elderly, a gait and sway dataset is devised and collected. This dataset is recorded in two parts, healthy athletes ground truth and elderly. The ground truth part contains recorded data from video cameras, a force plate, and a motion capture system (Vicon), for healthy athlete subjects. This part of the dataset is used to validate the possibility of measuring human gait and sway from vision data compared to the gold standard devices, force plate in the sway measurements and Vicon for body movements. This part of the dataset is related to *Ground Truth Data* research question.

The elderly data are collected for over 50-year-old people using video cameras as the main data type. A force plate is used to capture postural sway, too. Elderly data are collected in three stages, each three months apart. This part of the dataset is related to the *Elderly Data* research question.

Second contribution – Postural sway from vision:

Using the ground truth part of the dataset, a model is built to estimate the human body's postural sway from vision data, referenced to the force plate data as the gold standard in measuring body's sway. Three sway metrics, signal shape, sway region, and sway frequency, are defined to evaluate the estimated sway. This contribution is related to the *Postural* research question.

Third contribution – Gait from vision:

Using the ground truth part of the dataset, another model is built to estimate human body movements on selected joints from vision data, referenced to the Vicon system as the gold standard in motion capture. This contribution is related to the *Gait* research question.

Fourth contribution – Risk analysis:

The postural sway model in the second contribution and the gait model in the third contribution are used on the first phase of the elderly dataset to estimate postural sway and gait from vision data. Using the estimated postural sway and gait, the defined postural sway and gait parameters are measured. Based on the calculated parameters, a *sway-age* and *gait-age* for the elderly people are predicted. Comparing predicted age with the elderly chronological-age classifies the elderly in one of the defined risk groups. This contribution is related to the main research question, *Risk Analysis*.

1.4 Chapter Outline

The remainder of this thesis is organised as follows: Chapter 2 provides a general overview of the human gait and the postural sway. It presents the different parameters that are identified to measure the human gait and the postural sway. Also, this chapter reviews different studies of the the gait and the postural sway from the clinical and computer vision perspectives.

In Chapter 3, a human gait and sway dataset is described. This dataset has been collected in two phases: (1) Athletes' data, where video cameras, force plate, and motion capture system have been used to collect the gait and the sway data for healthy athlete subjects and (2) Elderly data, where the video cameras and the force plate have been used to collect data for subjects over fifty years old. Data recording setup, activities, and processing for each phase have been presented in this chapter.

With the availability of the dataset, the proposed methods for estimating postural sway and gait from vision data have been presented. Based on the ground truth data part of the dataset, the estimated signal for the body's postural sway from video has been validated and compared with the corresponding signal from the force plate in Chapter 4. Similarly, based on the ground truth part of the dataset, studying the capability of estimating the gait movements from the video data only has been discussed. Then, a selected gait parameters have been measured using the estimated movements in Chapter 5. Using the estimated parameters of the human gait and the postural sway from video on the elderly part of the dataset, the sway and gait age groups have been detected as well as a relative risk analysis for the elderly people has been presented in Chapter 6. Chapter 7 concludes and summarises the findings of this thesis and outlines future research directions.

Chapter 2

Literature Review

Studying human gait and sway was initiated from the medical aspect to differentiate between normal and pathological movement patterns. As an outcome from these studies, human gait and sway can be considered as a personal characteristic and can be used in different ways from different scopes. Increasing interest has begun in human gait and sway from different research areas, such as computer vision and sports science, and applications, such as security and surveillance systems.

Human gait and postural sway reflect the person's health condition as they are easily affected by any changes occurred to it, such as illness, weakness, and/or aging. To measure and assess gait and postural sway, many different parameters and techniques have been identified. With these parameters, body movement can be understood, abnormalities can be determined, and changes occurred to an individual's gait and sway over time can be identified. With the vast technological development, new devices and tools are utilised to measure more detailed and more accurate human gait and sway parameters.

Developed devices for accurate measuring human gait, such as motion capture systems (Vicon), and for accurate measuring postural sway, such as force plates, require special set-ups in special laboratory environment, which make them expensive and hard to be possessed personally. Wearable devices (sensors) have been invented to measure body movements while walking and standing. These wearable sensors have to be attached to the body for long periods of time to collect body movements data, which may lead to a feel of discomfort. Different kind of cameras, such as infra-red and RGB cameras, have been used as an alternative for expensive devices and wearable sensors to collected data for human different activities to analyse human movements.

Vision data have been used for monitoring and assessing human movements in clinical environments, such as aged-care facilities. Studies related to computer science have trying to utilise human gait and sway in different ways, such as human recognition and fall detection. Different computational models and algorithms have developed to increase the efficiency of identifying the human body and its part movements from the vision data.

This PhD thesis is aimed to build a model to define an increased risk of having a fall in elderly people by estimating human gait and postural sway movements from vision data, then use the estimated movements to measure selected gait and sway parameters. The risk is defined based on the differences of the measured parameters between different age groups.

This chapter reviews gait and postural sway in more details, especially from clinical and computer vision aspects. A dataset, ground truth and elderly data, is devised and collected as presented in Chapter 3. Using ground truth collected data, defined machine learning concepts (Gaussian process model, recurrent neural network, and long-short term memory) are utilised to propose methods to estimate postural sway and gait movements from vision data in Chapters 4 and 5, respectively. The accuracy of the measured gait and sway parameters from the estimated movements are validated using ground truth data as well. Gaussian mixture model is used in Chapter 6 to cluster elderly people data, which is collected in the dataset, into groups (*sway-age* and *gait-age* groups) based on the measured gait and sway parameters from vision data only. The difference between sway/gait-age group and the chronological-age group for an elderly subject is used to define a risk level of having a fall for that person.

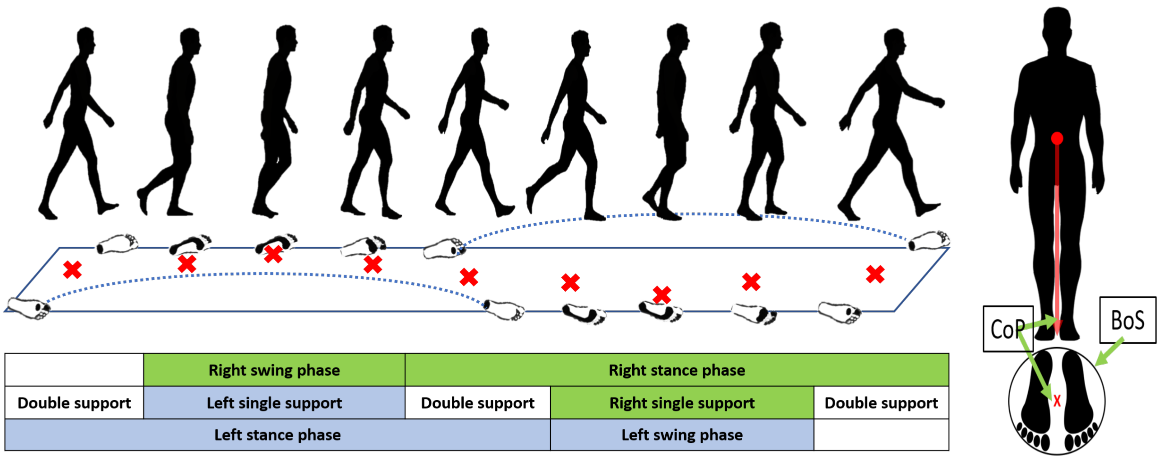
In this chapter, Section 2.1 presents a general introduction of the postural sway and the human gait parameters and the different methods to measure these parameters is introduced. Then, a literature review of the studies of human gait and postural sway from the clinical perspective is presented in Section 2.2 followed by a literature review of the studies from the computer vision perspectives in Section 2.3. From both perspective, studies of the gait and the sway in the research areas are reviewed, in particular their usability in applications such as abnormality and fall detections.

2.1 Gait and Postural Sway – A General Introduction

Gait is the manner or style of walking and *gait analysis* evaluates this style. Gait analysis is usually done by observing the individual walking naturally in a straight line. The normal forward step consists of two phases: the *stance phase*, during which one leg and foot are bearing most or all of the body weight, and the *swing phase*, during which the foot is not touching the walking surface and the body weight is borne by the other leg and foot. In a complete gait cycle, the part when both feet are in contact with the floor at the same time is called the *double-support*. Normal gait patterns have symmetries in different phases for both feet [Whittle 07].

On the other hand, the *postural sway* is the horizontal movement of the body centre of pressure (CoP) to maintain body balance within the body's base of support (BoS). A certain amount of sway is essential and inevitable while walking or standing due to small perturbations within the body, such as shifting body weight from one foot to the other, or from external triggers such as visual distortions or floor translations.

A human body's centre of pressure and base of support are illustrated in Figure 2.1(b). The gait cycle phases are shown in Figure 2.1(a) with the body sway displayed with a red $\times$ that represents the body's centre of pressure displacements (*postural sway*) over the gait cycle phases.



(a) (b)

Figure 2.1: (a) Gait Cycle: lembs movement and different phases in the cycle with postural sway movements illustrated by the red crosses along with the gait cycle. (b) Human body's centre of pressure (CoP) and base of support (BoS).

A more detailed review about gait and gait analysis is presented in Subsection 2.1.1. Body balance, functions and parameters to measure it, are reviewed in Subsection 2.1.2. As the main point of interest in this thesis is about gait and sway in elderly people, Subsection 2.1.3 reviews the related research in gait and sway in elderly people.

2.1.1 Gait Analysis

For the human gait, some general parameters, such as cycle time (cadence), stride length, and speed are considered to provide the simplest form of objective gait evaluation [Whittle 07]. In most locomotor disabilities, general gait parameters tend to change together [Whittle 07]. The general gait parameters are easily observed and determined from a video recording. These parameters give a guide for the walking ability, but little specific information about gait locomotor.

With the increased interest in gait analysis from different research fields, such as health care [Yang 15], sports science [Payton 17] and security [Sun 17], more gait factors and parameters have been defined for detailed gait measuremets as presented in [Muro-de-la Herran 14]. Also, different methods and technologies have been developed for measuring such parameters.

Gait parameters have been classified into five primary domains [Hollman 11]:

(1) Rhythm Domain, which contains cadence and temporal parameters, for example, stride time.

(2) Phase domain, which is characterized by distance divisions such as stance.

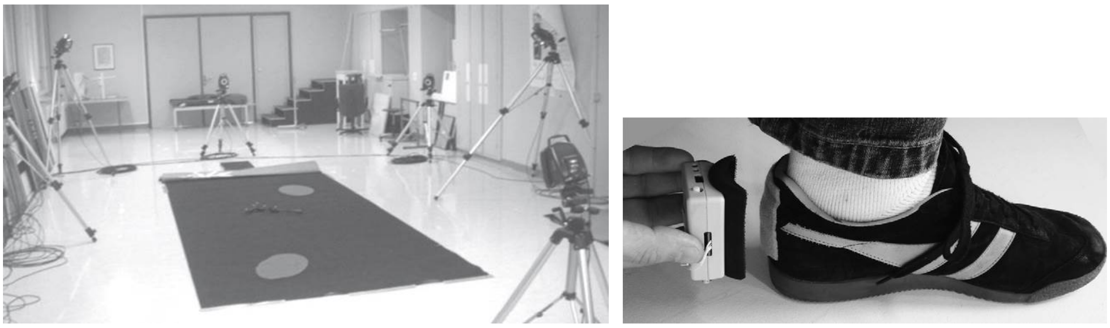
(3) Variability domain, which is characterized by gait cycle and step variability parameters such as stride length variability.

(4) Space domain, which contains gait speed, step length and stride length parameters.

(5) Base of support domain, which contains step width and step width variability parameters.

For recognizing and analysing human gait, three different approaches have been used: image processing, floor sensors, and sensors placed on the body (wearable sensors) [Hollman 11]. These approaches have been used to measure gait parameters with: 1) semi-subjective analysis techniques and 2) objective analysis techniques. Semi-objective methods usually consist of analyses that are carried out in clinical conditions by a specialist. This is time consuming, expensive, and out of the scope of this study. On the other hand, objective techniques are based on the use of different devices to capture and measure information related to the various gait parameters. With the improvement in all aspects of life, new technologies and approaches are proposed to make the measurements and assessments easier, faster, and more reliable.

Gait can be measured in a laboratory setting with one or more cameras (different types may be used such as, video and/or infra-red) placed around the walking area and linked to a computer [Kadaba 90]. The participant has markers located at various points of reference of the body. When the participant walks, the computer calculates the trajectory of each marker in three dimensions (3D). A complete breakdown of the movement of each joint can be given by calculating the movements of the underlying bones. With the development in the sensors and measurement techniques, many different devices can be added



(a) (b)

Figure 2.2: (a) Proposed lab set up and (b) S-sense sensor that can attached to shoes to collect spatial parameters of gait in [Mariani 10].

to measure gait. Such devices can be worn or attached to the participant's shoes to get more accurate coordinates for the spatial parameters, *e.g*, S-sense used in [Mariani 10] and shown in Figure 2.2.

To calculate the kinetics of gait patterns, most laboratories use force platforms, which measure the ground reaction forces and moments, including the magnitude, direction and location on the body's centre of pressure. The spatial distribution of forces can be measured with pedobarography equipment. Adding this to the known dynamics of each body segment enables the solution of equations based on the Newton-Euler equations of motion permitting computations of the net forces and the net moments of force about each joint at every stage of the gait cycle. The computational method for this is known as inverse dynamics.

Recently, smart phones contain accelerometers and gyroscopes, which, potentially, enable exquisitely sensitive measures of human movement performance beyond simple step detection in devices that are ubiquitous (Figure 2.3). Accelerometers allow the examination of fine details of movement performance that have not previously been available outside of laboratory-based environments and have been shown to be valid and reliable in the assessment of gait variability [Lord 11]. This type of data enables the analysis of the accelerations of the individual's trunk movements utilising measures such as the harmonic ratio, index of harmonicity, multi-scale entropy and recurrence quantification analysis [Riva 13]. Automatic, continuous, and long-term physical activity measurement in a free-living environment are enabled to be monitored using accelerometry techniques [Yang 10].

A gait analyser has been presented in [Majumder 18] using a motion sensor that obtains acceleration and angular velocity of walk from both legs. Using support vector machine, the healthy gait characteristics have been identified as two distinct baseline clusters corresponding to gender and age that will be

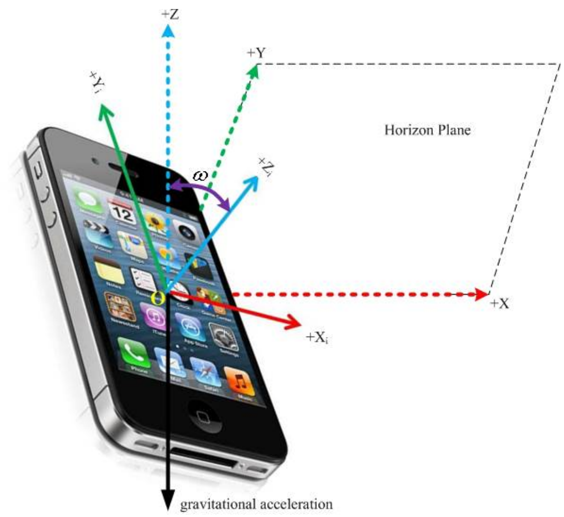


Figure 2.3: Accelerometery technique used within the smart phones for gait analysis [Sun 14].

used for an individual's gait evaluation.

Instead of professional sensors and laboratory conditions, unfixed iPhones have been used to analyse gait characteristics to identify human [Sun 14] by processing an embedded gait dataset in an iPhone to extract gait parameters, such as gait frequency, symmetry coefficient, then identifying the gait with weighted voting depending on the gait parameters.

An approach for gait analysis based on human joints identification has been proposed in [Prakash 18] to determine joint coordinates in uncontrolled environment. The extracted joints from the proposed method have been compared with a ground truth marker based identification for efficiency confirmation. With an acceptable accuracy of different proposed systems and techniques for gait and postural sway analysis, a crucial role of such techniques lies in replacing expensive and special gait and sway analysis equipment.

2.1.2 Postural Sway

The postural sway (body sway) maintains balance position with slight postural movement to assess body balance [Wang 10a]. Maintaining body balance is done by keeping the body's CoP within the body base of support. Maintaining balance requires coordination of input from multiple sensory systems including the vestibular, somatosensory, and visual systems [Gribble 04]. These systems sense different information related to different reference points. The vestibular system senses directional information that relates to the head position, which is related to organs that regulate the body equilibrium. The somatosensory system senses the spatial position and movement relative to the support surface or movement and posi-

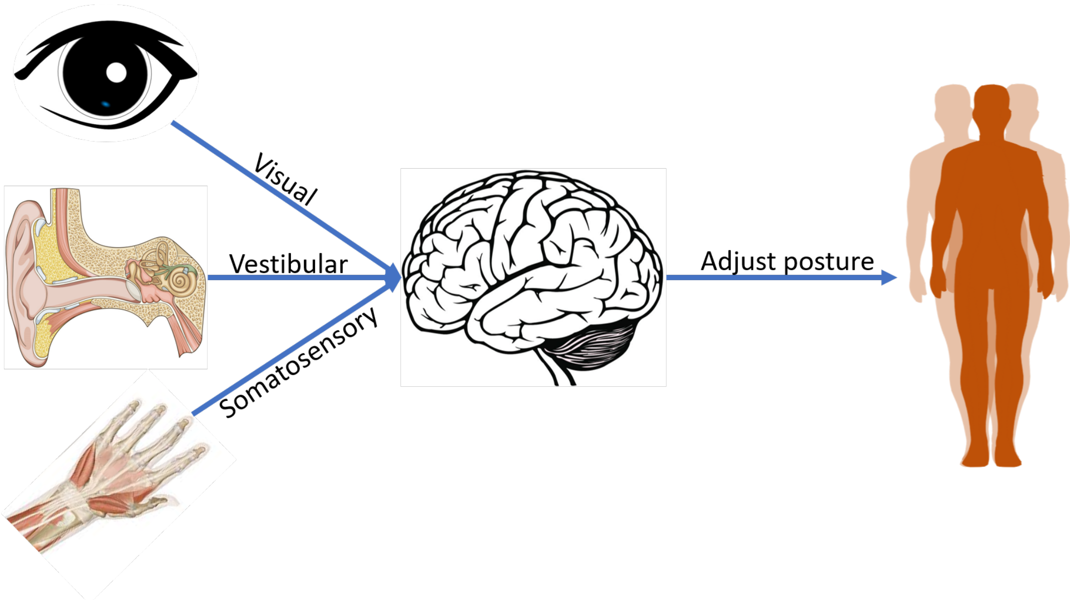


Figure 2.4: Maintaining balance by brain by coordinating the input from the vestibular, somatosensory, and visual systems to generate a signal for the body muscles to react to the environmental factors

tion of different body parts relative to each other, which is referred as to proprioception and kinesthesia of joints. Lastly, the visual system senses the spatial location relative to other objects, which is the reference to the verticality of the body and head motion. The senses must detect changes of spatial orientation with respect to the base of support, regardless of whether the body moves or not. There are environmental factors that can affect balance such as light conditions, floor surface changes, alcohol, drugs, and ear infection.

Maintaining postural stability relates to the brain's ability to integrate the information from the different sensory systems and the muscle motor processes of feet, legs, and trunk to modify these processes as a response to the environmental factors [Goebel 08] as illustrated in Figure 2.4. An increase in sway is an indicator of decreased sensorimotor control by these systems.

To identify balance deficits, different functional balance tests that focus on the maintenance of both static and dynamic balance have been developed. These tests usually involve a type of perturbation/change of CoP while walking or during quiet stance [O'Sullivan 13]. These tests allow assessment of an individual's postural control.

For example, but not limited to, some functional balance tests that have been defined to determine a person's ability/inability to balance by performing one or more tasks:

(1) Romberg Test [O'Sullivan 13], which is used to test the neurological function for balance by standing with feet together with eyes opened then closed.

(2) Berg Balance Test [O'Sullivan 13], where different functional activities have to be performed (such as bending, standing with feet together or single-leg stance, with eyes open or closed), which are then scored on a 5-point scale for each activity: Zero for the lowest level of function and four for the highest level.

(3) Performance-Oriented Mobility Assessment (POMA) [O'Sullivan 13], where a balance assessment under perturbed condition, such as while turning or rising up from a chair, is included. Some gait characteristics, such as gait initiation and step height, are also evaluated.

(4) Standing test for imbalance and disequilibrium (SIDE) [Teranishi 10], where the CoP is measured in different stances, such as standing with legs close together, standing on the dominant foot, standing on the non-dominant foot, tandem standing with dominant foot forward, and tandem standing with non-dominant for forward.

(5) Balance Error Scoring System (BESS) [Finnoff 09], which has similar stances to SIDE test, but the functional test is performed with closed eyes and on two different surfaces.

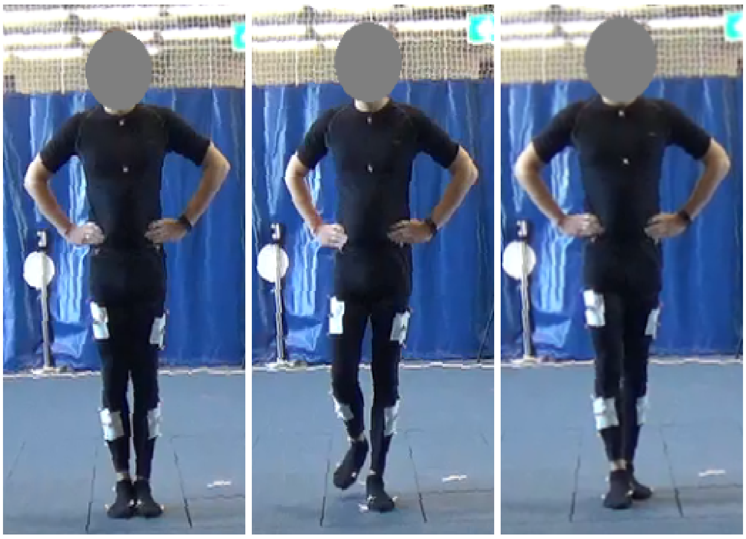
BESS is presented in details as it is the balance test that is considered in this study. BESS is a commonly used way to assess balance. It is known as a simple and affordable way to get an accurate assessment of balance. The BESS provides an objective method to assess the static postural stability. It is often used in sports settings to assess the effects of mild to moderate head injury on one's postural stability [Finnoff 09].

The BESS tests three separate stances on two different surfaces, firm surface (ground/floor) and medium density foam. The foam creates an unstable surface, which presents a more challenging balance task. Each of the three stances is required to be taken for 30 seconds on each surface with closed eyes and the hands on the hips. The three stances are shown in Figure 3.2:

1) Double leg stance: Standing with feet side by side (touching),

2) Single leg stance: Standing on the non-dominant foot (dominate leg is the preferred kicking leg), and

3) Tandem Stance: Standing heel to toe with the non-dominate foot in the back. The heel of the dominant foot should be touching the toe of the non-dominant foot.



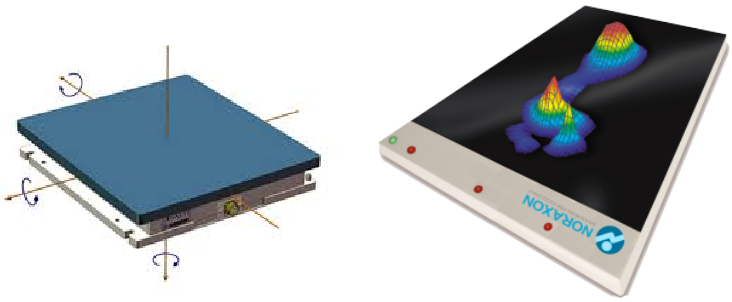
(a) (b) (c)

Figure 2.5: The three stances for the Balance Error Scoring System (BESS): (a) Double legs, (b) Single leg, and (c) Tandem stances.

The BESS is scored by a clinically trained examiner who looks for deviations from the proper stances. A deviation is noted when the participant opens the eyes, removes the hands from the hips, stumbles forward or falling, lifts the forefoot or heel off the testing surface, abduction or flexion of the hip beyond 30 degrees, or remains out of the proper testing position for more than 5 seconds.

With technological advances, balance functional tests are performed in the presence of one or more devices used to capture different body movements. Force plates and pressure plates, Figure 2.6, are used to capture CoP displacements as a single point in the force plate and multiple simultaneous points on the pressure plate. Such plates are placed on the ground and measure the CoP of the body that stands or passes on them. For balance assessment, first, functional tests can be done on these plates to capture the accurate CoP displacements over test time. Then, path length for a CoP displacements, sway velocity and sway area can be analysed to assess person's balance [Hof 05].

With quantitative assessments, minimal CoP path length is suggestive of good balance. Force plates are considered as the "gold-standard" of measuring CoP. The NeuroCom Balance Master (NeuroCom, Clackamas, OR, USA) is a commercially available dynamic posturography system that uses computerized software to track CoP during different tasks. These different assessments range from the sensory organization test looking at the different systems that contribute through sensory receptor input to the limits of stability test observing a participant's ankle range of motion, velocity, and reaction time. While



(a) (b)

Figure 2.6: (a) Force plate [1] and (b) Pressure plate [2] , devices that are used to measure CoP of an object.

the NeuroCom is considered the industry standard for balance assessments, it does come at a steep price (about 250,000 USD).

More recently, research has headed toward inexpensive and portable devices capable of measuring CoP accurately. Nintendo's Wii balance board (Nintendo, Kyoto, Japan) has been validated against a force plate and found to be an accurate tool to measure CoP [Clark 10] This is very exciting as the price difference in technology makes the Wii balance board a suitable alternative for clinicians to use quantitative balance assessments. Other inexpensive force plate for educational use has been designed to measure the developed forces during stepping, jumping, and other human-scale actions [3].

In addition to force/pressure plate measurement devices, wearable sensor postural sway systems are becoming more popular due to their portability and low cost. They can be used on the field of play for traumatic brain injury (TBI) assessment, as well as in a clinic or research labs. APDM's Mobility Lab iSway system (APDM, Portland, OR, USA) has been validated against gold standard force plate systems and has been shown to be an accurate and reliable tool for measuring postural sway, and dynamic balance (such as turning) during gait [Mancini 12].

2.1.3 Gait and Sway while Aging

There are normal changes that occur to an individual's gait and body sway due to aging. In postural sway, these changes come from the differences in reaction speed to sensory input from the visual system, vestibular and somatosensory to maintain body balance within the base of support and result in more frequent and larger body movements as illustrated in Figure 2.7. In gait, these changes come from

[1] http://www.amti.biz/fps-guide.aspx
[2] http://www.noraxon.com/products/pressure-and-force-measurement-technology/fdm-sx-pressure-plate/
[3] http://www.vernier.com/products/sensors/

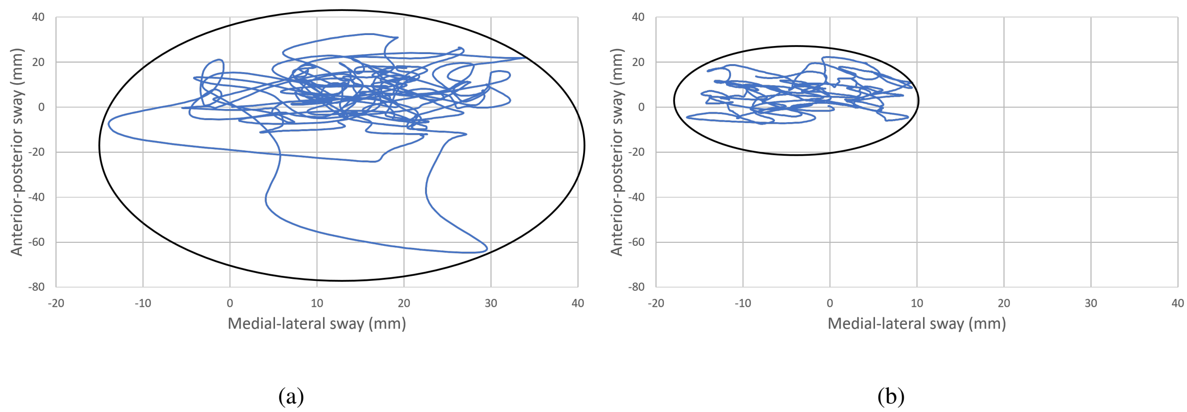


Figure 2.7: Illustration of differences in centre of pressure displacements that shows the wider area of body's sway for the elderly as well as the higher frequency of the movements (a) compared to a healthy young adult (b).

elderly people adapting their gait to feel more secure while walking, such as making the walking base wider and/or reduce the step length as illustrated in Figure 2.8.

Everyone can be at risk of having a fall, but elderly people are more vulnerable because of the decline in their ability to adapt their gait and maintain their balance when needed. Pathological conditions, which become more common with advancing age, also effect gait in elderly and increase the likelihood of falling.

Every year, an estimation of 30% to 40% of elderly population over the age of 65 year will fall at least once [Ambrose 13]. Fall injuries range from simple to fatal injuries, and in the case of no-injury, the fear of a fall may grow and significantly affect the person's life. Falls may cost the elderly to lose the mobility, confidence, and functional independence.

In the elderly, body-orienting reflexes, muscle strength and tone, and the step length and height all decline with aging and impair the ability to avoid a fall after an unexpected movement. The gait pattern in older people tends to be stiffer and less coordinated with poorer posture control. Older adults may also be less capable of weight shifting or taking a rapid step to avoid falls when their balance is perturbed [Ambrose 13].

The elderly gait pattern changes to improve walking security [Whittle 07]. Maintaining balance while walking can be obtained by both decreasing the stride length and increasing the walking base. Increasing the step cycle time leads to a reduction in the percentage of the gait cycle for which there is only single limb support. Figure 2.9 illustrates some normal gait parameters in young healthy adults and elderly people showing the wider walk base, decreased step and stride length, and increased double leg

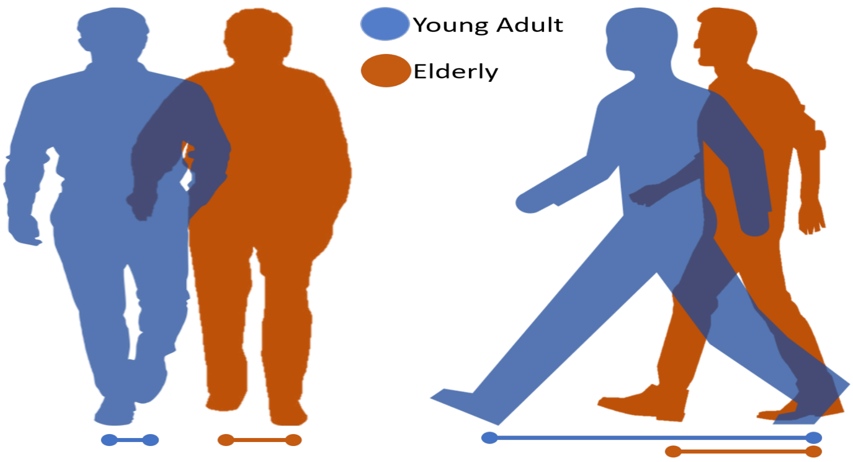


Figure 2.8: Illustration of gait differences between young healthy adults and elderly people in walk base (left) and step length (right).

supported time in the gait cycle.

These changes in gait parameters can be considered as an indicator for an increase in the fall likelihood while a person is aging. Quantitative gait markers have been identified in [Verghese 09]. These parameters, such as speed, cadence, and swing time variability, are considered as independent predictors of falls in older adults. So, studying these markers, especially variability, could improve current fall risk assessments and could be used to develop a method to estimate fall likelihood changes over time.

Age-related deterioration in postural control and its association with physiological termor and plantar flexors muscle volum has been examined in [Kouzaki 12]. During quiet standing, an accelerometer has been used to detect the physiological tremors, force plate have been used to capture CoP displacement and body acceleration, and ultrasound (Sonography) imagery has been used to predict muscle volume from the muscle thickness. Relative muscle activity, muscle coordination, and postural sway during various static balance training tasks have been investigated in [Donath 16] on young and older adults groups using surface electromyography on ankle and thigh muscles and electrodes over trunk muscles to capture muscle activities during the balance stances. Another investigation about sway-related control parameters and musculoskeletal measures of muscle function and health has been done in [King 19] on young and older female adult groups.

The interaction of the CoP displacements and velocity in relation to the base of support is dynamically changing while walking has been investigated in [Lugade 11] for young and older adult groups. Another study determining age affect on the CoP trajectory during gait has been carried out in [Sole 17]. From the force plate, CoP trajectories have been extracted and a canonical correlation analysis has been used to test their correlation with age. Another study compared CoP displacements behaviour, velocity, and

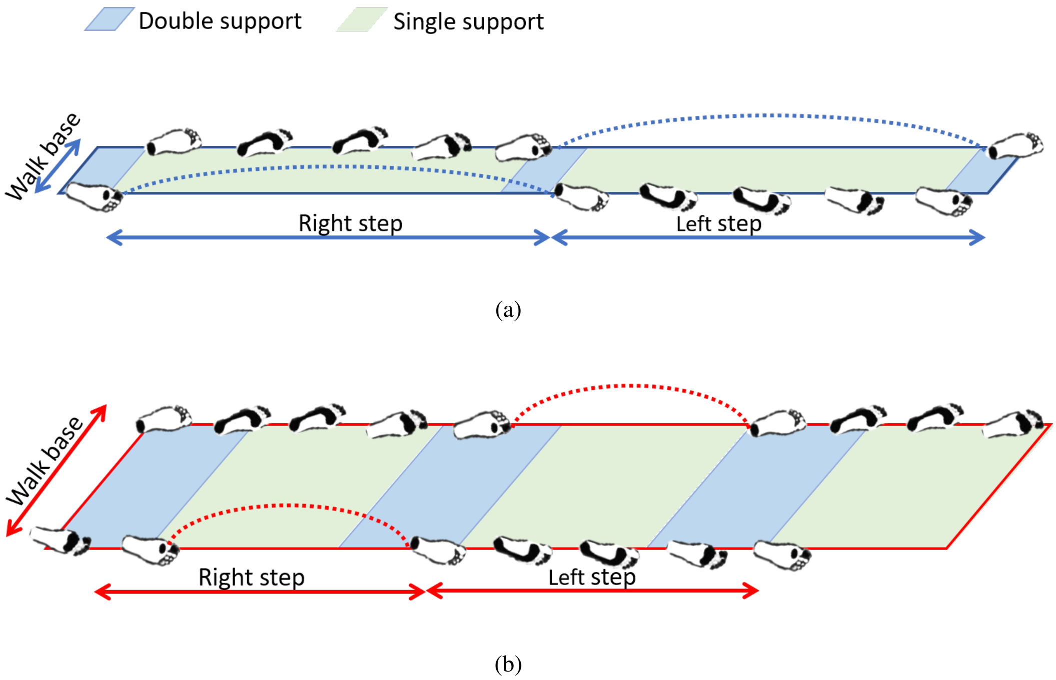


Figure 2.9: Comparison between (a) young adult and (b) elderly gait cycle showing the differences in step and cadence length, walk base, and double and single leg support time for each gait cycle.

total body sway, for two different age groups has been presented in [Roman-Liu 18]. Values for both sway displacements and velocity have been increased for the older age group compared to the younger age group.

2.2 Gait and Body Sway – Clinical Perspective

Determining gait patterns and analysing these patterns have been started by Murray in the 1950s [Murray 67] to diffrentiate the normal gait patterns from gait disturbances in persons with neuromuscular and musculoskeletal pathology. The standard movement patterns for pathologically normal people that have been produced by Murray [Murray 67] has to be considered as a base reference to comparing the gait patterns of pathologically abnormal patients in clinical environments.

From a clinical perspective, gait and postural sway are usually used to differentiate the pattern of movements between people with normal and abnormal gait or sway. Gait and postural sway are also used in rehabilitation for monitoring the patient's recovery process and in fall analysing accidents to identify the causes and circumstances of such accidents.

2.2.1 Abnormal Gait

Gait analysis, in the clinical routine, identifies pathological from normal movements using a simplified model of the human body structure. This analysis is performed at different levels that are specified by the complementary techniques that are used to assess different aspects of neuromuscular function, such as:

(1) Kinematic variables, which describe the body displacement by observing the angular joint variations and the relative body segment motion in space,

(2) Kinetic parameters, which quantify the connections between action-reaction forces, moments and powers of each body segment, and

(3) Muscle activation variables, which evaluate the electrical muscle activity during the gait cycle.

Medical research classifies the components of gait for the treatment of pathologically abnormal patients. While interpreting kinetic and kinematic gait data to detect the gait phases is essential in clinical gait analysis to evaluate gait abnormalities, [Khan 19] entails a generic approach to segment the gait into sub-phases based on a number of distinctive features that are extracted from the hip joints motion data.

Recent technologies, such as radar have been used in [Seifert 17] for indoor monitoring. Radar is considered to be a privacy-preserving and non-wearable sensing mode, therefore recently attracted much attention for indoor monitoring role. With the associated features with gait motions, including biomechanic simulators and electromagnetic modeling, gait abnormalities have been detected using radar.

2.2.2 Rehabilitation

Gait analysis in clinical rehabilitation is used in the diagnosis, treatment, monitoring, and implementation of methodologies that mitigate the effect of some pathologies associated with the movement. Getting back to a normal walking pattern is considered to be one of the primary objectives of the rehabilitation process. This analysis characterizes human locomotion by quantifying, following up and interpreting the temporal sequence of humans' movements. In a clinical environment, kinematic and kinetic data that describes the displacements, angles and forces on the lower limbs and the joints during a gait cycle is required to be collected. The primary three sources of information are video, Electromyography (EMG, the measurement of the electrical activity of muscles), and force platforms. Then, the gait pattern is evaluated by a therapist to determine if there is a specific weakness and to put in place or adjust a rehabilitation programs to address these issues [Kirtley 06].

Measuring and analysing gait parameters after rehabilitation time with surgically treated ankle fractures is used to detect the significant improvements of temporal and spatial gait parameters, as well as of the functional outcome in patients with this surgery as presented in [Suciu 16]. Similarly, [Herbold 17] analyses gait parameters for patients in rehabilitation after total knee arthroplasty to quantify both the improvements made and deficits that remain in gait parameters.

For accurate assessment of balance and gait impairments to guide and track rehabilitation, [Horak 15] discussed the role of body-worn movement sensors for balance and gait assessment and treatment in rehabilitation. An advantage of using new sensitive technologies for measuring human balance and gait behaviour is to document mild disability and changes with rehabilitation compared to clinical tests of functional performance.

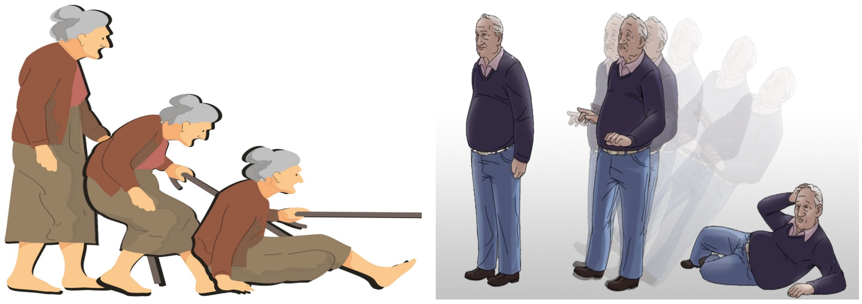
However, human gait analysis and the interpretation of its dynamic patterns are currently completely dependent on the experience of the specialist. This experience requires an expensive and long training, coupled with the need to have a high number of patients with different patterns and pathologies that allow the training specialist to identify the characteristics of each movement (Gait Patterns) with a certain degree of certainty.

2.2.3 Falls in Elderly

Since a fall may cause serious injuries, especially in the elderly population, it has been a point of interest for clinical/medical research and studies. Most of these studies assess gait and sway after a fall has already happened to determine the causes and circumstances of that fall.

According to [Robinovitch 13], which studied recordings and reports of fall accidents occurring in long-term care facilities, the most frequent cause of falling was incorrect weight shifting (balance) and walking was the activity that was associated with the highest risk of falls, followed by standing quietly. An incorrect weight shifting happens when self-induced shifting of body weight cause the centre of gravity (same as centre of mass) moves outside the base of support of the human body. As people age, maintaining balance becomes increasingly difficult and postural sway, both lateral and anterior-posterior, increases with time.

Different studies investigate the pathological reasons that affect the gait in a way that may lead to a fall. Neurologic abnormalities affecting gait occur early in several types of non-Alzheimers dementias. Persons who did not have dementia at base line with neurologic gait abnormalities were at increased risk for the development of dementia [Verghese 02]. The presence of neurologic gait abnormalities



(a) (b)

Figure 2.10: Illustration of two activities: (a) Walking and (b) standing quietly that are associated with the highest ratio of falls, according to [Robinovitch 13].

strongly predicted non-Alzheimer's dementia, especially vascular dementia, but not Alzheimers disease. The association between gait status and the risk of non-Alzheimers dementia remained strong even after adjustment for demographic, medical, and base-line cognitive variables. Elderly persons with a combination of cognitive, vascular, and extrapyramidal features including abnormal gait were at increased risk of progression to dementia over a three-year period.

Sometimes, there is no specific disease that can be identified for the gait and balance disorder. The term higher-level gait disorders (HLGD) is used to describe this. HLGD patients show slow gait with shorter strides, poor balance with falls, and gait initiation problems, including freezing of gait [Demain 14]. A modified gait abnormality rating scale (GARS-M) has been proposed to quantify the gait abnormalities in individuals with conversion disorder that have neurologic symptoms that are not identified by an underlying organic cause. Often the symptoms manifest as gait disturbances [Vandenberg 15].

Gait assessment has been recommended as a reflection element of fall risk in older adults [Allali 15]. Different clinical examinations have evolved to build on collective clinical experience in risk assessment diagnosis as well as predicting major adverse outcomes such as falls and disability. Most methods that have been employed in clinical practice and in research settings to identify gait disorders include eliciting self-report of mobility difficulties from patients, observation of walking patterns by clinicians, and quantitative gait assessments using instrumented methods.

Another study with an aim to test the reliability and validity of a preferred-standing test for measuring the risk of falling has been presented in [Swanenburg 13]. A significant difference between elderly fallers and non-fallers has been detected in the measured test positions as well as a difference between elderly and young adults.

Investigating the association between gait variability, local dynamic stability of gait, and history of falls in the elderly population has been conducted in [Toebes 12]. Measurements of such parameters can be an indicator of increased risk of falling.

Objective measurement of postural sway predicted incident falls on elderly people as has been conducted in [Johansson 17]. Another study in predicting incident falls in elderly population have been done on the measured trunk sway, quantified as angular displacement in anterior-posterior and medial-laterar planes, in [Mahoney 17]. Falls can be predicted when the trunk sway increased as the reported fall accidents were related to increased trunk sway after a one-year period for the same population.

Gait and postural sway measurements and analysis were initiated from a clinical perspective and have been used to (1) differentiate between normal and pathological gait patterns, (2) monitoring movement improvements in the rehabilitation environments, and (3) analysing reasons and circumstances that may lead to a fall.

2.3 Gait and Body Sway – Computer Vision Perspective

The original research on measuring human gait and sway was entirely for medical purposes with the aim of identifying the normal gait from a pathological one. The outcomes of these studies have considered the gait as a unique characteristic for the individual. Based on that, the interest in gait grows from computer vision and pattern recognition researchers, especially in biometrics, for human identification and recognition porposes. Recently, computer vision approaches have been considered as one of the main ways for detecting falls based on body movements [Mubashir 13]. Fall detection is one of the challenges in health care, especially for the elderly. Next, recent work for utilising human gait and/or sway computer vision are presented.

2.3.1 Human Recognition and Identification

Recognizing people from their gait has several characteristics over other biometric-based approaches, such as fingerprints, face analysis and iris. These techniques require an individual's cooperation and attention and/or physical information. Also, these methods may be incorrect/inaccurate because of low resolution of the videos or images. On the other hand, an individual's gait can be captured without physical contact. A comparatively low resolution is not a problem for recognizing people from their gait. This is why human recognition from their gait has received much attention from computer vision researchers.

Some developments on gait recognition approaches have been reviewed in [Wang 10b]. The general gait recognition system has been addressed from three points of view:

(1) Gait image representation,

(2) Feature dimensionality reduction, and

(3) Gait classification.

The gait recognition approaches have been categorized into model-based, where information gathered from the body is used to construct a recognition model, and model-free, where the gathered/recreated gait features represent the gait from a sequence of binary silhouette images. For an automatic gait recognition, the general framework consists of:

(1) Subject detection,

(2) Silhouette extraction,

(3) Feature extraction, which can be model-based or model-free features,

(4) Feature selection, and

(5) Classification, which can be a direct classification, based on the similarity of temporal sequences, or based on a state-space model, as the three main categories for classification methods.

Different gait representations have been proposed to improve recognition rates, such as gait energy image (GEI)(Figure 2.12), motion silhouette contour template (MSCT), static silhouette template (SST), and gait flow image (GFI)(Figure 2.11) [Lam 11]. Another representation by [Tao 07] suitable for recognition combined averaged gait image that decomposed by Gabor filters. A further simple gait representation based on simple features, such as extracted moments, has been described in [Lee 02] for the purpose of person identification and classification. Using a support vector machine, the extracted feature vector from side view silhouettes of a human walking action has been used for human gender classification in different lighting environments.

A marker-less, model-free approach, based on the block matching algorithm is presented in [Goffredo 06]. The method consists of tracking the relevant points on the human silhouette, followed by the evaluation of the rotations of the principal body segments, to estimate the centre of mass (CoM) trajectories.

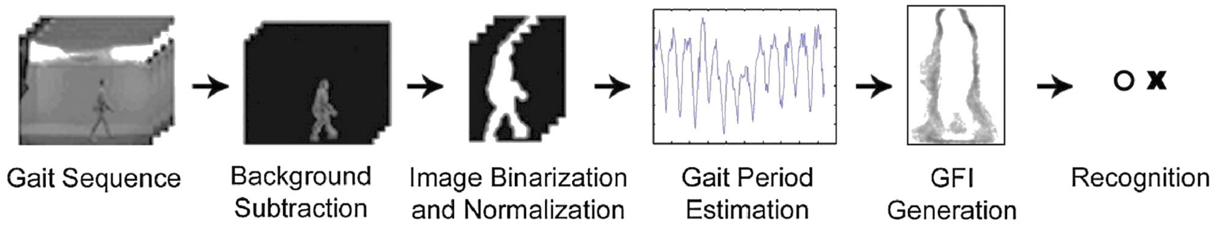


Figure 2.11: Gait flow image (GFI), an example of the gait image representation that has been proposed to be used for gait recognition [Lam 11].

The majority of the proposed approaches to analyse and recognize gait are two dimensional (2D) methods, which analyse video sequences captured by a single or multiple cameras. Estimating 3D human pose from a single camera using vision-based techniques is important in different applications, such as sports science, gait analysis and entertainment and game industry. Vision-based techniques are an inexpensive and non-intrusive alternative to optical-based motion capture system, which is highly accurate in estimating 3D human pose [Hen 09]

A proposed method based on the 3D tracking and recognition, which is robust to the changes of viewpoints, has been presented in [Zhao 06], using video sequences that were captured by more than one camera as an input to set up a 3D model of a human. With static parameters, that represent the length of key segments, and dynamic features, the motion trajectories of lower limbs, the motion is tracked by applying a local optimization algorithm. Finally, matching and recognition are achieved with linear time normalization.

A balanced Gaussian process dynamic model (GPDM) is presented in [Urtasun 06] to learn smooth prior models of human pose and motion for 3D people tracking. These priors can be learned from modest amounts of training motions including stylistic diversity. They are shown to be effective for tracking a range of human walking styles, depict weak and noisy image measurements and significant occlusions. The quality of the results, in light of such a simple measurement model, attest to the utility of the GPDM priors.

An activity-independent method to recover the 3D configuration of a human figure from 2D locations of anatomical landmarks in a single image has been presented in [Ramakrishna 12]. To achieve this: (1) A statistical model of human pose variability that can describe a wide variety of actions has been developed, (2) Simultaneously estimating 3D camera and body pose while enforcing anthropometric regularity. To achieve compaction, camera pose variability has been separated from the intrinsic deformability of human body. To compactly model the intrinsic deformability across multiple actions, a sparse linear representation has been used in an overcomplete dictionary. The parameters of this sparse linear representation have been estimating with a matching pursuit algorithm.

Estimating the non-rigid human 3D shape and motion from image sequences taken by uncalibrated cameras is an ill-based problem. Factorizing 2D observations into camera parameters, base poses and mixing coefficients are listed solutions to this problem in [Wandt 15]. When a sufficient camera motion is required to reconstruct 3D shape correctly, convincing 3D reconstructions from arbitrary camera motion have been obtained based on a-priorly trained base poses in [Wandt 15]. A periodic motion such as walking patterns can be estimated using an efficient and accurate algorithm that is defined by strong periodic assumptions on the coefficients. Based on temporal bone length constancy, [Wandt 15] proposed a regularization term to extend this approach to non-periodic motion without predefined skeleton or anthropometric constraints.

A deep convolutional neural network has been proposed in [Alotaibi 17] to extract discriminative features and to tackle the problem of gait recognition from videos. A combination of hand-crafted features and deep-learning based features are extracted in [Wu 18] to build a gait descriptor for sake of gait recognition.

For action and gait recognition, in [Battistone 18], an instance of LSTM, named Time based Graph Long Short-Term Memory (TG-LSTM) network has been proposed on top of a deep neural network to jointly exploit the spatial and the temporal information of the input data. In [Xu 19], a hybrid approach is proposed to build a discriminative model for human gait recognition in wild scenarios such as multi-view, multi-walking condition, and multi-clothes condition.

To tackle the problem of cross-view gait recognition and to build a view-invariant features for gait recognition, a restrictive triplet loss has been used in [Tong 19a] to optimise the parameters of a neural network based model, which has been learned to recognise the gait from video sequences.

In [Tong 19b], a generative adversarial network (GAN) paradigm has been proposed by replacing the generator network with a variational autoencoder (VAE) to recognise the human gait from multiple views. For human identification from gait, a deep convolutional neural network (CNN) has been employed in [Wu 16] to tackle this problem via learning the similarity between the samples of the same person and enlarging the difference between the gait of the different subjects.

A multimodal-based approach has been used in [Kumar 18], where the data from motion sensors are fused with the data from the cameras to be used for person identification from gait. The motion sensor data are modelled with the LSTM, while the visual features are extracted using 3D Convolutional Neural Networks.

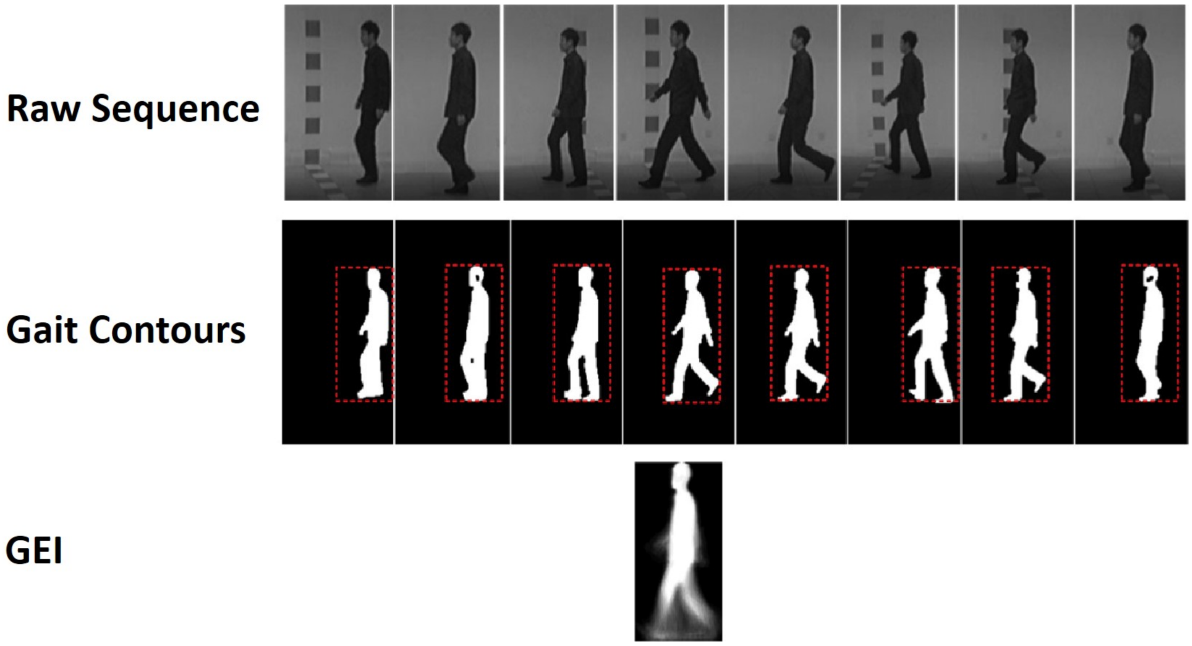


Figure 2.12: The generation process of gait energy image (GEI) [Tong 19b].

Moreover, on the applications of using human gait, in [Li 18], an algorithm for classification of gait disorders has been proposed based on extracting the trajectories of the 3D human skeleton captured by Kinect sensors.

Apart from using video data, the gait recognition from smartphones data is studied in [Zou 18]. A convolutional neural network and recurrent neural network methods have been utilised to model the gait biometrics of the subjects. A recent comprehensive study for studying the gait as a biometric and for gait recognition has been provided in [Zhang 19].

2.3.2 Abnormal Gait Detection

Instead of using gait analysis in human recognition and identification, other computer vision researchers have used it to differentiate between normal and abnormal gait patterns, which can be used in video surveillance applications, such as [Bovyrin 05].

Body silhouettes have been used to detect if the observed walking pattern appears to be normal or not [Bauckhage 09]. A homeomorphism between 2D lattices and silhouette shapes has been presented to address the requirement of abstracting gait characteristics that allow gait classification across individuals using support vector machine. Another method has been proposed in [Wang 06] to determine different styles of walking and to detect the deviation from usual walking patterns. The extracted silhouette from videos as well as the frame-to-frame optical flows have been used to generate motion metrics based on histogram representations of the silhouette-masked flows, then eigenspace transformation has been used for gait analysis.

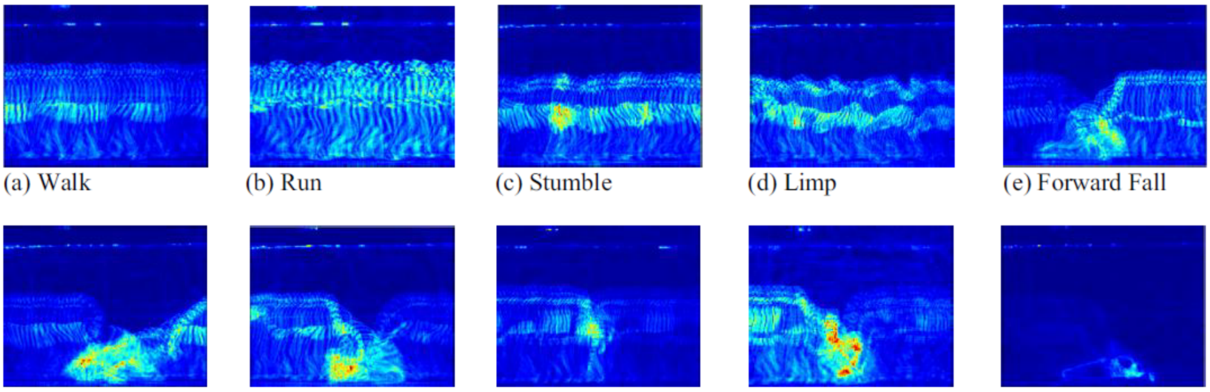
Using a vision-based approach, some gait features have been identified from RGB image sequences in [Nieto-Hidalgo 16] to determine some dynamic gait parameters and analyse them to distinguish between normal and abnormal gait patterns. Gait parameters, such as cadence length and average gait cycle time, are calculated by defining the foot positions after the extracted silhouette of the body is segmented into lower and upper parts. The gait then has been classified into normal or abnormal based on the calculated gait parameters.

Analysing gait to detect existing or new anomalies can play an important role in diagnosing musculoskeletal and neurological disorders, although it can be difficult without prior knowledge of such gait patterns. Based on human joint positions from both marker-based motion capture data and Kinect skeleton over time, [Nguyen 16] have created a model to distinguish abnormal human gait from a normal one. Normal gait cycles have been decomposed from sequences of normal gait images to create the normal gait model. The relationships between pairs of bone joints located in the lower body have been represented by feature vectors, then have been clustered as abnormal pattern if the detected gait model falls below the specified normality likelihood. Another proposed framework for automatic musculoskeletal and neurological disorders classification based on 3D motion data has been presented in [Rueangsirarak 18]. To analyse relative movement between joints, [Rueangsirarak 18] have proposed two features, 3D Relative Joint Displacement (3DRJDP) and 6D Symmetric Relative Joint Displacement (6DSymRJDP), to capture the relationships between joints over time and then classify the gait into normal or abnormal based on these relative joint features. Another method on the joints' motion of the 3D human skeleton captured by a Kinect sensor has been presented in [Li 18] for classifying gait disorders related to neuro-degenerative diseases, such as Parkinson and Hemiplegia.

Gait abnormality is an indicator of a deficiency in body locomotor that may cause a fall. Using computer vision approaches and the advantages of gait analysis from videos, faltering and falling can be detected from individuals' gait.

2.3.3 Fall Detection

The goal of a fall detection systems is to automatically detect cases where a human falls and may have been injured. A natural application of such a system is in home monitoring of patients and elderly persons, so as to automatically alert relatives and/or authorities in case of an injury caused by a fall.



(a) Walk (b) Run (c) Stumble (d) Limp (e) Forward Fall

(f) Backward Fall (g) Sideway Fall (h) Bend down (i) Sit down (j) Lie down

Figure 2.13: Integrated time motion occurrence (ITMI), different scenarios [Foroughi 08].

Vision-based is one of the main categories in fall detection approaches, other main categories are: wearable device based, such as accelerometer, and ambience device based, such as audio and video. Vision-based fall detection approaches have been classified into the following categories by [Mubashir 13]:

(1) Spatiotemporal: Detect different events from spatiotemporal features that provide crucial information of human activities.

    In [Foroughi 08], falls have been detected using a combination of the eigenspace approach (to perform feature reduction and obtain feature victors which are used to classify the motion) and integrated time motion images (ITMI, which are considered as a spatiotemporal database that contains motion information and time stamps of motion occurrence, Figure 2.13). Support vector machines (SVM) has been used to classify falls in the system presented in [Shi 09]. The motion information is recorded by the accelerometers and a high-speed camera is used for the analysis of falls. Another method, which extracts changing pixels from the background and reports temporal contrast, has been used to develop an asynchronous temporal contrast vision sensor for fall detection in [Fu 08]. Then, an instantaneous motion vector computation reports fall events.

(2) Inactive/change of shape: Falls can be detected using algorithms based on shape change analysis and inactivity detection.

    Analysing human shape deformation has been used in the proposed classification method for fall detection in [Rougier 11] by performing segmentation to extract the silhouette. Additional edge points inside the silhouette are extracted for matching two consecutive human shapes using the shape context. An adaptive approach has been used to detect moving objects by using bounding boxes and background subtraction in [Vishwakarma 07]. Fall detection model is based on feature extraction analysis, detection and classification. Features, such as centroid angle to the horizontal axis of the bounding box can detect falls if it reaches a value less than 45 degrees. The fall detection method in [Anderson 09] determines the number of states for the object at each frame, then dealing with voxel person, which is linguistic summaries of the object's states, that reconstructed from silhouette. Another method for analysing body sway from a 3D voxel reconstruction from silhouette has been presented in [Wang 10a], using two inexpensive calibrated webcams to extract sway parameters from both standing and walking subjects. The voxel person is built from back-projected silhouettes extracted from multiple camera views as in [Wang 09]. A Vicon marker-based motion capture has been used as ground truth. A good agreement was obtained for body sway during standing. For walking, the overall agreement has been lower.

(3) Posture: Falls can be detected from collected posture information, which can be identified and utilised from vision data.

Human behaviours can be analysed using calculated projection histograms for their postures and classifying them to the trained posture maps toward fall detection [Cucchiara 05]. Another classification approach based on a neural fuzzy network has been introduced in [Fleck 08] to classify human postures into: Standing, bending, sitting, and lying after computing projection histograms and applying discrete Fourier transform.

(4) 3D head position analysis: Within vision data, head tracking determines the occurrence of large movement that can be analysed to detect falls.

In 3D head motion based analysis, the principle is based on faster vertical motion than horizontal motion in a fall situation [Jansen 06]. The method uses information extracted from images obtained using 3D visual approaches in combination with a context model. The contextual model interprets the fall occurrence differently. It depends on the time, location, and duration of the fall event. [Rougier 05] have obtained image streams from a monocular camera. This methodology of fall detection is based on 3D head trajectories and the idea that the object's head remains visible in the image sequence and undergoes a large movement when a fall occurs. The 3D ellipsoid is used for estimating bounding area around the head. The 3D ellipse is a projection of ellipses in 2D image planes. A particle filter extracts the 3D head trajectory for tracking. The 3D head trajectory also contains features, such as 3D velocities, which are applied to fall detection.

All of these techniques and approaches are only for detecting a fall when it is happening. A system for detecting a likelihood of possible fall occurrence is still needed to intervene early so as to prevent such falls and avoid bad consequences.

2.4 Summary

Gait and postural sway reflect the human health condition and are easily affected by changes to it, such as injuries, illness, and aging. Different parameters have been defined to measure and analyse human gait and sway using different devices and techniques.

Analysing gait and body sway have been initiated in a clinical environment for (1) detecting abnormalities that can be a sign for one or more system disorders, (2) monitoring movement improvements in rehabilitation environments, and (3) determining the causes and circumstances of the fall accidents after a fall has happened.

Because of the advantages of the gait over other human recognising biometric methods, gait has become an interesting research area from a computer vision point of view. Human gait and body sway have been used to identify and recognize people for different applications, such as security. Similarly to clinical studies, in the area of fall detection, many researchers focus on detecting falls when happening or in just about to happen.

In terms of cost and set-up, gait and postural assessment requires clinical/laboratory set-up for equipments and/or sensors that are used for this purpose, in addition to their high cost. Even for wearable sensors, such as accelerometers, a need to be worn continually and placed the same way every time for consistency of data collection, which is supposed to be hard specially with elderly.

For these reasons, an accurate, inexpensive and easily accessible tool for quantitatively measuring gait and postural sway is needed and must be suitable to be used with daily activities. If such a tool was available, it could enable earlier detection, better ongoing monitoring, and immediate assessment of treatment interventions of balance disturbances in elderly and could lead to a reduction in the likelihood of injuries related to falls.

This work aims to utilise vision techniques to measure, analyse, and assess gait and body sway as an inexpensive alternative to predict falls several weeks or months before they may actually happen by quantifying variabilities in gait and postural sway. The following chapters present the methodologies, algorithms, results and discussion for this work.

Chapter 3

Dataset

Human gait and/or sway datasets are usually recorded for clinical or computer vision research purposes. Existing datasets that include gait and postural sway activities have usually been clinical datasets, collected in health care settings and, hence, were confidential and unavailable to my research. Moreover, video cameras or a motion capture system that are needed to assess the accuracy of the modeling may not have been included.

On the other hand, from a computer vision perspective, computer vision datasets usually do not include postural sway data. Moreover, when a dataset contains gait information, it would be for tasks such as person tracking, action recognition, human recognition, and/or identification.

This research tries to employ computer vision algorithms and techniques to identify gait and sway related health issues that may result in a possible fall over time, especially in elderly people. To achieve this goal, two ethics approvals and research permissions, for the two parts of the dataset, have been approved by University of Canberra Human Research Ethics Committee[1] to collect our dataset that contains both gait and postural sway activities to be used in our study. 'Gait and sway' dataset consists of two main parts, a ground truth dataset and an elderly dataset. Participants in each part have signed a consent form before recording.

This chapter device the dataset recording framework and explains preparation in details. The next chapters discuss the experiments, tests, and results on this dataset.

The rest of the chapter is organised as follows: In Section 3.1, the dataset framework is explained. Section 3.2 presents the dataset recording activities. Section 3.3 displays the different devices that are used in the dataset recording. For the two parts of the dataset, Section 3.4 presents the ground truth part

[1]This research has been approved by the University of Canberra Human Research Ethic Committee, project numbers: 15-122, 15-193

(a) (b) (c)

Figure 3.1: Lab setup for ground truth part collection using Vicon and video cameras (a) and (b). The force plate is embedded in the ground. (c) Shows Vicon markers on one of the subjects.

in details, while Section 3.5 presents the elderly part of dataset. Section 3.6 discusses the preparation steps that are required for the different collected data in the dataset. The chapter ends with Section 3.7 that summarizes the dataset design, recording process, and preparation.

3.1 Dataset Framework

The main goal of this research is to use the vision data to measure gait and sway parameters to define the likelihood risk of having a fall in elderly people by analysing these parameters. So, part of the data has been collected for elderly people with chronological age at least fifty years and are grouped into three chronological-age groups: $50 \leq$ age < 60, $60 \leq$ age < 70, and age ≥ 70. Also, to investigate the changes that occurred on gait and sway parameters over time, elderly data have been collected in three phases separated by three months.

To prove that the vision data is accurate enough to be used for measuring gait and sway parameters, another part of the dataset has been collected that includes, in addition to the vision data, the gold standard in capturing data for: 1) accurate body joint movements in the three 3D using motion capture system, Vicon and 2) accurate body's center of pressure displacements using force plates. Figure 3.1 shows the lab setup for collecting the ground truth data and the Vicon markers placed on one of the subject's body joints. Subjects in this part are healthy adults.

A detailed presentation of the 'Gait and Sway' dataset is discussed in the following sections.

3.2 Recorded Activities

'Gait and Sway' dataset contains two activity types: (1) human gait information, which has been captured while participants' normal walking in a straight line and (2) human body sway, which has been captured while performing one of the balance tests. The *Balance Error Scoring System* (BESS) is the balance test that has been used in this dataset to capture participants' postural sway as discussed in the following text.

Balance Error Scoring System (BESS)

The *Balance Error Scoring System* (BESS) [Finnoff 09] is an example of a widely used clinical balance test. BESS provides an objective method to assess the static postural stability. The normal BESS needs to be completed on two testing surfaces: ground/floor and foam pad. The foam pad creates an unstable surface, which is a more challenging balance task. Three stance postures are required to be taken for 30 seconds on each surface:

1) *double leg* stance with feet side by side,

2) *single leg* stance on the non-dominate foot (the opposite leg of the preferred kicking leg), and

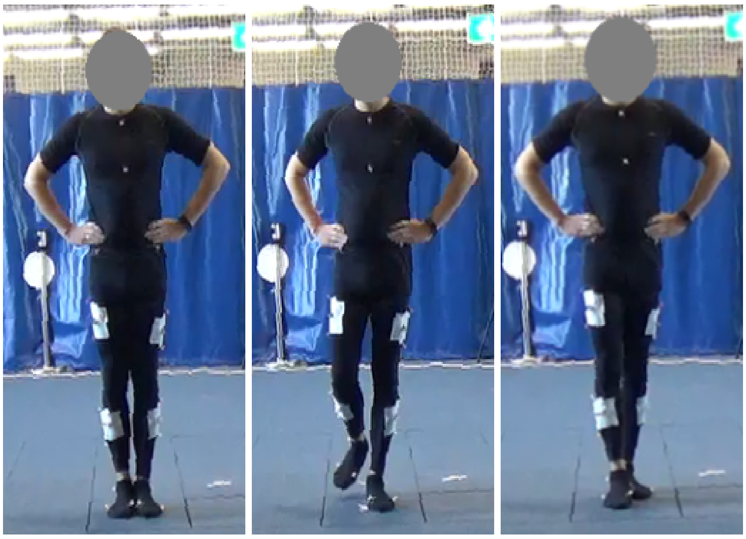
3) *tandem* stance (standing heel to toe with non-dominate foot in the back).

For all positions, the eyes are closed and the hands are on the hips. The BESS positions are shown in Figure 3.2.

In this dataset, only the BESS postures on a hard surface have been considered. These postures have been assessed on the force plate for an accurate capture of the body Centre of Pressure (CoP) displacements for 20 seconds. CoP displacements while standing can measure the postural stability, which is an important feature that protects people from a fall and helps to complete the desired actions [Huang 13].

3.3 Devices

In the two parts of the dataset, three kinds of devices have been used to collect the data, video cameras for vision data, force plate for CoP displacements, and Vicon system for 3D human movement motion capture. The devices that have been used to collect the dataset are shown in Figure 3.3. Devices usage, specifications and installation are discussed in detail in the following section.



(a) (b) (c)

Figure 3.2: BESS stances: (a) double leg stance, (b) single leg stance, and (c) tandem stance.

(a) (b) (c)

Figure 3.3: The devices that are used to collect data in ‘Gait and Sway’ dataset: (a) video camera to collect vision data, (b) force plate (AMTI on top and Kistler on bottom) to capture body’s centre of pressure (CoP) displacements, and (c) Vicon cameras to capture joint movements in the 3D space.

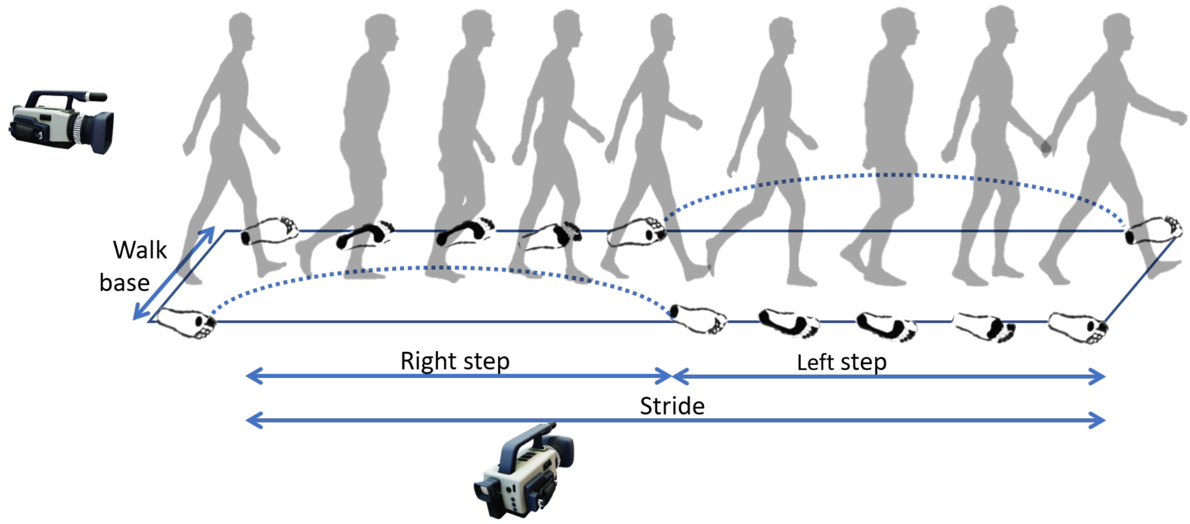


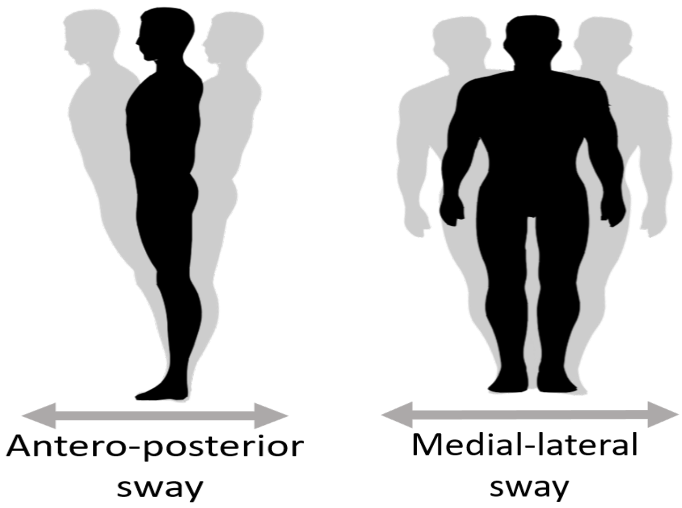
Figure 3.4: Examples of gait parameters.

Video Camera

As this work investigates measuring human gait and sway parameters from vision data, the main recording device is a *high definition* (HD) video camera that has been used in both parts of the dataset, the ground truth and the elderly data. A SONY HDR-CX405 (Figure 3.3 (a)) digital HD video camera recorder has been used to capture gait and balance activities at 25 frames per second.

For gait, some gait parameters have to be observed and measured from the front (or back) of the person, such as *walk base*, other parameters need to be observed and measured from the side, such as *step length*. To get a chance to measure any gait parameter from any side, two identical HD video cameras have been used for collecting data in the two parts of the dataset from frontal and side view. Figure 3.4 shows examples of gait parameters and illustrates the video cameras position to measure them.

While standing, the human body sways in the two horizontal directions leading to medial-lateral sway (side-to-side) and anterior-posterior sway (front-to-back) as illustrated in Figure 3.5. Using the two HD video cameras, both types of the body sway can be captured, but, as the medial-lateral sway is more related to controlling the body balance, the frontal view has been considered for capturing and measuring the body sway. While walking, a medial-lateral sway is generated as the body weight is shifting from one leg to the other as illustrated in Figure 3.6.



(a) (b)

Figure 3.5: Human body sway while standing: (a) anterior-posterior and (b) medial-lateral sway.

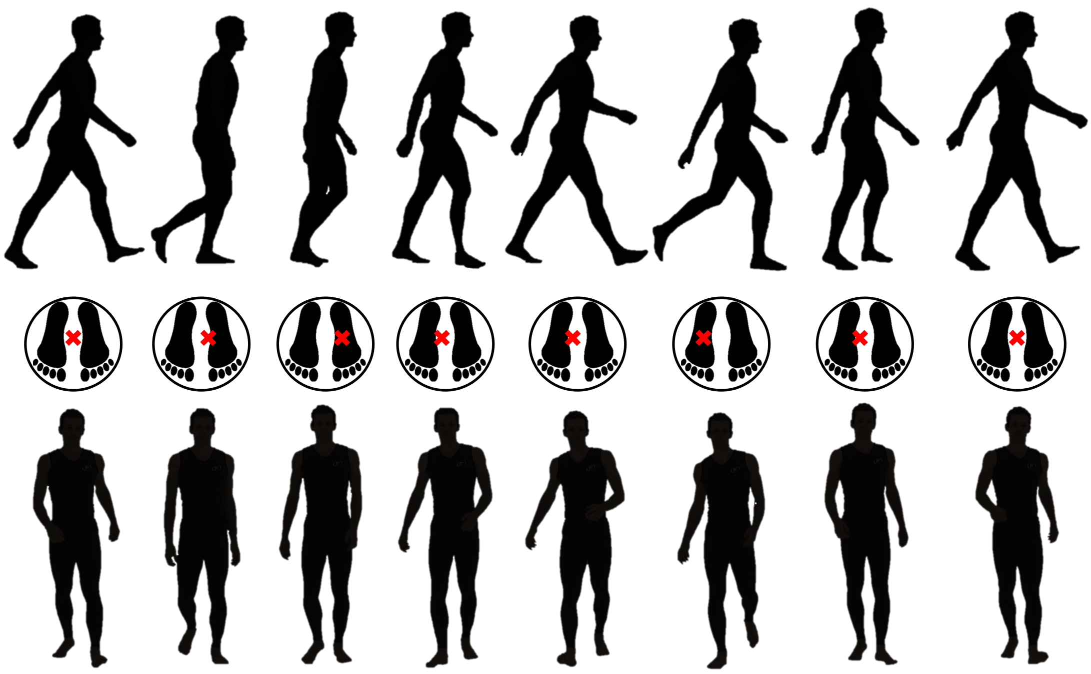
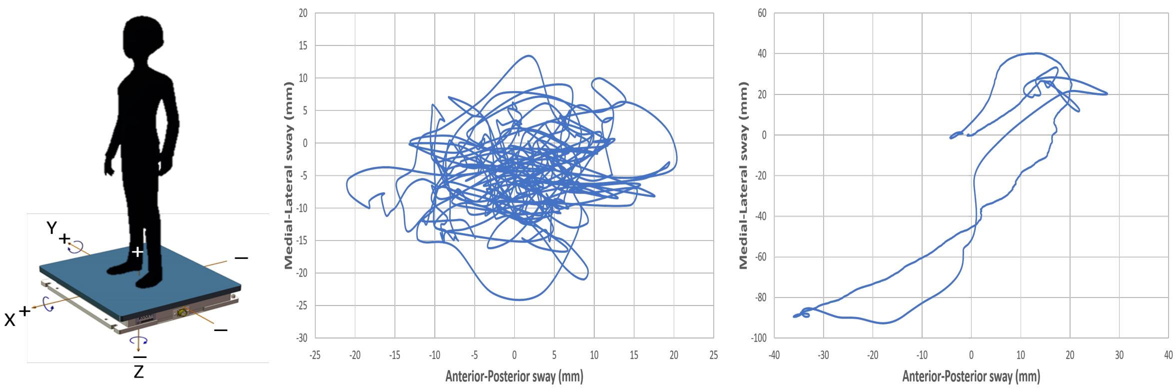


Figure 3.6: Sway while walking, while the body moves forward (the upper line) the body weight shifts from one leg to the other (middle line) and the medial-lateral sway can be observed (lower line).

Force Plate

To establish a high accurate reference for the CoP measurement during the balance test and walking, a force plate has been used in the both parts of the dataset. A force plate has been used to measure the three dimensional components of the body's CoP, X, Y, and Z on its surface as illustrated in Figure 3.7(a). While the Z component represents the ground reaction force for the body weight, X and Y components represent medial-lateral sway and anterior-posterior sway, respectively. Figure 3.7(b) and 3.7(c) show an example of captured movements of the CoP while standing still and when stepping on the force plate while walking, respectively.

For the ground truth, an AMTI force plate [fpA] has been used to capture the CoP movements while a Kistler force plate [fpK] has been used in the elderly part of the dataset (Figure 3.3 (b)). both force plates capture the CoP movements at a frequency of 1000 Hz.



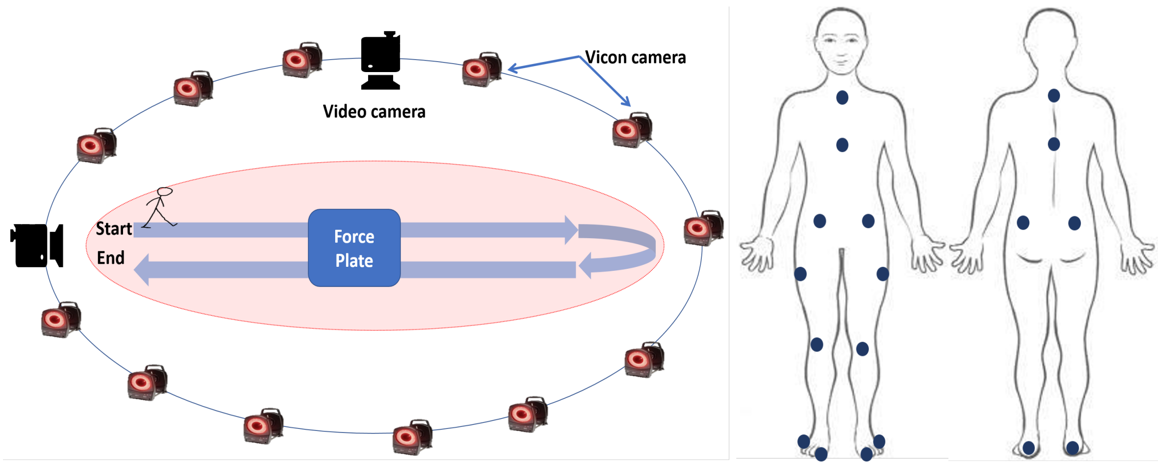
(a) (b) (c)

Figure 3.7: (a) Illustration of the three dimensional components of the body's centre of pressure CoP on the force plate surface, (b) Original force plate signal for (CoP) movements during one stance of a balance test, and (c) Original force plate signal for CoP movements when stepping on force plate while walking.

Vicon system

In order to have a highly accurate reference for the human body parts movement over the video frames, the Vicon system is used in the ground truth part of the dataset as a gold standard in the 3D motion capture.

T-series Vicon cameras [Vic] have been used to capture the body part movements from markers that have been placed on these parts. T-series Vicon cameras record 100 frames per second for the markers placed on the participant's body parts.



(a) (b)

Figure 3.8: (a) Ground truth recording lab setup, (b) Vicon markers places on the subject's body.

3.4 Ground Truth Dataset

This part of the dataset has been used to build an acceptable accuracy ground truth for the collected data to compare with. The ground truth dataset contains video recordings as well as data from the Vicon system, which accurately captures the 3D motion from markers that are placed on the subject's body. A force plate has also been used in this part of the dataset to capture the CoP displacements of the human body while standing or stepping on it.

In the ground truth dataset, seventeen (17) active lifestyle participants, have been recruited from the university students and staff, eleven (11) males and six (6) females with ages between 24 and 50 years, have performed normal preference walking in straight line including making a U-turn at the end of the recording area and stepping on the AMTI force plate placed in the middle of the walking area. The three stances of the BESS test have been performed on AMTI force plate. Each subject has made the sequence of walking and BESS test activities three times. These activities have been recorded by two video cameras, one at the front and the other on the side of the recording area as discussed before. Twelve T-series Vicon cameras have been used around the recording area to capture 3D motion from sixteen markers that have been placed on the participant's body parts. Vicon markers have been placed on different joints that are related to body parts that are considered as major motor reactors in walking and maintaining body balance as shown in Figure 3.8(b), such as legs, feet, and trunk. The recording studio setup is shown in Figure 3.8(a).

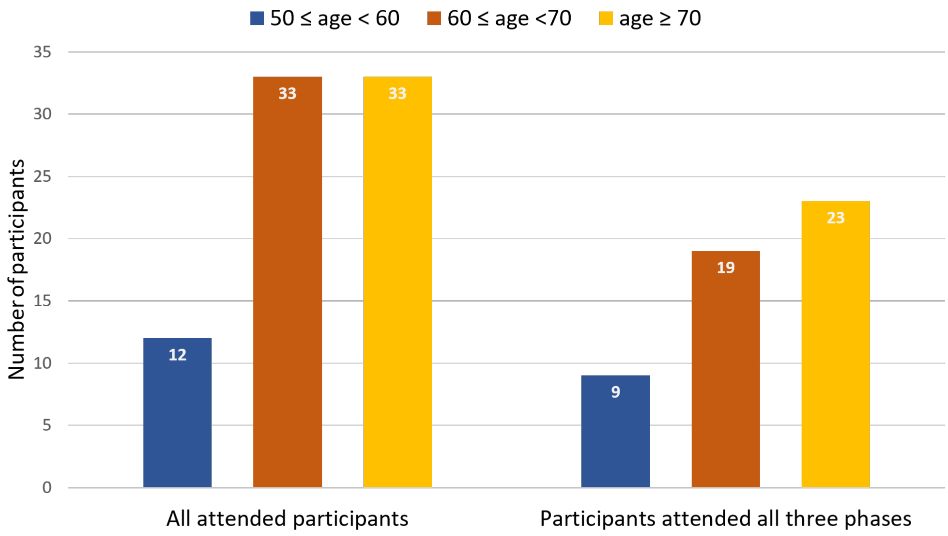


Figure 3.9: Number of elderly people who participated at the phase–1 data recording (on the left) and in all three stages (on the right) in the dataset collection.

3.5 Elderly Dataset

To observe and measure changes in gait and postural sway over time in elderly people, this part of the dataset has been collected in three stages, three months apart. Participants were recruited by releasing a media report in the news asking for elderly people over 50 years to participate in the study[2,3,4]. Taking in consideration any history of falls, questions about previous fall and daily activity were asked and recorded. Also, any fall occurred within the three months between recordings was considered.

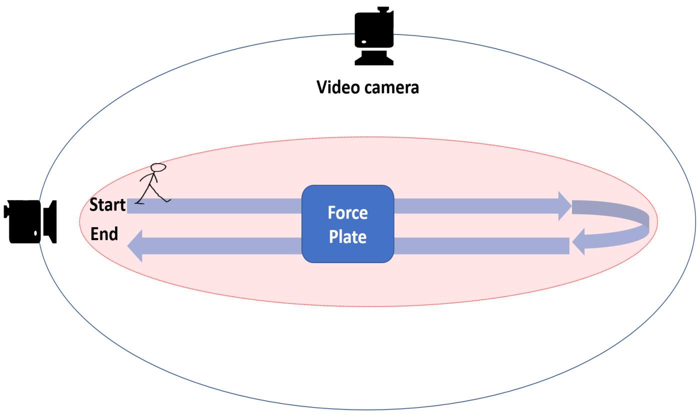
The number of participants started with seventy eight (78) elderly people in the first phase, eighteen males and sixty females over fifty years. The number of participants attending all three phases was fifty elderly people, 37 females and 13 males. The reasons for the absentees varied between being away during the next phase recording time, having orthopaedic surgery that affected their walking and standing, or even losing their interest in completing the next recording sessions. Figure 3.9 illustrates the number of participants grouped in ten years age groups at the beginning of the data collection process and the number of elderly people participated in the three stages of this part of the dataset.

In this part of the dataset, the vision data have been collected by the same two video cameras that have been used in the ground truth dataset part. Sway data while standing or walking have been collected using a Kistler force plate in the middle of the recording area as illustrated in Figure 3.10(a).

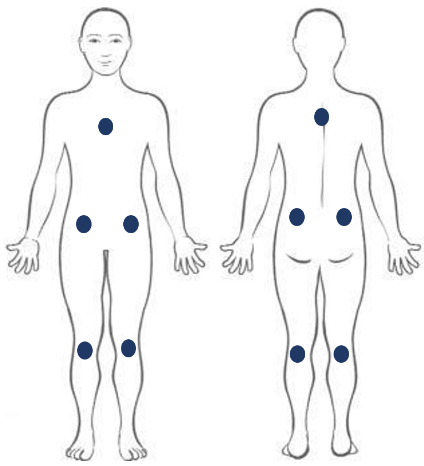
[2] https://www.canberratimes.com.au/story/6036110/university-of-canberra-study-looking-to-develop-gait-monitoring-app-to-prevent-falls/

[3] https://www.canberra.edu.au/about-uc/media/newsroom/2017/february/app-to-prevent-falls-focus-of-uc-phd-study

[4] https://www.abc.net.au/news/2017-02-23/university-of-canberra-gait-study-fall-prevention/8297266



(a)



(b)

Figure 3.10: (a) Elderly dataset recording setup, and (b) distinctive reflector points that were placed Placed on elderly participants' body

To facilitate body part movement tracking over video frames, distinctive colour points have been placed on the participant's upper torso, hips and knees as illustrated in Figure 3.10(b). For consistency, the points have been placed on the same spots as the Vicon markers in the ground truth data on the selected body parts. Torso movements reflect the body sway either in standing or walking more than other body parts. Legs, and feet are the body parts that are responsible for the walking action.

The participants have been asked to walk normally in a straight line for about 10 metres with making a U-tern at the end of the recording area. Then, they have performed the BESS balance test on the force plate. The sequence of the walk and the balance test have been recorded twice for each participant in each session. The two video cameras have been placed at the front and the side of the recording area, as shown in Figure 3.10(a). The force plate has been placed on the floor in the middle of the recording area to capture the body sway when stepping on it while walking, as well as the postural sway while standing on it doing the BESS balance test.

Elderly Recording Difficulties

Some difficulties have been faced during recording this part of the dataset. One of them has been related to the recording place and the force plate equipment. The force plate was a shareable research equipment that needed to be moved from one building to other. The recording area itself was a shared area that has not been continuously available for the dataset recording.

Although I have met very nice and kind people during the recording sessions, I had some difficulties in the recording process. The main difficulty has been in performing the balance test, especially, the tandem and single leg stances. Some participants could not close their eyes for the entire 20 seconds or even part of it. Some participants could not comply with the position of the non dominant foot in the tandem or single leg stances either for having an issue in that foot or feeling more secure with the stronger leg.

3.6 Post-recording Data Preparation

Because of the different recording sampling rates in the different devices, some necessary preparations have been required on the different kinds of recorded data, video recordings, Vicon, and force plate data. Where the force plate and the Vicon system in the ground truth part have been systematically synchronised, the data preparation includes video-views alignment and video-force plate alignment in both parts of the dataset and video-Vicon alignment for the ground truth.

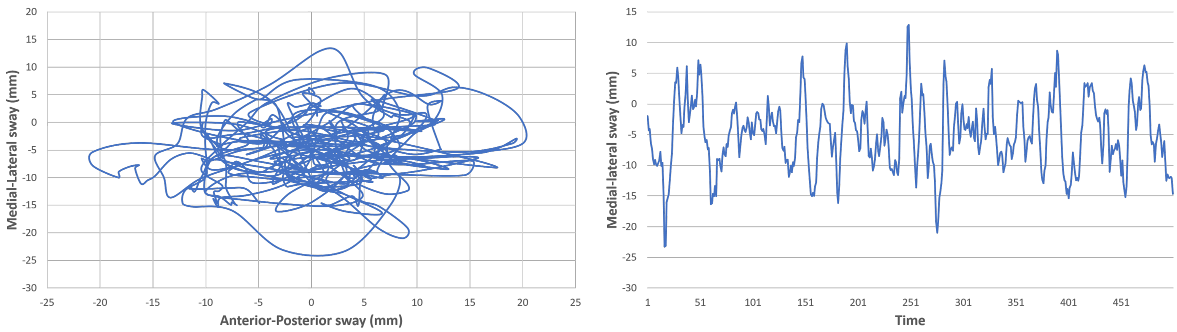
Video – Views Alignment

For both parts of the dataset, the ground truth and the elderly data, the two video cameras have been manually operated, which resulted in non-synchronised video recordings for the single subject from the two views, front and side.

Using the Adobe Premiere pro video editing tool, which can open up to four different views simultaneously, the two views of the video recordings have been aligned based on manually selected frames from both views (*ex.* shown in Figure 3.11). Once the two views have aligned, the same tool has been used to split and save the videos into single activity content videos, a walk in one direction or one of the balance test stances.

Each walking video starts with the appearance of most of the participant's body in the both views (front and side) and ends with the beginning of participant's body's disappearance from either view. The balance test video for each stance, double leg, tandem, or single leg, starts when the 'start' order and ends when 'stop' order can be heard in the video recording.

Figure 3.11: Video alignment using Adobe Premiere pro editing tool. To the left, the side view and to the right the front view. Both views on the manually selected frame (heel strike) to align the two views on.



(a) (b)

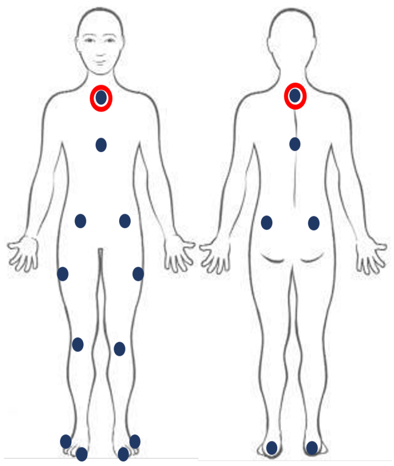
Figure 3.12: (a) Force plate original signal and (b) extracted medial-lateral sway.

Video – Force Plate Alignment

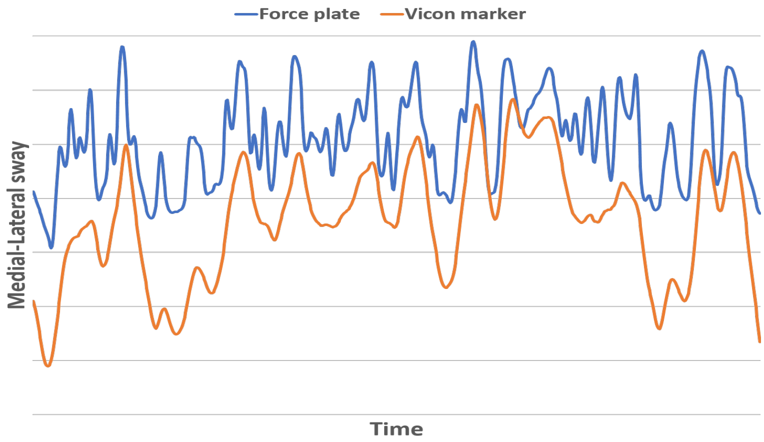
The directional sway of the interest, the medial-lateral sway (side-to-side sway), was extracted from the force plate signal by taking the X component from the measured CoP (Figure 3.12) to be used in the experiments.

The force plate signal for the balance test includes body sway for the test time, the exact 20 seconds, for each stance. Because of the time of the human reaction in recording and cutting videos, parts of second between tell/hear the order and press the button to start or end recording/cutting the video, milliseconds divergence between video's time length and force plate signal length may have occurred.

A preliminary experiment on the balance data of ground truth has been carried in order to identify which body part movements (Vicon markers) most reflect the CoP movements (force plate). The upper torso markers movement (front and back, Figure 3.13(a)) have been most correlated to the force plate captured signal as shown in Figure 3.13(b). Based on that, the upper torso coloured spot has been tracked



(a)



(b)

Figure 3.13: (a) Illustration of the similarity between the centre of pressure (CoP) movements, which are captured by the force plate (blue) and the tracked point on the upper torso over video frames (orange) and (b) The upper torso Vicon markers that show most correlation with the captured CoP from the force plate.

over the video frames to simulate the CoP displacements.

The force plate signal is captured at a high sampling rate, which results in a noisy signal. As the signal of interest (body sway) is characterised by low frequencies, a low-pass filter has been used to cut off the high frequencies to reduce the noise. Also, the force plate signal has been down sampled to match the video recording rate of 25 frames/second.

3.7 Summary

Because of lack of local accessible datasets that contain gait and sway activities, especially for elderly people, this gait and sway dataset has been recorded. This dataset has been recorded in two parts: 1) A ground truth part to establish and validate a method for estimating, measuring and analysing body part movements while walking and standing. Ground truth part of the dataset has been collected for healthy athletes and the different collected data types, from video force plate, and Vicon, have been correlated; 2) An elderly data part, which has been recorded in three phase separated by three months to form a normative elderly dataset. Elderly part of the dataset has been collected for participants over fifty years. The validated method from the ground truth part has been used on the elderly dataset part to estimate and measure body part movements.

The following chapters present experiments on the ground truth part, proving the possibility of estimating gait and sway movements from the vision data with an acceptable accuracy compared to the gold standard, Vicon, and force plate. Then, gait and sway parameters in the focus of this study are measured from the estimated movements and compared to the corresponding measurements from Vicon and force plate. After verifying the proposed methods for estimating gait and sway movements and measuring their parameters, experiments for using the examined methods to measure and analyse gait and sway for elderly people are presented. A likelihood risk of having a fall is defined based on these parameters.

Chapter 4

Postural Sway from Vision

Human *postural sway* is the horizontal movement of the body's centre of gravity to maintain body balance within the base of support as illustrated in Figure 4.1. A certain amount of sway is essential and inevitable due to small perturbations within the body, such as shifting body weight from one foot to the other, or from external triggers such as visual distortions or floor translations.

Chapter 2, the literature review, gave a general review about the human postural sway and addressed it in more detail from two different discipline perspectives, clinical and computer vision. It also presented the various devices, equipment, and tests that are commonly used to measure and assist the human postural sway.

This Chapter investigates measuring sway parameters from vision data by estimating the CoP movements from tracked body joints over the video frames. Using ground truth part in the dataset that has been described in Chapter 3, the proposed model for measuring sway parameters is verified by using the corresponding data that has been collected by the gold standard device in measuring the CoP, a force plate.

Next, Section 4.1 presents more of the related research that try to estimate and measure human postural sway from vision data. Then, the proposed methodology for estimating the sway movements from video and measuring the sway parameters from these estimated movements is discussed in Section 4.2. Experiments setup is presented in Section 4.3 followed by the results and the discussion of the results in the Section 4.4. The chapter summary is presented in Sections 4.5.

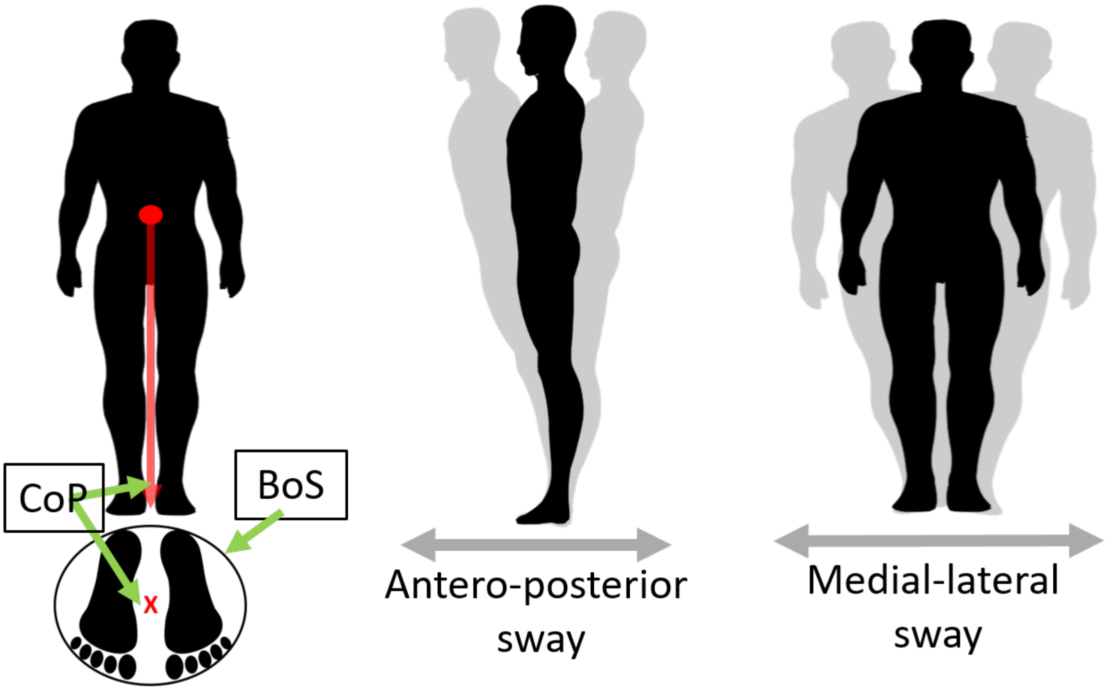


Figure 4.1: Human postural sway, horizontal body movements to keep the body's CoP (Centre of Pressure) within the body's BoS (Base of Support).

4.1 Related Work

Postural sway can be measured by using one or more devices that are designed to capture the total displacement of the body *centre of pressure* (CoP) relative to the base of support during the time of performing one of the balance tests. As discussed in Chapter 2, these devices are either wearable devices, such as accelerometre, or non-wearable devices, such as cameras and force plates. Using different metrics, such as *sway area*, *speed*, *frequency*, and *total path length* [Wollseifen 11], human postural sway can be analysed by a specialist to understand the human body movements and diagnose balance related issues.

Devices, such as force plates or wearable sensors, accurately capture the postural sway of the person who stands on the force plate or wears a particular sensor. Despite the highly accurate measurements of these devices, they have some downsides as well. While force plates are considered as the gold standard in measuring CoP movements for the object placed on it, they require a special set up and they have limited availability in everyday environments, such as homes, which makes their cost high. On the other hand, wearable devices are easier to use, they need to be attached to the body to collect the movements information over periods of time, which may lead to a feeling of discomfort.

Therefore, my research aims to find a way to measure body sway using equipment that is *simpler*, *cheaper*, and *more mobile* than force plates, thereby allowing frequent, unobtrusive measurements in the daily life of the people at their home. This is especially a necessity with elderly people. Elderly people are more likely to forget to wear particular sensors, so an unobtrusive system is preferable. Furthermore, with the normal degradation of the balance-control system with aging, a monitoring of slow changes over time would provide an opportunity to introduce countermeasures, such as different exercise programs.

Finding a practical and inexpensive alternative to measure human postural sway is one of research points from the different disciplines. With the evolution in computational imaging and image processing algorithms, studying and analysing human movements has received much intention from computer vision researchers for different purposes. The dominating areas of interest are recognising and identifying a person from the walking style and detecting falls.

In [Goffredo 06, Goffredo 09], a marker-less, model-free study based on the block matching algorithm (BMA) was presented. The method consisted of tracking the relevant points on the human silhouette, followed by the evaluation of the rotations of the principal body segments, and then estimation of CoP trajectories. Their method has been proven effective in correctly estimating the anterior-posterior component of a trajectory.

An inexpensive setup was also presented by [Allin 08]. The system consisted of a single uncalibrated camera, used to film one-minute video sequences of elderly patients in a community centre. The camera was placed in front of the subject, who was asked to perform a series of tasks. The gold-standard was human evaluation by physical therapists, using the Berg Balance Scale (BBS) [Finnoff 09]. The trajectory of the postural sway was extracted by using a template tracker for the head and feet and the results matched those obtained by the traditional visual method of the BBS. The advantages of this method over previous accelerometer, marker or force plate methods is the simplicity of the setup, as well as the low cost and easy availability of the equipment.

In [Ciptadi 14], a movement analysis system was proposed to calculate information that is usually recorded by force plates by using a 3D video camera. Based on 3D reconstruction of the human body in real-time, the force plate is replaced with a video camera. However, applying it to the sway measurement task would be difficult because of the complexity of tracking and recognising all different body parts that are related to the changes in the body's centre of gravity. [Wang 10a] presents another method for measuring body movements where sway and walk from reconstructed 3D voxel data using two calibrated web camera views and compares the output with movements captured by a Vicon motion capture system. Data of this work consists of only one subject for the sway experiments and four for the walking and does not include the gold standard for measuring CoP movements, the force plate.

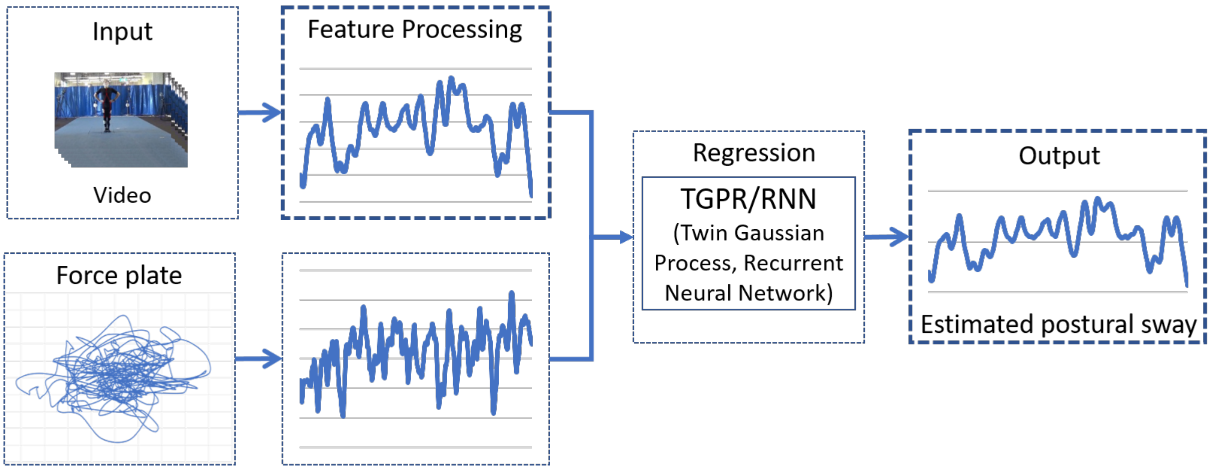


Figure 4.2: Proposed methodology: (from left to right) Beginning with the video frames with annotated joint locations in the first frame, these points are tracked over the frames to extract medial-lateral sway, which is passed to the regression model (i.e. Gaussian process regression or recurrent neural network) to estimate the centre of pressure movements, originally measured by the force plate.

In the next section 4.2, a novel method is proposed to estimate the human postural sway from RGB video recording. The estimated sway is then compared to force plate captured data to validate the method's accuracy. Then the experiments, results and discussion that prove the model's validity are presented in Sections 4.3 and 4.4, respectively.

4.2 Proposed Method

The proposed method is built on the ground truth part of the dataset discussed in Chapter 3 that contains video recording, force plate data, and Vicon data (3D motion capture data) for each participant. As the medial-lateral sway (the horizontal right-to-left body movements) reflects the controlling of the body balance more than the anterior-posterior sway (the horizontal front-to-back body movements), the frontal view of the video recording is considered in this proposed method and experiments.

The proposed method (Figure 6.1) starts with a video sequence as an input, followed by feature processing on that sequence. Regression was used to build a model to estimate the medial-lateral postural sway. Put differently, the feature processing step prepared the input video sequences to extract relevant information reflecting the medial-lateral sway, from which a computational model can be built. The regression step employed two non-linear regression methods, namely Twin Gaussian process regression (TGPR) and Recurrent Neural Network (RNN), to model the postural sway from the video pre-processed features by linking them to the ground truth data from the force plate. The 3D motion capture data served as an additional way to assess the accuracy of the model.

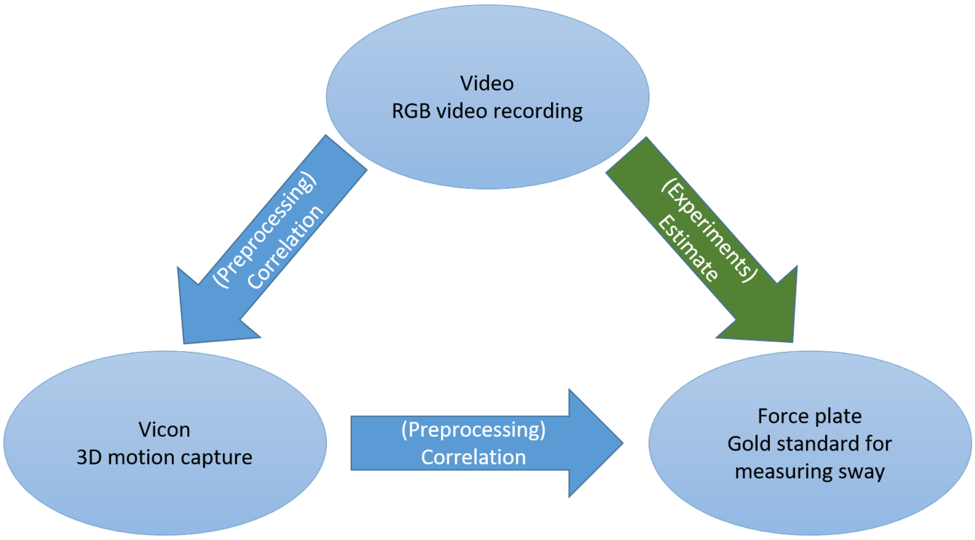


Figure 4.3: The 3-way correlation between *force plate*, *Vicon system*, and *video camera* for human postural sway as described by this work

This part of the work describes a study that establishes a 3-way correlation between the clinical gold standard (force plate), a highly accurate multi-camera 3D video tracking system (Vicon) and a standard RGB video camera as shown in Figure 4.3. To this end, the balance part of the ground truth recorded data is used. The BESS (the Balance Error Scoring System) balance test [Finnoff 09] was recorded on the force plate, while simultaneously recording the 3D Vicon data, and the RGB video camera data. Then, using Gaussian process regression and a recurrent neural network, models were built to predict the medial-lateral sway in the force plate data from the RGB video data. The predicted results show high correlation with the actual force plate signals, which supports the hypothesis that medial-lateral postural sway can be predicted from video data alone with acceptable accuracy.

The problem of modeling medial-lateral postural sway from a computer vision perspective is addressed by estimating the postural sway from tracked joints over video frames and validate this estimation. The balance test part of the ground truth part of the recorded dataset, which includes video data (*RGB camera*), data from a motion capture system (*Vicon*) and data from a *force plate*, is used in this chapter. Because of the different collected data types, a feature pre-processing is required (4.2.1) to prepare the data to be fed in the regression methods, TGPR and RNN, that are described in 4.2.2.

Gaussian process regression and recurrent neural network models are built and trained to map extracted features from video space measurements (pixels) to the force plate measurement space (millimetre). The trained models are then used to estimate the force plate signal from extracted features from video. The correlation between force plate signal and the estimated signal from video is used to validate the model accuracy.

4.2.1 Feature Processing

Different sources for collecting data lead to different data types, images (frames) from the video recording, 2D CoP displacements from the force plate, and 3D movements of the markers from the Vicon system. The feature processing step prepares the different data types from the different sources to be used in the proposed method.

The force plate captures the 2D CoP displacements of the object that is placed on it. As the medial-lateral sway is the CoP direction of the interest, this part of signal is separated from the original data to be processed and used in our proposed method. Data resampling and removing high frequencies are the pre-processing that performed on the force plate data.

Data Resampling

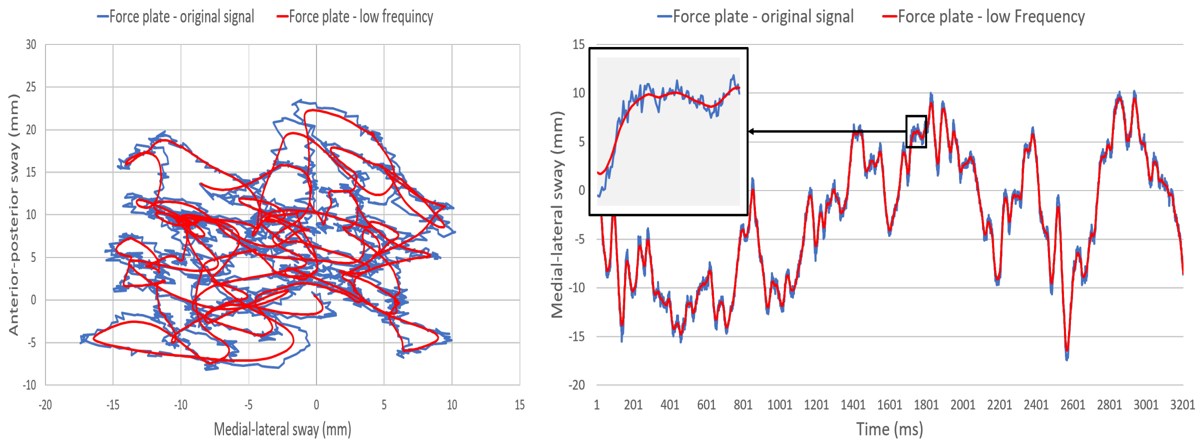
The video and force plate signals are recorded in two different domains. The frame rate of the recorded videos is 25fps, while the force plate captures the body's CoP movements at $1,000$Hz. In the first step, the force plate sampling rate needs to be aligned with the video frame rate. Using a resample factor of 40, the force plate time-domain data is decimated into video recording time-domain.

Remove High Frequency

The high sampling rate in capturing the force plate data results in a noisy signal. Since the signal of interest (postural sway) is characterised by low frequencies, a *low-pass filter* is used to cut off the high frequencies reducing noise and making it suitable for the regression to learn the pattern of the movement. The well-known Butterworth filter [Butterworth 30], 1st order with 50Hz cutoff frequency, is applied as a low-pass filter on the force plate signal. An example of a smoothed signal is shown in Figure 4.4.

Feature Tracking

The main problem of estimating the postural sway from videos with a monocular view is the lack of apparent movement changes for the body over the time. In the balance test, a small movement of the body part, such as the torso, to the left or right, may lead to a big peak in the force plate signal. This means we need to extract high-level features, which are able to represent the body movements and lead to reliable sway estimation.



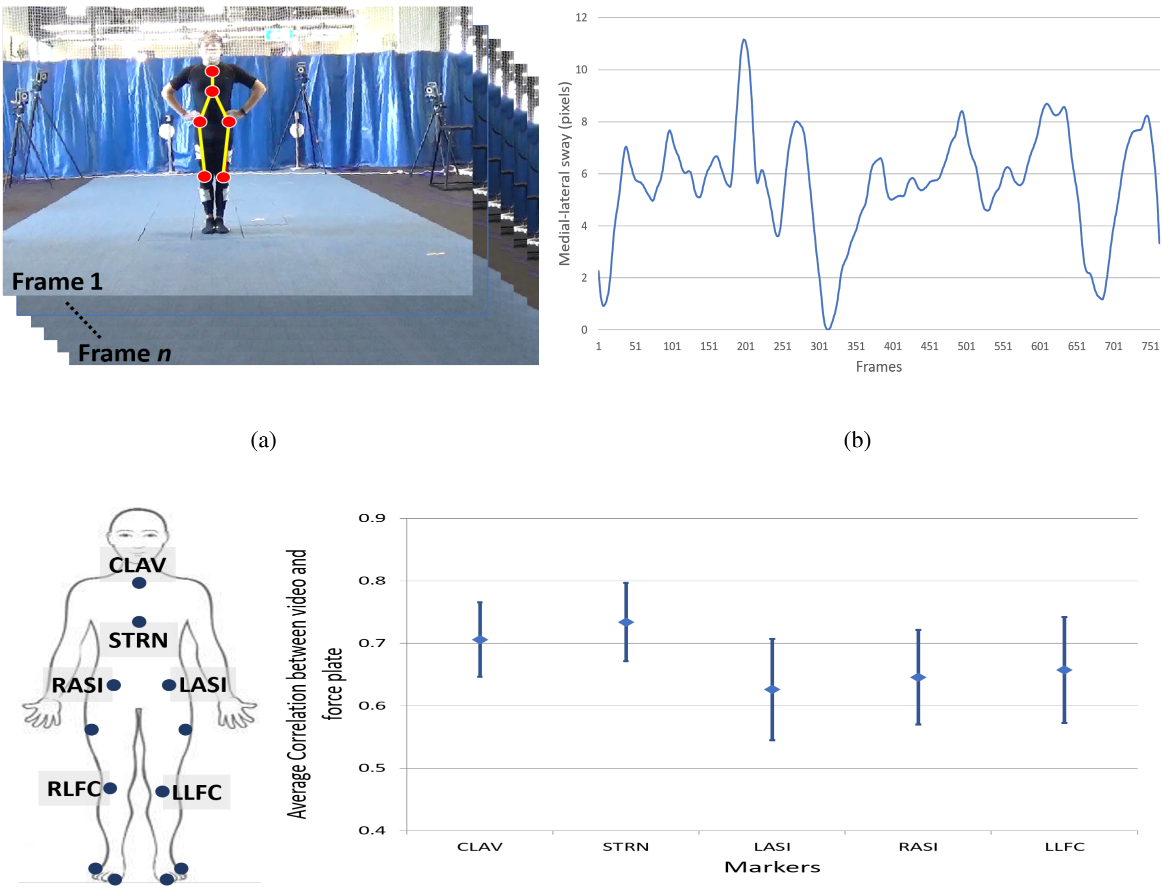
(a) (b)

Figure 4.4: Original center of pressure (CoP) displacements collected by the force plate (blue) and the force plate signal after removing the high frequencies (red). (a) The force plate signal in the 2D space representing the media-lateral and anterior-posterior sway. (b) The extracted medial-lateral sway with a closer look to the signal before and after removing the high frequencies (the black square).

Most information about the postural sway stems from the relative movement of the body parts over time. To this end, we rely on detecting and tracking information around a set of body joints. Initially, some recent body part localisation approaches [Yang 11, Radwan 15] were tried to generate the input to estimate the lateral postural sway. Moreover, amplifying the motion around the detected body parts have been tried using the method of [Liu 05]. Both of these two approaches did not lead to good correlation with the force plate signals due to either inaccurate estimation or due to the noise added in the process of detecting the body parts.

To track the medial-lateral postural sway from a given video sequence, the movements of the body part joints were estimated during the BESS balance test. Starting with the joints that have been marked manually in the first frame then a *Kanade-Lucas-Tomasi* (KLT) tracker [Lucas 81] is used to track these joints in subsequent video frames. In the balance analysis, trunk movements affect the postural sway more than foot and leg movements. This is because when standing still, legs and feet move less. The experiments are relying on the joint locations of the torso, hips, and knees only.

A high correlation between the tracked joints and the medial-lateral sway derived from the force plate signal is found, especially the joints of the upper torso. Figure 4.5(a) shows an example of labelling joint locations in the first frame and Figure 4.5(b) shows the extracted postural sway for one of these joints (upper torso one). The sway like signals are extracted from the tracked markers on torso, hips, and knees. Note, these are the same markers that the Vicon 3D motion capture system uses. Then, we



(a) (b)

(c) (d)

Figure 4.5: Tracking joint locations: (a) Labelling the joints in the first frame and applying the KLT algorithm to track these points over time. (b) Extracting a medial-lateral sway like signal from a tracked point (upper torso). (c) The names of the selected Vicon markers that are corresponding to the tracked points over video frames. (d) The Correlation values between estimated sway signals for tracked joints and the force plate signal for one of the balance test stances of one of the subjects.

calculate the correlation coefficient between these signals and the original medial-lateral sway extracted from the force plate signal. From the correlation coefficient values, it is possible to decide which joints better represent the postural sway. The strong correlation between extracted video features demonstrate the validity of using a frontal monocular camera to estimate the lateral postural sway, especially for the upper body markers. Figure 4.5(c) illustrates the markers place on the body and their names and Figure 4.5(d) shows an example of the correlation between the selected markers tracked movements from video and the medial-lateral sway movements from the force plate for one stance of the balance test. Only one of the knee markers is included as in double stance the knees are touched together, in tandem stance, one knee is hidden by the other, and in the single-leg stance, only one leg is engaged.

In this study, a Vicon motion capture system with markers attached on the body parts of the subjects was used to track the correct positions of the joints from different views with a high degree of accuracy. The purpose was to validate the tracking results from RGB camera data.

There are markers on similar places on the front and the back of the body and they show highly correlated movement patterns. This is important to know for future developments, as it allows the body to be observed from either the front or back with similar results. Marker selection for the regression model is based on the average correlation values between extracted medial-lateral sway from the force plate and the tracked labelled joints over all video frames of a sequence.

4.2.2 Regression

To predict the medial-lateral sway signal from the preprocessed features (tracked body part) from the video frames in the real world measurements (millimetres), two regression methods are experimented, Gaussian process regression and recurrent neural network. The first one predicts the sway values on a per-frame basis, while the second one utilises the embedded structure of the input signal (a.k.a. *source* $\mathbf{x}_i$ at frame i) and output signal (i.e. the corresponding force plate value (a.k.a. *target* y_i) over time. Both methods are described in more detail below.

Gaussian Process Regression

A *Gaussian process* [Rasmussen 03] is the straightforward generalisation of a normal distribution, where the mean and covariance are $m(\mathbf{x})$ and $k(x, x^{'})$, respectively. To keep the correlation between both the inputs and outputs, we employ the well-known *Twin-GPR* (TGPR) technique.

In other words, the TGPR predicts $y = f(\mathbf{x})$, where $f \sim \psi(m, k)$, ψ is the Gaussian process model that encodes the set of mean and covariance functions and is built from the training data [Radwan 13]. In the proposed method, the input $\mathbf{x}_i$ consists of visual features (the selected joints location) that are extracted at frame i and output y is the corresponding force plate value. The training data are stacked together and aligned with the target values, then passed to the TGPR to build the model.

The TGPR model works frame-by-frame without considering previous data. This leads to better estimation for the smoothed signals. On the other hand, when a sudden shift occurs in the data, TGPR fails to predict values at this point efficiently.

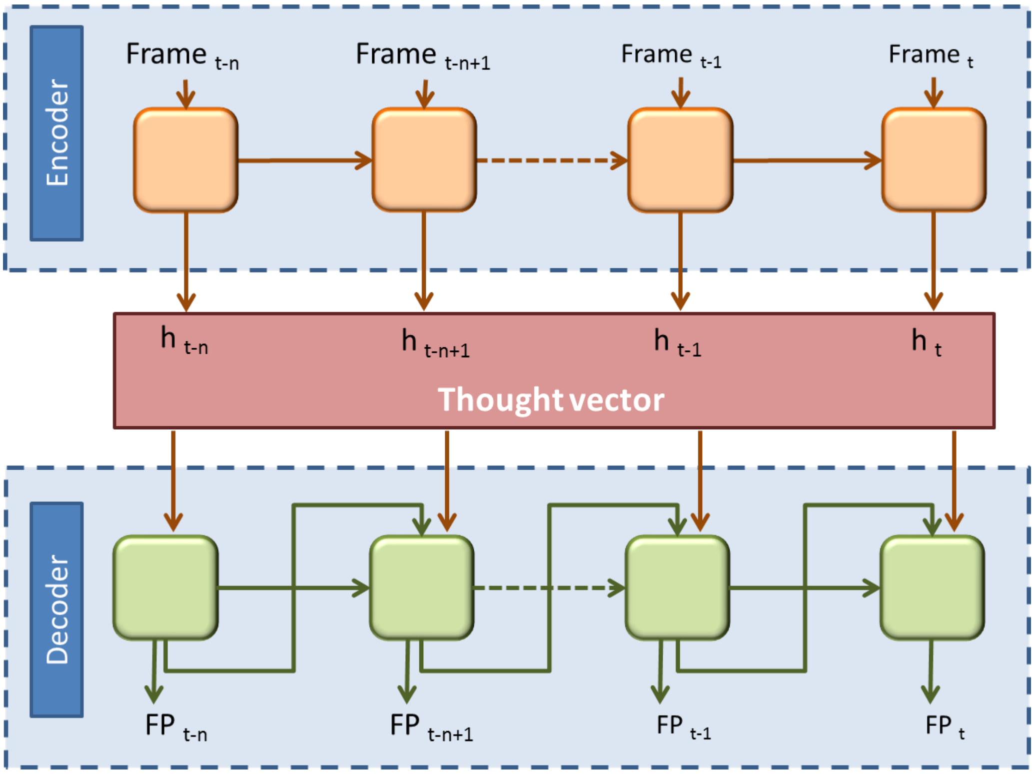


Figure 4.6: Sequence-to-Sequence recurrent neural network (RNN) framework. Top row: A batch of size n of the input sequence up to frame t. Bottom row: Corresponding target sequence to be predicted. The row in between is the so called thought vector, which encodes the current state of the hidden units to produce the output.

Recurrent Neural Network

So far, the current observation has been used to estimate the state in the current frame; however, the sequential structure of the input and output signals has not yet been employed. In this section, building a RNN to model the dependencies between the subsequent observations of the input signals (Encoding) is predicted towards predicting a sequence of structured output signals (Decoding). In this model, the prediction of the current state depends not only on the observation of the current frame, but also on the state of the previous frames.

Given an input video signal $X = \{x_1, x_2, \ldots, x_n\}$, where x_i are the features extracted from frame i, and a target signal $\mathbf{y} = \{y_1, y_2, \ldots, y_n\}$, the input and output signals are split into chunks of size n. The RNN approach has shown outstanding performance in machine translation [Cho 14, Sutskever 14, Bahdanau 14] by learning the conditional distribution $p(\mathbf{y}|X)$ in two steps that first encode the source signals into fixed-length hidden states and then decode the target based on the observations and hidden states. Drawing inspiration from these methods, the problem of predicting the force plate signals from the video signals is composed as an RNN encoder-decoder process. The encoder transfers an input sequence to a state (thought) vector **h** $= \{h_1, h_2, \ldots, h_n\}$. Each hidden state is updated iteratively by

$$h_{(t)} = f(h_{(t-1)}, \mathbf{x}_{(t)}) \tag{4.1}$$

where f is the non-linearity function.

Literally, the thought vector takes the input signals and transforms them to the space of the target signals. It is up to the RNN units to decide how much information should be passed to the decoder in each step. In this experiments, f is used as one gated recurrent unit (GRU [Cho 14]) to loop through n time steps and to transfer the input to an output-like space, Figure 4.6. The encoder applies the non-linear function and results in the thought vector **v**. This thought vector is calculated by applying a non-linear function q on the hidden states as follows:

$$\mathbf{v} = q(h_1, h_2, \ldots, h_n). \tag{4.2}$$

Unlike [Sutskever 14], for each time step, the cost function is applied not on the output of the last video frame in the input sequence, but on the output of each time step (*i.e,* frame). Thus, the output for each frame is estimated via the decoder process by

$$y_{(t)} = g(h_{(t)}, y_{(t-1)}, \mathbf{v}). \tag{4.3}$$

The non-linear activation function g is applied on the output of every frame (as shown in the lower part of Figure 4.6). This means at each time step, the previous output state is considered as well as the thought vectors as input to a fully-connected 'dense' layer. Then, the function g is applied to produce the estimated output at this time step.

4.3 Experiments

In this section, the experiments of estimating medial-lateral sway from monocular video are presented using the two discussed regression methods TGPR and RNN, and their results are compared with the ground truth from the force plate. The movements of the labeled joint that is corresponding to the Vicon marker placed on the upper body are used in the results because they are highly correlated to the force plate signal in the three stances of the BESS balance test as shown in Figure 4.7. In this section, the metrics that are used to compare the estimated and ground truth signals are presented, followed by the

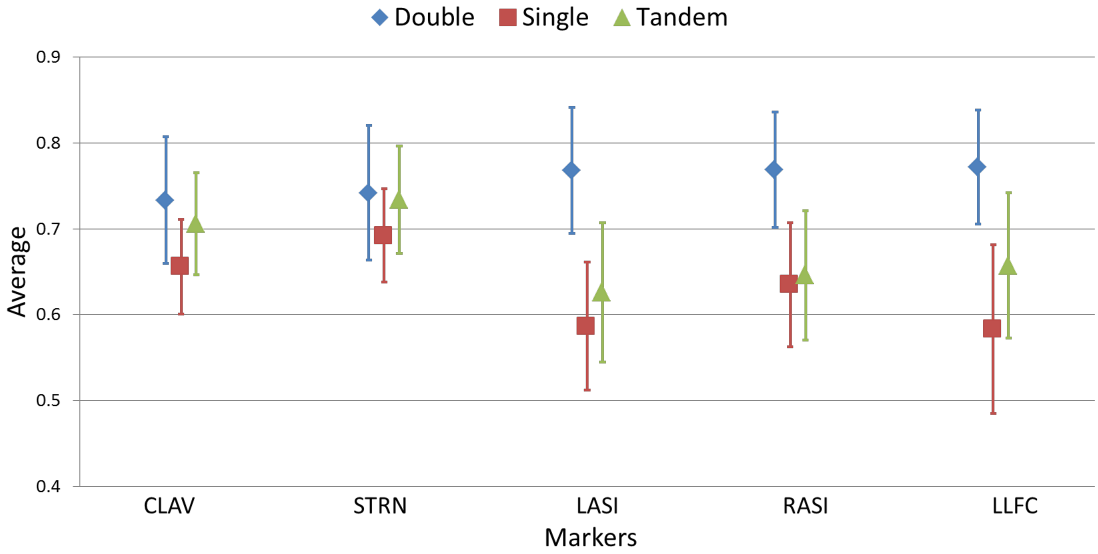


Figure 4.7: Average correlations between predicted postural sway from different tracked markers from videos and force plate signals for BESS stances: double stance (blue diamond), single leg stance (red square), and tandem stance (green triangle) with 95% confidence interval.

experiments of estimating the medial-lateral sway from a video sequence using TGPR and RNN, which are compared to the results using the force plate signal.

Sway Metrics

Postural sway is usually determined by measuring the movements of the body's CoP captured by a force plate. The area enclosed by the movements of the CoP in the $X - Y$ plane is known as the sway area, which is used as a basic measurement for the postural sway [Wollseifen 11]. Total path length, sway speed and frequency are other measurements that are commonly used to describe the amount of postural sway from force plate data. In addition to using input from a frontal monocular camera, which makes it quite difficult to compute the sway area, the medial-lateral sway is the body movement of the interest, as it reflects the body's balance while standing or walking and considered as one predictor for the increased body sway and therefore the decreased balance control [Roman-Liu 18].

To analyse and compare the medial-lateral sway, $1D$ equivalents are devised to these $2D$ metrics that can be used. *Sway signal shape* represents the general pattern of medial-lateral sway over time period. Then, the mean absolute error (MAE) is used to measure how far the estimated sway is from the corresponding ground truth force plate signal. The correlation between estimated and ground truth signals is also calculated to assess the extent the signals are correlated. *Maximum sway* range and *sway frequency within threshold* are further proposed to analyse the postural sway based on the body medial-lateral sway.

Sway Signal Shape

The similarity in shapes between medial-lateral sway in ground truth from the force plate and the predicted medial-lateral sway from video can be used to confirm that the predicted signal is approaching the ground truth signal. Mean absolute error (MAE) and correlation values are used to quantify this similarity.

Maximum Sway

If one direction of the medial-lateral sway is noted as d, the maximum sway can be determined by the difference between the farthest reached points in both directions d and $-d$. (In this study, this refers to the left-right movements of the body.)

Sway Frequency

Within the specified ranges, a sway frequency represents the number of times the direction of the body's medial-lateral sway changes within one of these ranges in a given time period. In the experiments, the ranges defined in Figure 4.8 are used. Bigger maximum sway and high sway frequencies close to the maximum sway range (*red* in Figure 4.8) reflect a person's instability and indicate a lower control of balance.

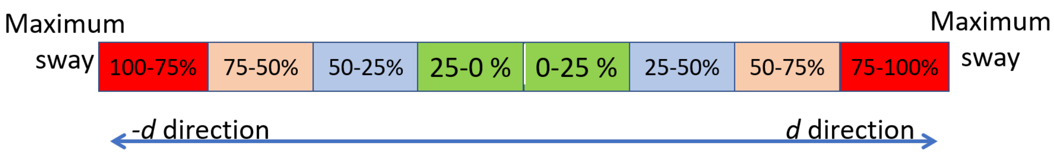


Figure 4.8: Visualisation of sway ranges. The more frequent medial-lateral sway values in ranges that are close to the maximum sway, the higher the likelihood of a future fall occurring.

4.4 Results and Discussion

The predicted medial-lateral sway using TGPR regression method shows an average MAE 2.26$mm \pm 1.2mm$ compared to the ground truth for the *Double leg* stance. The corresponding average MAE using the RNN method is 2.39$mm \pm 1.2mm$. The average MAE between predicted and ground truth postural sway for the *Tandem* stance is 5.43$mm \pm 2.4mm$ using TGPR and 4.88$mm \pm 2.2mm$ using RNN. For the *Single* *leg* stance, the average MAE between predicted and ground truth postural sway is $8.15mm \pm 6.1mm$ using TGPR and $7.95mm \pm 6.1mm$ using RNN.

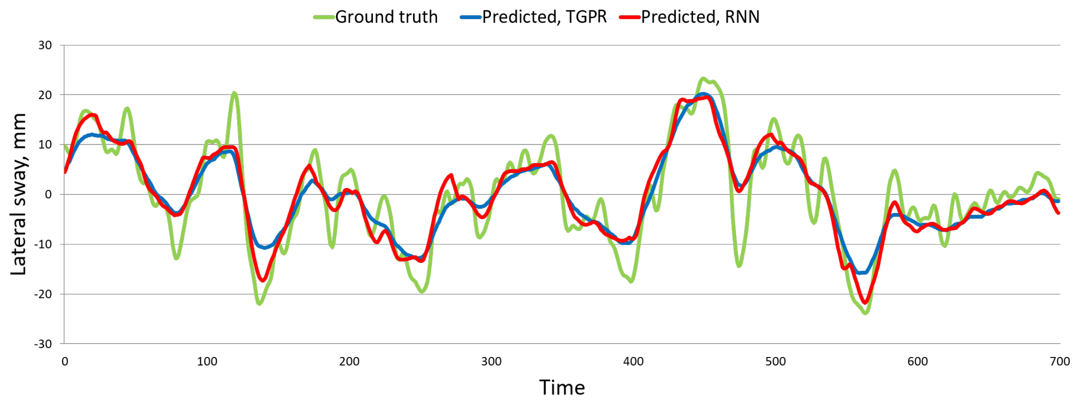
The correlation between predicted and ground truth postural sway using the TGPR regression method shows an average 91% for the *Double leg* stance, 86% for the *Tandem* stance, and 82% for the *Single leg* stance. In comparison, using the RNN method, the average correlation between predicted and ground truth postural sway is 90% for the *Double leg* stance, 86% for the *Tandem* stance, and 73% for the *Single leg* stance. Table 4.1 summarises the average values for the MAE and correlation between predicted and ground truth sway using the TGP and RNN methods for the three stances in the BESS balance test.

Table 4.1: Average mean absolute error (MAE) and correlation between predicted medial-lateral sway and ground truth signal using (a) TGPR and (b) RNN ± the standard deviation

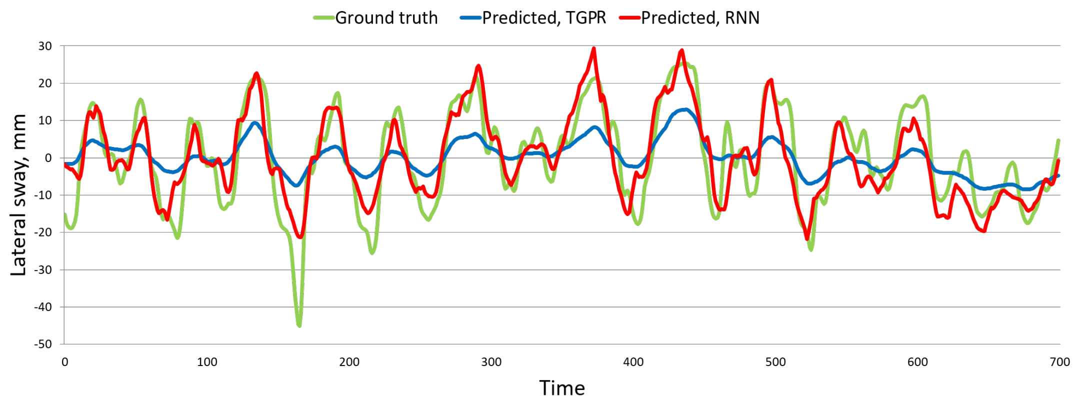
Description	MAE (mm)		Correlation	
	TGP	RNN	TGP	RNN
Double	2.26 ± 1.2	2.39 ± 1.2	91%	90%
Tandem	5.43 ± 2.4	4.88 ± 2.2	86%	86%
Single	8.15 ± 6.1	7.95 ± 6.1	81%	73%

Examples of estimated medial-lateral sway from the tracked STRN joint in the video sequences using TGPR and RNN regression methods are shown in Figure 4.9 for the three stances in the BESS balance test. The predicted medial-lateral sway using TGPR is smoothed out, which is a main characteristic of the Gaussian process regression algorithms. Consequently, TGPR is not as good in predicting sudden moves. On the other hand, as shown in the Figure 4.9, RNN is better in predicting sudden moves, which are represented by the high peaks in the graphs. Sudden moves occur more frequently in the single leg and tandem stances where maintaining the balance becomes more difficult than in the double leg stance.

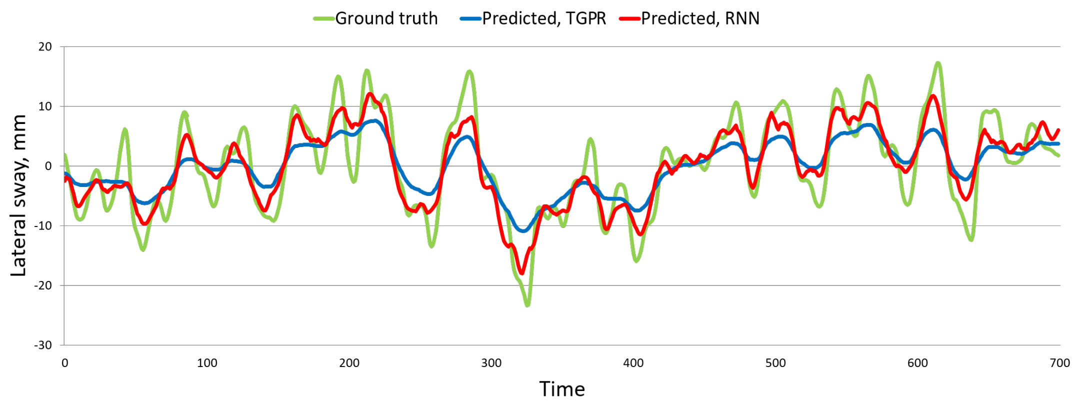
The sway ranges, shown in Figure 4.8 as quartiles of the maximum sway of each subject, are used to calculate the sway frequencies in the predicted medial-lateral sway and compared to the sway frequencies calculated from the ground truth in the same ranges. Examples for sway frequencies are shown in Figure 4.10. In the double stance, most of the medial-lateral sway occurred within the ranges that are close to the mid-point where the balance is more maintainable in this stance. Because of the smoothness in TGPR predictions, changes in the direction of the body sway are imperceptible enough to be counted as a sway change. Single leg and tandem stances have more moves to count within the ranges that are closer to the maximum sway. The RNN method more accurately approaches the sway frequencies of the ground truth in these stances (see Figure 4.10(b and c)).



(a) Double leg stance

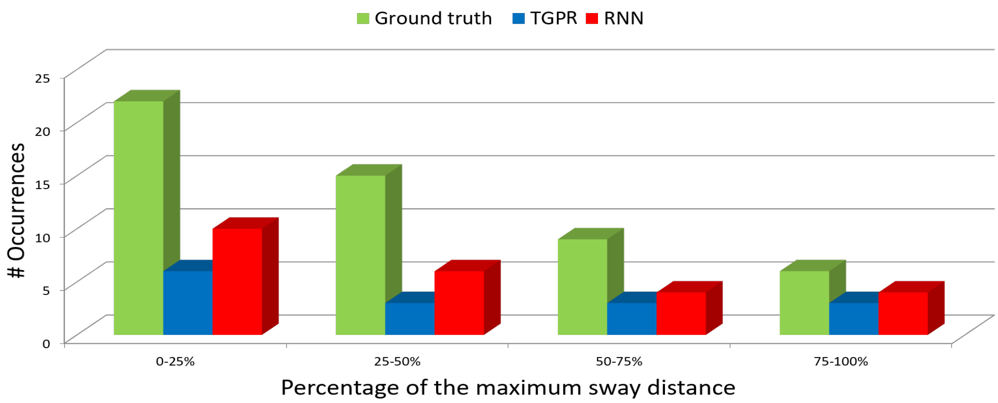


(b) Single leg stance

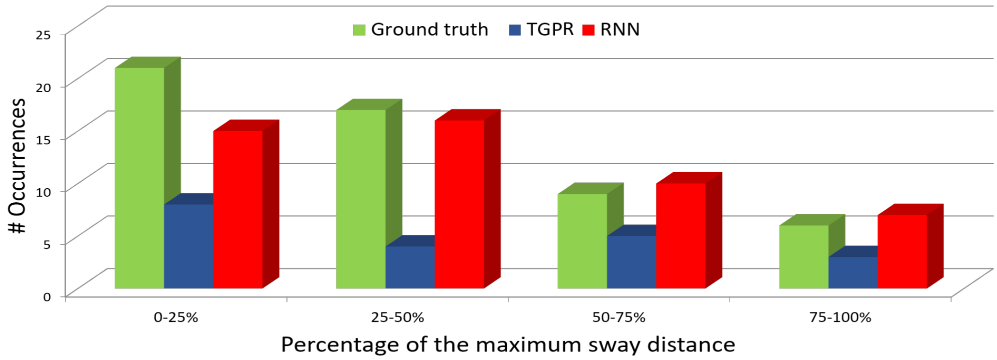


(c) Tandem stance

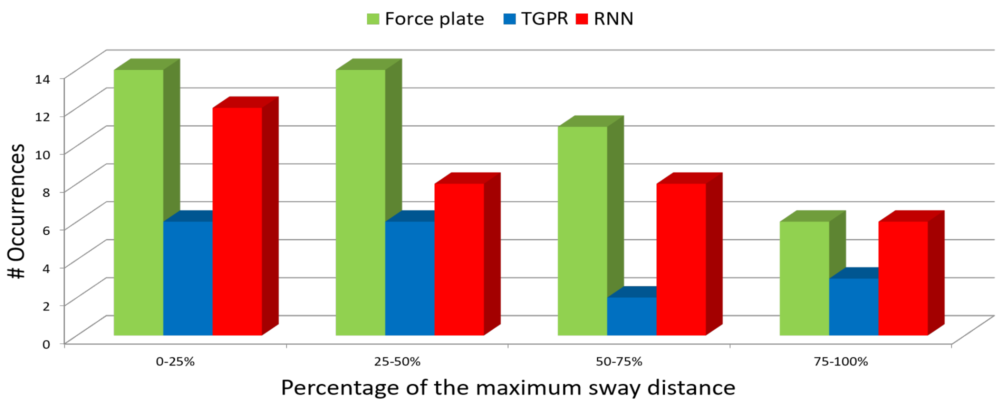
Figure 4.9: Examples, from different subjects, of the predicted medial-lateral sway from a tracked joint in the video sequences that corresponds to the Vicon marker placed on the upper torso in the three BESS test stances: (a) Double stance, (b) Single leg stance, and (c) Tandem stance.



(a) Double leg stance



(b) Single leg stance



(c) Tandem stance

Figure 4.10: Example of sway frequencies that are counted within specified ranges related to the maximum sway for the ground truth signal and predicted signals using TGP and RNN in (a) Double leg stance, (b) Single leg stance, and (c) Tandem stance. Results are presented as histograms where the bins correspond to the quartiles of the maximum sway range.

4.5 Summary

Medial-lateral sway is an important direction of the human postural sway. A larger medial-lateral sway indicates poor balance maintaining, which increases the likelihood of a fall in the future. In the current clinical practice, force plates are the gold standard to measure the postural sway. However, they are a clinical environment equipment that requires special installation, is expensive and not mobile.

In this study, the goal was to investigate approaches to predict the medial-lateral sway from tracked joints in RGB video sequences, which would open up the opportunity to use everyday video technology in the assessment of postural sway. Using the new recorded dataset that includes a force plate and a Vicon 3D motion capture system as a ground truth, as well as RGB video cameras, a model is established to predict the medial-lateral sway from simple RGB video input with accepted accuracy.

Using the regression methods TGPR and RNN, subject independent models are built to investigate predicting the medial-lateral sway from a tracked single joint are built. This joint is labelled in the first frame of the video and corresponds to the Vicon marker placed on the upper torso. Regression methods are used to predict the body movements in the real world measurements from pixels in video recordings.

The TGPR based method shows better prediction performance for the medial-lateral sway with smoothed movements, as can see in the double leg stance in the BESS balance test. On the other hand, the RNN based method showed better prediction performance for the medial-lateral sway than TGPR in the tandem and single leg stances, where sudden movements occur more frequently.

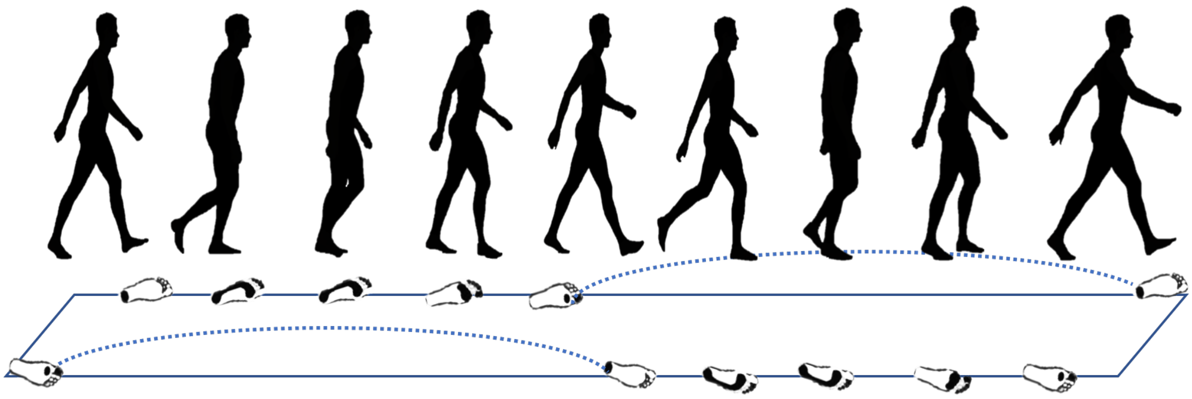
Chapter 5

Gait from Vision

Gait is the manner or style of walk. People's gait can be an indicator of their health as it is affected by pain, illness, weakness, and ageing. Gait analysis evaluates this style of locomotion [Whittle 07]. One aspect of gait analysis is to detect gait variations. It is usually performed by an experienced observer with the help of cameras, sensors, and/or other devices to measure and assess different gait parameters. Frequent gait analysis, to observe changes over time, is costly and impractical. However, monitoring and assessing these changes can play an important role defining the likelihood risk of having a fall.

This chapter investigates measuring gait parameters from vision data by estimating the 3D feet movements from tracked joints over the video recording frames. Using the gait ground truth part in the dataset that is described in Chapter 3, the proposed model for estimating gait parameters is verified by using the corresponding data that is collected from the motion capture system (Vicon).

Next, Section 5.1 presents more of the related work in utilizing human gait from vision data. Then the proposed method for estimating gait movements from predicted 2D joint locations, which represent selected body parts, from videos is discussed in Section 5.2. A long-short term memory (LSTM) regression model is used in the proposed method to predict the 3D (Vicon) joint locations, which was recorded simultaneously with the videos as ground truth, from predicted ones in video recordings. Experiments setup is presented in Section 5.3 followed by the results and discussion in Section 5.4. The chapter is summarised in Section 5.5.



	Right swing phase	Right stance phase		
Double support	Left single support	Double support	Right single support	Double support
Left stance phase			Left swing phase	

Figure 5.1: A gait cycle illustrates swing and stance phases for both right and left legs as well as single and double support time for an ideal gait cycle.

5.1 Related Work

While walking, one limb provides body support (stance phase for that leg), while the other leg swings forward (swing phase for that leg) in preparation for stance phase. The combination of stance and swing phases forms the gait cycle as shown in Figure 5.1. In normal *walk*, a symmetry occurs in the movements of both feet as well as the body's sway when its weight shifts from one foot to the other.

A person's walk can be affected by pain, weakness, aging or injuries. Thus, gait abnormalities can be an indicator of a person's health [Pirker 17]. Gait abnormalities can be detected by an experienced physiotherapist who observes the walking style and measures some gait related parameters to analyse the gait with the help of different devices. These gait parameters are divided into:

(1) *Temporal and spatial*, such as walking speed and step and stride lengths, and can be measured by a stop watch and a measuring tape. Floor sensors, accelerometers, and/or wearable sensors can be added for more accurate measurements.

(2) *Kinematics and kinetics*, such as joint movements and angles, and the forces involved to produce these movements. Specific devices are used to measure such parameters, *e.g.*, motion capture cameras and force plates.

(3) *Electromyography*, which measures muscle activities during walk.

These parameters have been discussed in more details in the review, Chapter 2.

Early research on measuring and analysing human gait was entirely for medical purposes to distinguish a normal gait pattern from a pathological one. Gait analysis was usually performed by an experienced physiotherapist who observed the walking style.

For accurately measuring and characterising human gait, different devices are used to measure body movements, mechanics, and muscle activity. These devices are either *wearable* sensors, such as accelerometers or gyroscopes [Hollman 11, Muro-de-la Herran 14], or *non-wearable* devices, such as force plates. Most of these are expensive and need to be installed and used by a specialist in a laboratory environment. Cameras are used widely in gait analysis to record the walking activity first, then analyse the person's gait by slowing the motion of the walk action in a video replay and the movement of the legs and feet for a detailed assessment and analysis.

With the advances in image processing algorithms, analysing gait has become an interest for computer vision researchers, *e.g.*, to recognise and identify humans from their body movements. Gait is considered to be a biometric characteristic of an individual.

As the human gait is considered to be a biometric characteristic of an individual and with the advances in image processing algorithms, human gait and sway became an interest for computer vision researchers. Most computer vision studies on gait use the general shape of the body and/or the moving pattern for abnormal gait detection [Bauckhage 09, Wang 06, Nieto-Hidalgo 16], human recognition [Wang 10b], fall detection [Mubashir 13], and for safety and surveillance purposes.

Human identity recognition systems using gait have focused on image representation, feature dimensionality, and gait classification [Wang 10b] to improve human recognition. On the other hand, for abnormal gait detection, body silhouettes have been used in [Bauckhage 09] to detect and classify the observed walking pattern into normal or abnormal gait based on analysing recorded videos of seven subjects walking in normal and abnormal ways. In [Wang 06], the extracted silhouette, with frame-to-frame optical flow and motion metrics based on histogram representations of silhouette-masked flows, was used to determine different styles of walking and detect deviation from usual walking patterns using two separately recorded datasets, one for subjects simulating abnormal gait and the second dataset for professional actors performing pathological gaits.

Gait analysis for clinical purposes, especially spatial-temporal parameters, such as step and stride length, that can be noticed in videos, is receiving increasing attention in computer vision to provide an inexpensive tool to identify and detect gait abnormalities. These spatioal-temporal parameters have been used to classify human gait into normal or abnormal patterns using a vision dataset with 30 subjects (15 normally walking, 15 pretending walking abnormally) in [Nieto-Hidalgo 16].

In this Chapter, a method is proposed to estimate the human gait from RGB video recording. The estimated gait signals are compared with the corresponding recorded signal from the Vicon system to validate the method's accuracy. In the next sections: the proposed method is presented in details (Section 5.2) followed by the experiments setup, results and discussion, Sections 5.3 and 5.4, respectively.

5.2 Proposed Method

For the goal of using video cameras only to estimate and analyse human gait, selected spatial gait parameters that can be captured and measured from frontal and side views have been considered:

1. step base,
2. step length, and
3. stride length.

In this proposed method, movements of selected body parts (feet, torso) are estimated from video using predicted 2D joint locations. The estimated movements are used to derive spatial gait parameters (step and cadence length, walk base). Estimated movements and gait parameters are compared with the ground truth Vicon data and parameters derived from it, respectively. The long-term goal is to investigate the use of simpler and cheaper video technology as an alternative to costly specialist devices and to include more gait parameters to be estimated and analysed from recorded videos.

The goal is to provide a gait analysis method that is accurate enough to provide an alternative to highly accurate but expensive devices, such as force plate and motion capture systems. These devices also need a special setup and/or need to be worn most of the time. To achieve this goal, both frontal and side views in RGB video cameras are considered. Some parameters, such as walking base and sway, are more obvious from the frontal view while others, such as step and cadence length, are easier to measure from the side view.

To determine the accuracy of the calculated gait parameters from videos, Vicon data is used as an accurately captured ground truth for body movements. First, an existing method, the DeepPose [Toshev 14], is used on video frames to estimate the body joint locations. Second, joints of the limb related to the walking action are selected from both video and Vicon. The movement of feet and legs represents the walking activity, whilst upper body movements reflect the body sway when walking or standing.

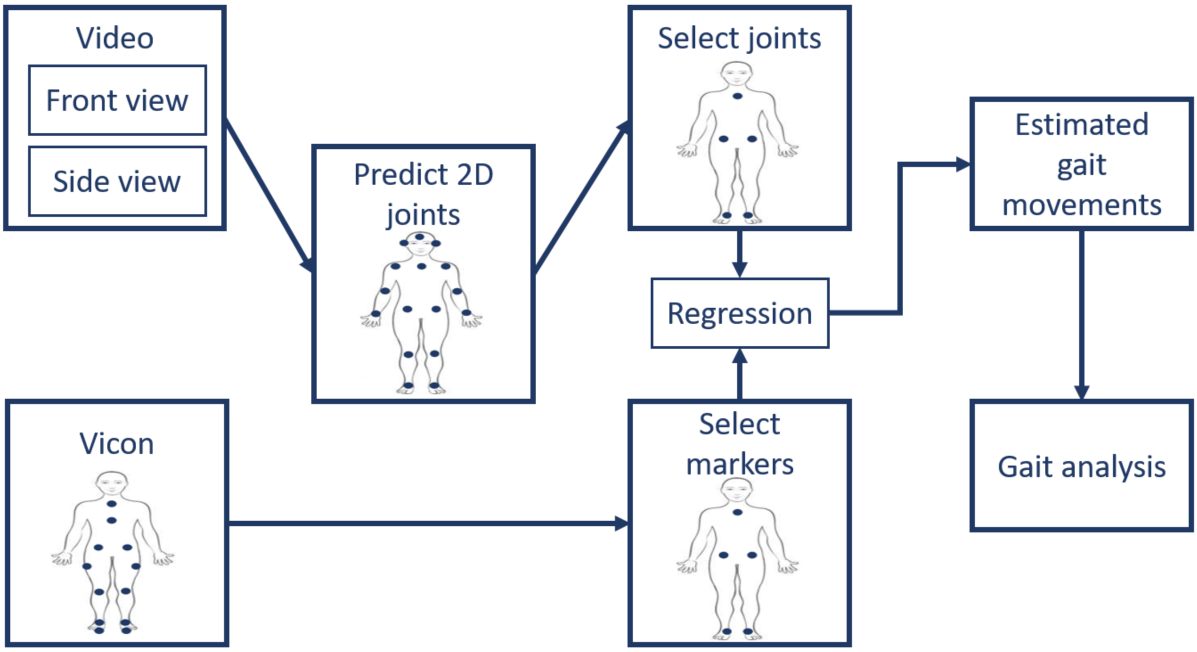


Figure 5.2: Proposed method: Movements of selected body joint locations from video are regressed with movements from corresponding Vicon markers in order to estimate body part movements and use them in gait analysis. Note that while the Vicon and real life distances are in millimetres, the respective image metric uses pixels. The Long-Short Term Memory (LSTM) regression method is used to estimate joint movement measurements in millimetres for the gait parameter calculations.

Then, a regression method is used to predict the real measurements for the selected spatial gait parameters from the estimated joints from the video (Figure 5.2). Next, the methods for pre-processing, gait estimation and gait analysis are described .

5.2.1 Feature Processing

Because of the variety of data produced by the Vicon system and video cameras, the following steps have been taken to prepare the data for gait estimation and analysis.

Joint Extraction

The main body parts engaged in the walking action are feet and legs. The torso sways when the body weight shifts from leg to leg while walking. In the ground truth part of the recorded dataset, the motion capture markers are placed on these body parts. To estimate these body parts' movements from video recording, the DeepPose method [Toshev 14] is used. The DeepPose method estimates human pose by extracting the 2D joint locations of 18 different body parts. 2D joints related to feet, hips, and upper body (torso) are selected for subsequent use in gait estimation and analysis. In the DeepPose method, a generic convolutional deep neural network (DNN) is learned. Using a cascade of DNN-based pose predictors allows for increased precision of joint localisation. Starting with an initial pose estimation, based on the full image, DNN-based regressors are learned to refine the joint predictions by using higher resolution sub-images. The method is used on both side and frontal views.

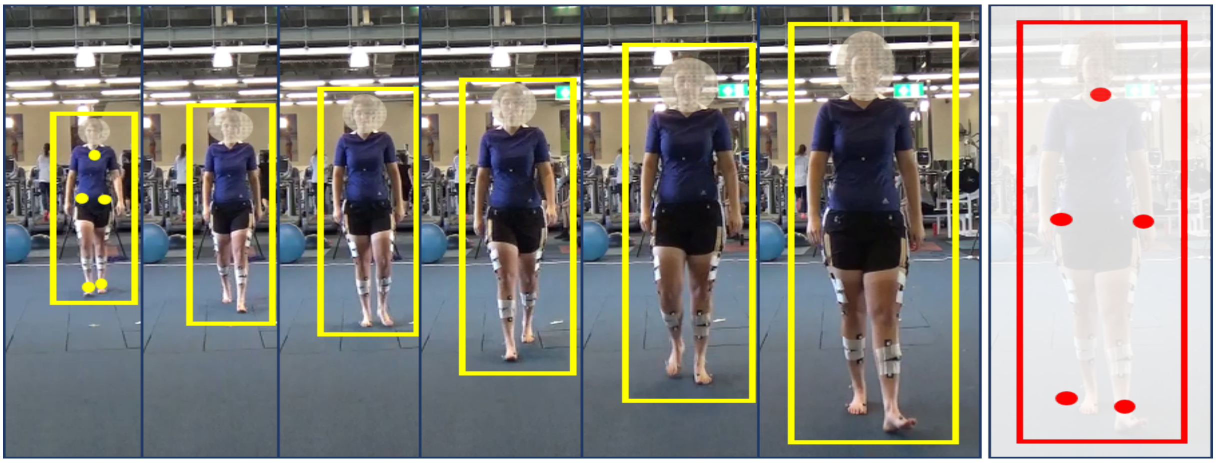
Joint Normalisation – Frontal View

Although the extracted joints from the frontal view are clear and represent the body movements over the frames, the movements decay when the subject is too far from the camera. To avoid this distortion, predicted joint locations are normalised to the biggest bounding box that surrounds the body over all video frames as shown in Figure5.3(a). Figure5.3(b) shows the estimated signal for one foot before and after normalising process.

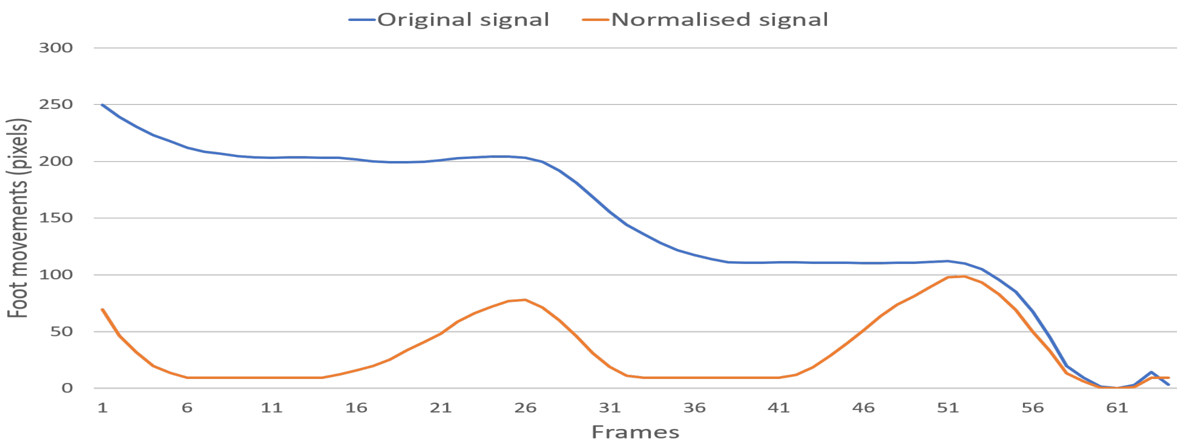
Data Re-sampling

The video and Vicon data are recorded at different frame rates. The video frame rate is 25Hz, while the Vicon system captures the markers' movements at 100Hz. The higher Vicon sampling rate results in a noisy signal. Since the signal of interest (markers' movements) is characterised by low frequencies, the well-known Butterworth filter [Butterworth 30] is applied as a low-pass filter on the Vicon data. It removes the high frequencies in order to reduce the noise and make the data better suited for gait analysis through regression with an aim to learn the pattern of movements.

The output of the pre-processing steps are signals that represent the selected joints movements over the video frames and the movements from the corresponding Vicon markers over time. Since the selected gait parameters to be measured are related to the human feet movements, the work is based on the feet markers that are placed on them (Vicon) or detected from video frames.



(a)



(b)

Figure 5.3: (a) Predicted 2D joints are normalised to the biggest bounding box surrounding the body over the video frames.(b) Estimated signal for one foot from the front view before and after normalising process.

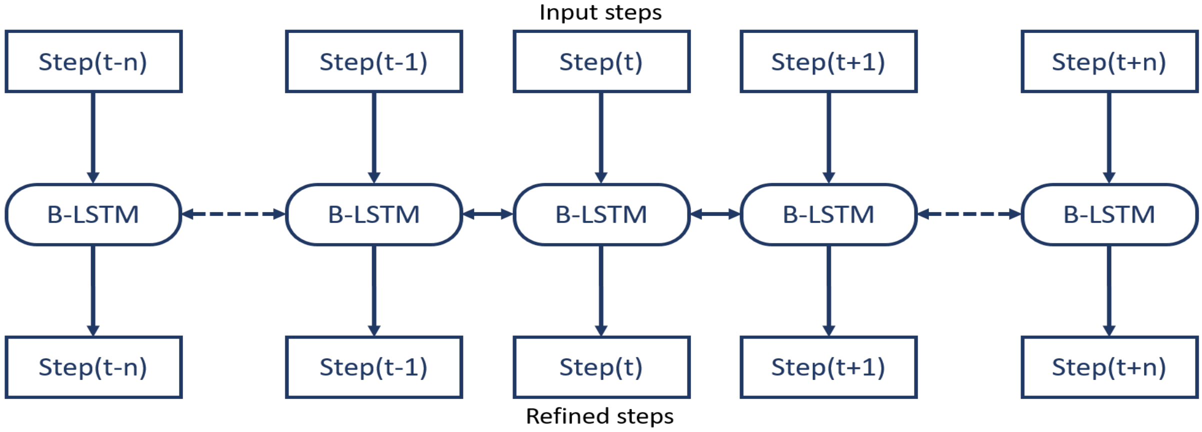


Figure 5.4: The proposed LSTM model

5.2.2 Regression

Pixel is the measuring unit in the extracted gait signal from video frames, where the real world measurements in millimetres as well as the Vicon data space. A regression method, long-short term memory (LSTM), is used to predict the gait signal in the scale of the Vicon data space. Two LSTM units are used in the proposed method. The output signal at each time t is estimated by

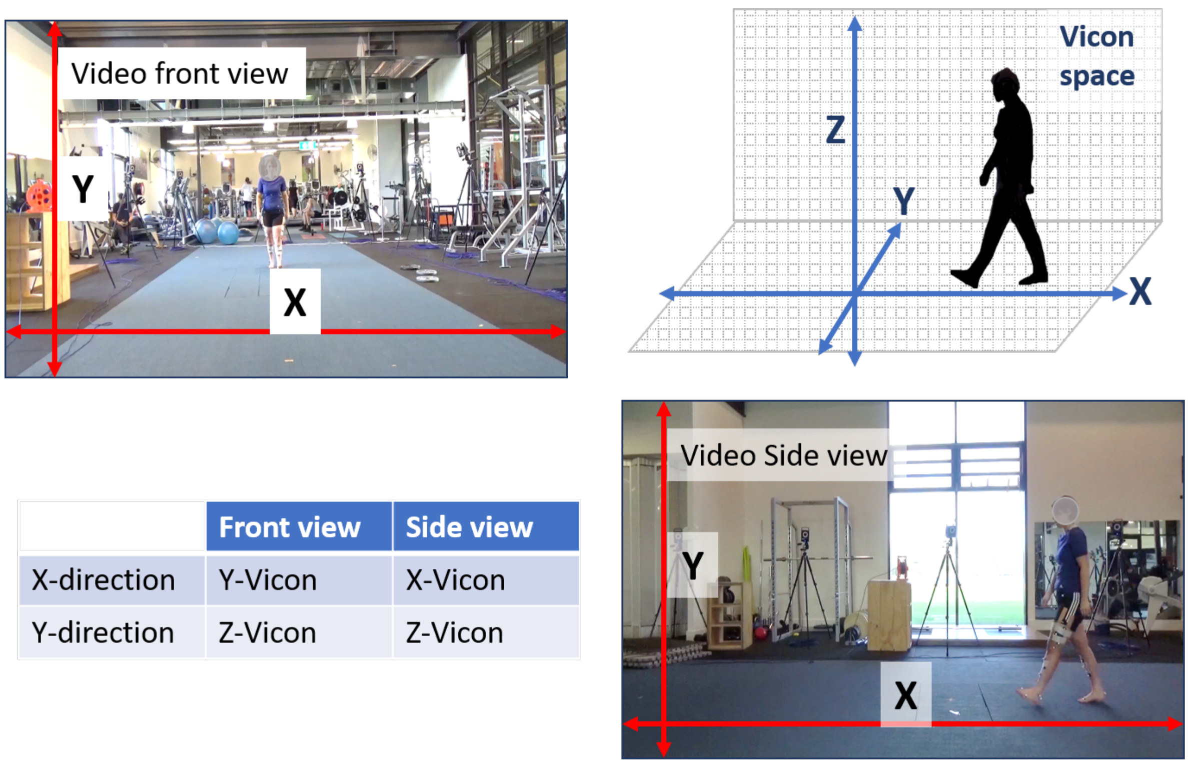
$$y(t) = \sigma(\overleftarrow{h_t}, \overrightarrow{h_t}) \tag{5.1}$$

where σ is the non-linear activation function of the concatenation or averaging of the forward passing, $\overleftarrow{h_t}$, from $t-n$ to $t-1$ and the backward passing, $\overrightarrow{h_t}$, from $t-1$ to $t-n$, where n is the history size of LSTM unit [Graves 13].

More precisely, the prediction task considers the relationships between the Vicon data and the video signals. The LSTM model is designed based on a many-to-many structure, as illustrated in Figure. 5.4 where the input and the output are of the same size. The sequential connection in its middle layer shows the process of encoding the temporal relationships between the subsequent frames. The input of the model is the signal of one view for a typical joint of the detected pose, which is passed to the two bi-directional LSTM units as an input. Then, the output is passed to a fully connected layer to predict the final output signal.

5.3 Experiments

To measure gait parameters from vision data, the feet movements has to be estimated from video frames in the real world measurements (metre). In this section, the experiment for applying the proposed method on the walking part of the ground truth dataset is presented. First, feet movements are estimated from video and the selected spatial gait parameters to be measured from these movements are identified. Second, estimated movements are compared with corresponding Vicon data for the feet marker movements and the measured parameters are compared with the gait parameters derived from the Vicon data as well. Vicon data is considered as an accurate reference for the collected data and hence, used as the ground truth or gold standard in this study. Figure 5.5 illustrates the Vicon space directions – X, Y, and Z – and shows the corresponding directions from both video views, frontal and side.



	Front view	Side view
X-direction	Y-Vicon	X-Vicon
Y-direction	Z-Vicon	Z-Vicon

Figure 5.5: Vicon and video coordinate systems and their correspondence. The table illustrates which camera view and direction will be used to peer within the Vicon dimension

5.3.1 Gait Parameters

Spatial gait parameters is one type of gait parameters that can be observed from the video recordings. *Stride length*, *step length*, and *walk base*, which are examples of the spatial parameters, that are considered in this work to be measured and analysed from video recordings. The stride length is the distance between successive points of heel strike of the same foot. In normal gait, the stride length is twice the step length, which is the distance between corresponding successive points of heel strike of one foot and the other foot. The walk base is the perpendicular distance between the two lines that pass through the heal strike points, respectively, for the two feet. These three spatial parameters are described in Figure 5.6:

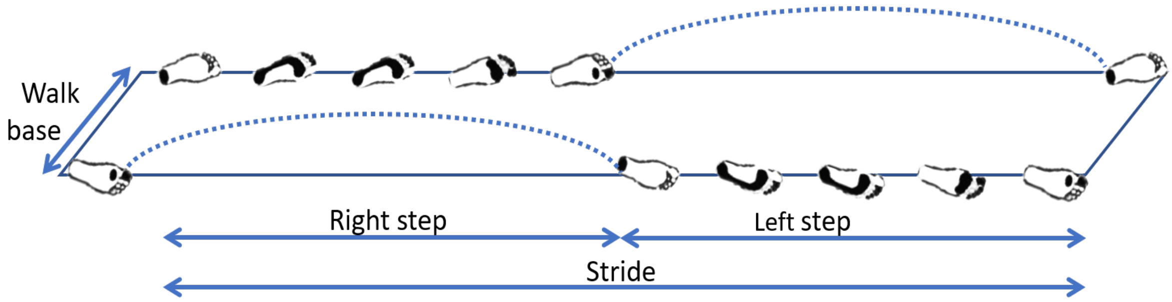
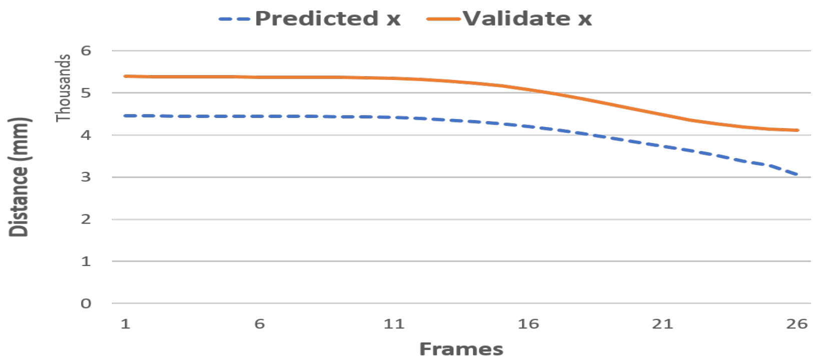


Figure 5.6: Gait parameters considered in this study: stride and step length and walk base

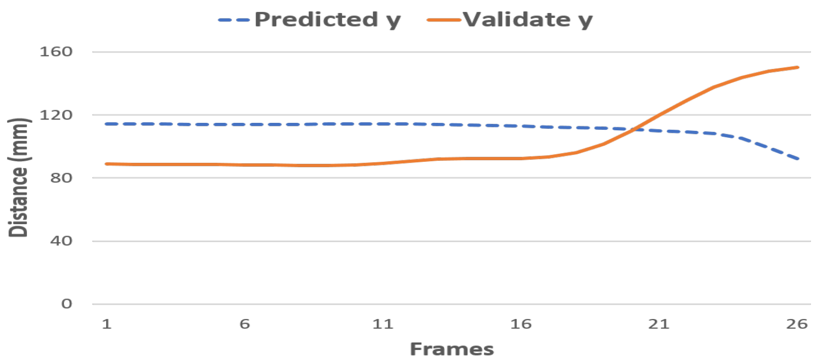
5.3.2 Gait Estimation from Video

Synchronised video and Vicon data have been cut into single strides (from heel strike to next heel strike for a single foot) as a learning unit to be fed into the proposed LSTM network. The heel strike points have been determined by the lowest point reached by the heel marker in the Vicon system for the ground truth and the foot joint detected from the video for the vision data. Then the heel strike points have been used to estimate the gait parameters from the corresponding signals from the Vicon dimensions in the case of the ground truth and from video view and direction in the case of vision data. Heel strikes have been determined using the Z-dimension from the Vicon system as well as the Y-direction from both frontal and side video views. Step and stride lengths have been determined from the the X-dimension in the Vicon system and from the X-direction from the side view. Lastly, the walk base has been determined from the Y-dimension in the Vicon system and from the X-direction from the front view. An example of predicted gait movements for one stride using the proposed regression method and the corresponding ground truth is shown in Figure 5.7.

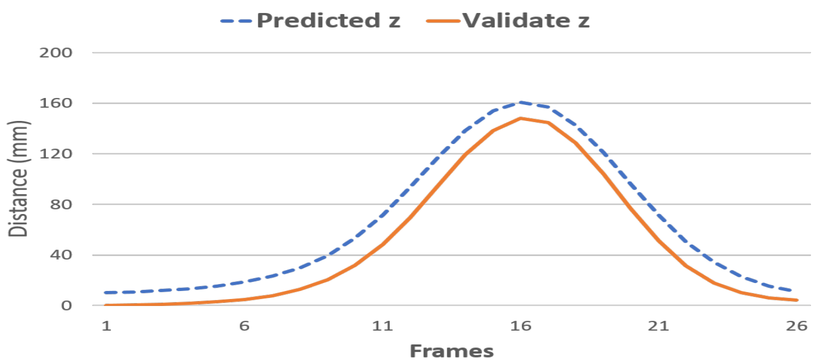
An example for a sequence of strides for one foot are shown in Figure 5.8 for the X-direction and the Z-direction.



(a) X-direction

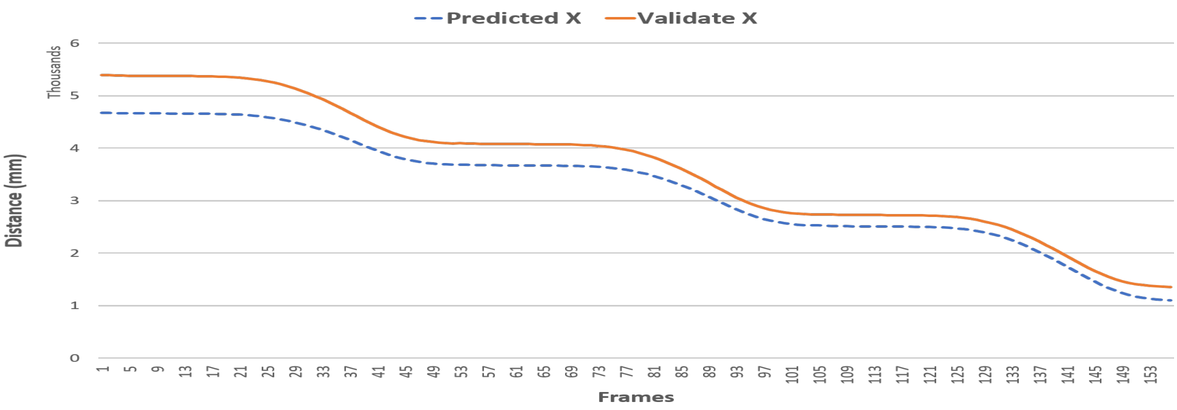


(b) Y-direction

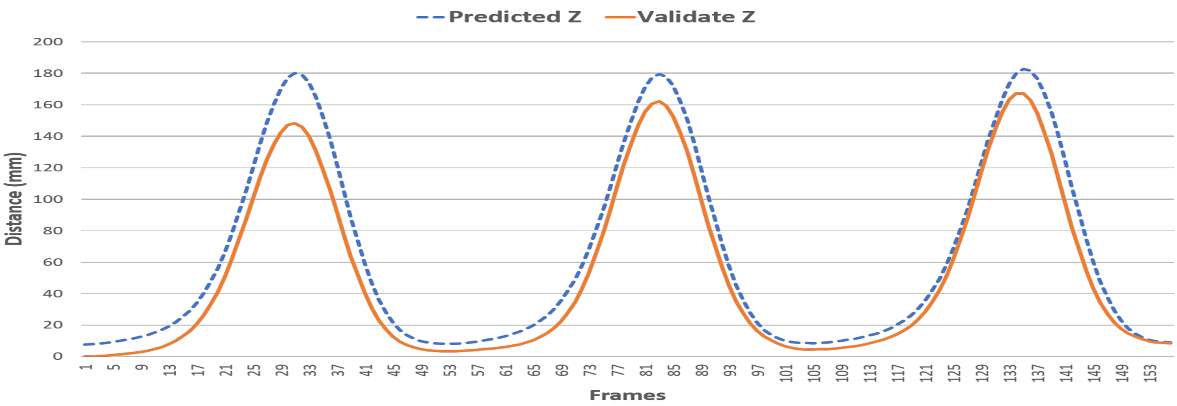


(c) Z-direction

Figure 5.7: Examples of predicted stride compared to ground truth. (a) X-direction from side view with Vicon X-direction, (b) X-direction from frontal view with Vicon Y-direction, and (c) Y-direction from frontal view with Vicon Z-direction.



(a) X-direction



(b) Z-direction

Figure 5.8: Example of predicted and ground truth movements in sequence of strides in (a) X-direction and (b) Z-direction.

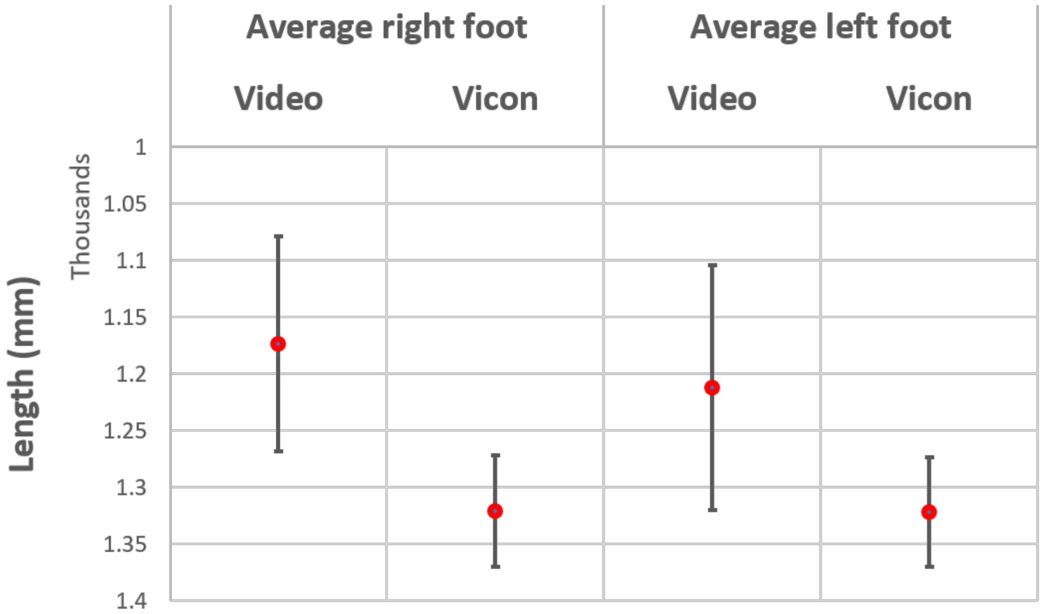


Figure 5.9: The mean stride length from the estimated joints movement from video and Vicon for booth feet with 95% confidence interval.

5.4 Results and Discussion

The predicted foot movements in the X-direction from side view and Z-direction from frontal view (heel contact and off) are correlated with the corresponding Vicon movements with an average of 90% and 95%, respectively, over all subjects as shown in Figures 5.7 and 5.8. Movements in the X-direction are estimated from the side view where the subject crosses the scene, which contains some background objects (*e.g.*, a camera tripod) that can lead to the 2D prediction drifting to them, which produces outlier movements in the signal, thus affecting the predicted gait movements. The smaller correlation in the X-direction is explained by errors multiplying from the movement extraction phase. Relying on the high correlation of estimated movements with the Vicon data, vision-based data can be used to measure and analyse human gait.

Spatial Parameter Measurements

As working with 2D joints presentation, stride and step lengths are measured from predicted feet movements in the side view, while step base is measured from predicted feet movements in the frontal view.

The stride length calculated from estimated feet movements shows an average of 1.17 m for the right foot with a mean square error (MSE) of 0.036 m compared to the Vicon measurements (1.30 m). An average of 1.12 m for the stride length for the left foot with an MSE of 0.044 m to the Vicon measurements

Table 5.1: Performance evaluation (mean and mean square error (MSE) measures) for the stride and step length predictions for the right and left foot for the video and Vicon data

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Stride (metre)</td><td colspan="2">Step (metre)</td></tr>
<tr><td>Mean</td><td>MSE</td><td>Mean</td><td>MSE</td></tr>
<tr><td rowspan="2">Right</td><td>Video</td><td>1.17</td><td rowspan="2">0.036</td><td>0.585</td><td rowspan="2">0.040</td></tr>
<tr><td>Vicon</td><td>1.30</td><td>0.650</td></tr>
<tr><td rowspan="2">Left</td><td>Video</td><td>1.12</td><td rowspan="2">0.044</td><td>0.563</td><td rowspan="2">0.047</td></tr>
<tr><td>Vicon</td><td>1.30</td><td>0.650</td></tr>
</table>

(1.30 m) (Table 5.1). The step length derived from estimated feet movements shows an average of 0.585 m and 0.563 m for the right and left foot, respectively, while the average step length for both right and left foot from the Vicon data is 0.65 m.

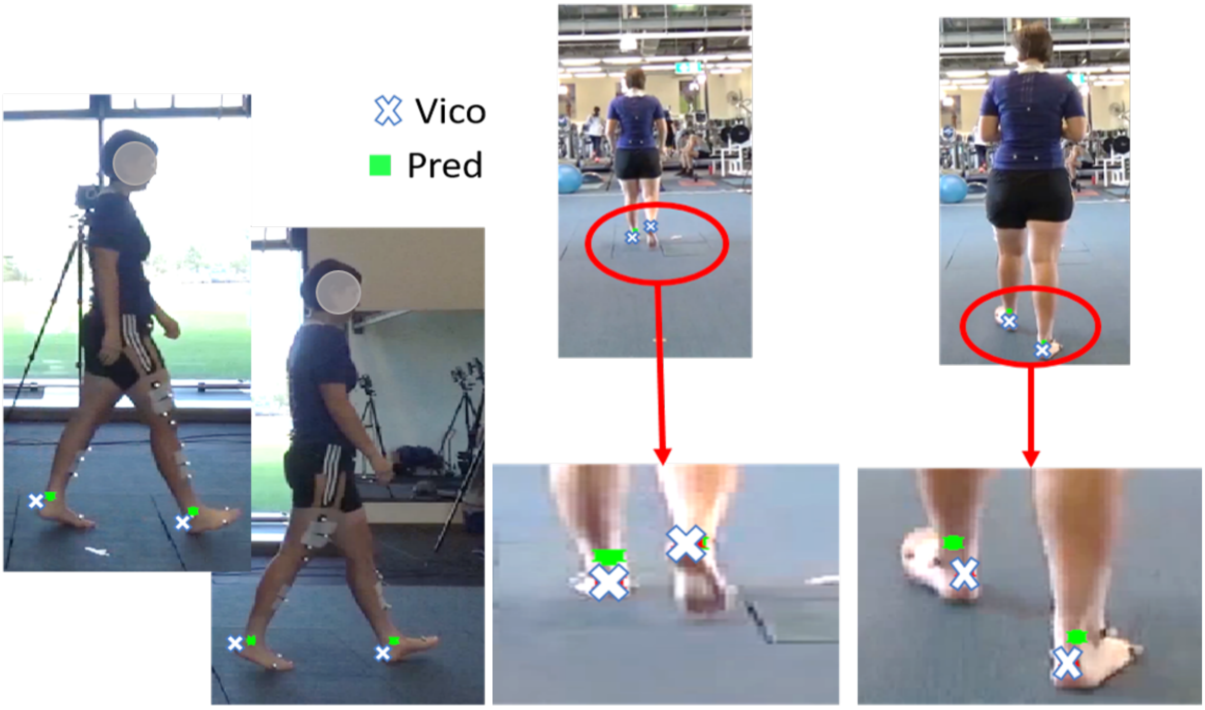
Although the gait parameters measured from predicted feet movements from video and the Vicon markers are close, the slight difference can be traced back to how accurate the extracted 2D feet joints represent the actual feet movements. In the Vicon data, the heel strike is well defined because of the marker that is placed on the heel, while the video extracted 2D joint does not represent the heel accurately in some cases as shown in Figure 5.10 (a).

The walk base measurements show an average of 4.9 cm for the predicted gait movements from video compared to an average of 6 cm for the Vicon data. Walk base is relatively small. The slight differences between estimated joints from video and Vicon markers as shown in Figure 5.10 (b) and (c) explain the difference in the walk base measurements.

The results of the experiments for estimating human gait from vision data and measuring selected gait parameters provides the opportunity for self monitoring and frequent measurement of gait parameters at much reduced equipment cost. Foot movements, that have been estimated from video, are highly correlated with the Vicon data, enabling gait analysis by measuring selected spatial gait parameters (step and cadence length, and walk base) from estimated movements. Using inexpensive and reliable cameras to record, estimate and analyse a person's gait can be helpful; early detection of its changes facilitates early intervention.

5.5 Summary

New technologies and approaches are proposed to make the measurement and assessment of health conditions easier, faster, and more reliable. Although some progress has been made in using computer vision techniques for human gait analysis, a need for a technique that measures and analyses human gait



(a) (b) (c)

Figure 5.10: Examples of a foot's predicted joints (square) and Vicon markers ×. (a) side view, (b) example of an accurately estimated joints (the right foot), and (c) example if an inaccurately estimated joints for heels.

in an inexpensive and reliable manner still exists.

In this Chapter, a method to estimate the human gait from video has been presented and the utility of automated gait analysis has been explored by comparing the results with 3D Vicon data in the collected dataset. Experiments in this Chapter demonstrated the possibility to measure and analyse gait from estimated gait movements from video – the approach is 90% correlated to the ground truth Vicon data. However, the frame-to-frame human pose estimation has generated some errors in the predicted joint locations, which affect the output signals that represent gait movements, and thus also the derived parameters. This work could be extended by utilising a 3D construction method to analyse gait from monocular view, and including more parameters for gait analysis from video, such as foot and hip angles for more precise gait analysis.

Chapter 6

Risk Analysis Based on Gait and Postural Sway

Human postural sway is the oscillation around the vertical, which is generated to control a person's balance while walking or standing. Changes in postural sway patterns are considered as reflecting of changes in brain signals and in physical health that can be affected by different factors, such as, a person's aging process. Increasing postural sway, distance and/or frequency, increases the likelihood of falling.

Maintaining body balance is achieved by the coordination of input from the different sensory systems, *vestibular*, *somatosensory*, and *visual systems* [Gribble 04]. Each of these systems gathers different information related to different reference points. Directional information that relates to head position and other organs that regulate the equilibrium is sensed by the vestibular system. The spatial position and movements relative to the support surface and the position of different body parts relative to each other are sensed by the somatosensory system, and spatial location relative to other objects is sensed by by the visual system. Maintaining balance stability is related to the brain's ability to integrate the information from the different sensory systems and the muscle motor process of the different body parts to modify these processes as a response to the environmental factors, such as illumination, flooring, medication, alcohol/drug usage, and/or ear infection.

Aging affects the efficiency of the person's sensory systems as well as the brain-to-muscle integration to respond to the environmental changes. Thus, maintaining body balance becomes harder while aging and the likelihood of having a fall increases.

While walking, the body weight shifts from one leg to the other generating the walking style as well as the body sway. While the sway is maintained and controlled by the brain-muscles signals, the walk style can reflect the person's health condition as it is easily affected by it. Elderly people resort to different styles that can help them maintaining balance and increase their feelings of safety, such as, reducing walking speed, step length and/or increasing the walking base to secure their movements. More detailed discussion about gait and sway changes while aging is presented in Chapter 2.

This chapter presents experiments on the recorded dataset that analyse a person's risk of having a fall by classifying this person into one of the sway/gait age groups based on his/her body sway or gait parameters' measurement. Defining the likelihood risk of having a fall allows the early intervention, such as appropriate exercise, to avoid the fall accident.

In the next sections, the proposed method for the risk analysis based on estimated gait and sway from vision data is presented first in Section 6.1, followed by experiments setup for using sway and gait data separately in Section 6.2. Results for each experiments are presented in Section 6.3, followed by the discussion in Section 6.4. Lastly, the summary is presented in Section 6.5.

6.1 Methodology

The proposed research methodology starts with data pre-processing, which prepares the video, force plate, and Vicon data to be fed into the next step, the neural network. Different neural networks for sway and gait are used to predict the video sway and gait signal, measured in pixels, in the real world space, measured in mm. For each subject, the sway and gait measurements, *i.e.* maximum sway and stride length, are calculated. Using the ground truth part of the dataset, a Gaussian mixture model (GMM) is used to build age group clusters based on the calculated measurements, Section 6.1.1. Another GMM is used to classify the test subject into one of the age group clusters, Section 6.1.2. Comparing that subject's classification with his/her real age can be used to detect early risk.The first part of the proposed methodology (*feature extraction, neural network training, and features estimation and measurements*) are discussed in details for postural sway in Chapter 4 and for gait in Chapter5. The next subsections discuss in detail the remaining part in the proposed methodology to detect and analyse fall risk from estimated gait and sway.

6.1.1 Sway/Gait Age Group Modeling

The Gaussian mixture model is used in a semi-supervised manner, where the ground truth signals, which belong to the athlete participants in the collected dataset (Chapter 3), are modelled with the participant

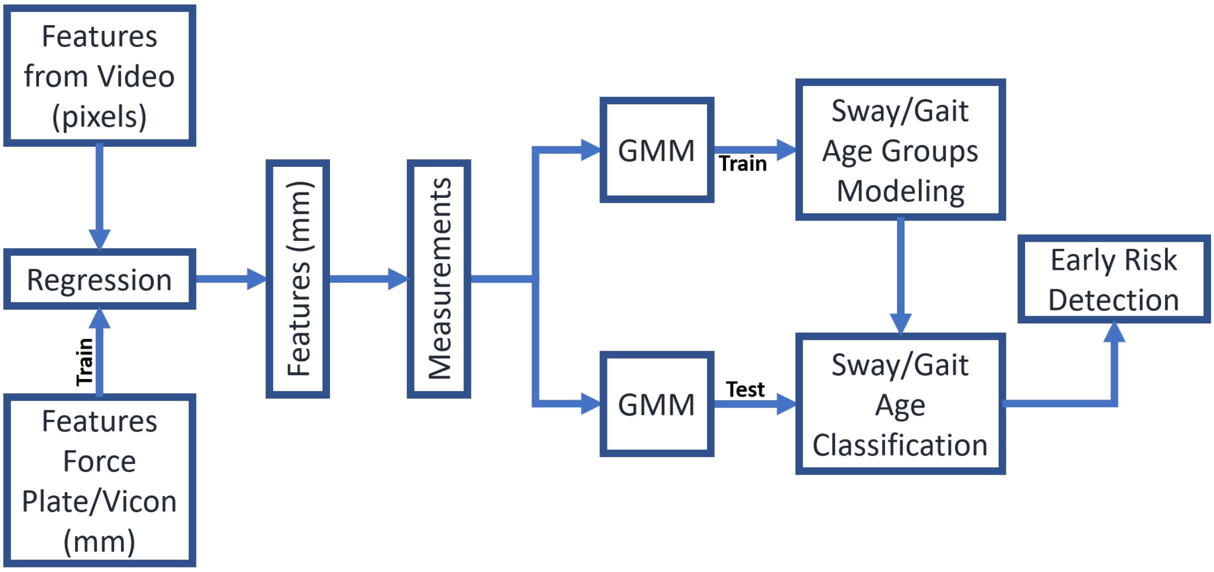


Figure 6.1: The proposed methodology trains a regression model to estimate gait and sway movements in the real world space from video tracked point space (pixels) to Vicon and force plate space (mm). Then, sway/gait age group clusters are generated by training a Gaussian mixture model (GMM) using gait and sway measurements from the estimated movements. In testing, the trained regression model is used to predict gait and sway movements from video, measure gait and sway parameters, then the trained GMM is used to classify these measurements for the testing case into one of the age group clusters. Lastly, an early risk analysis is produced from the gait/sway age classification

age labels as they are considered to be within one group of age. The data for the older are fitted in an unsupervised manner based on the Euclidean distance of their gait and sway parameters measurements from the healthy athlete age group.

Given the calculated measurements $x = (m_1, m_2, ..., m_n)$, where n is the number of measurements calculated for the selected signal (sway or gait), two Gaussian mixture models are built to model the distributions of the input data, X. The GMM is a generative approach that can be used to estimate the likelihood of an input signal (sway or gait) pertinence to a specific age group. A GMM is parameterised by the weights of the components, $W = (w_1, w_2, ..., w_K)$, where K is the number of components, and mean, μ and co-variance, cov. Each component has a mean μ^k and Co-variance cov^k. These parameters are learned using the common Expectation-Maximisation (EM) algorithm [Lawrence 90].

The probability of a sway/gait signal belonging to a specific age group (C_k) is given as following:

$$p(C_k|x) = \frac{w_k \mathcal{N}(x|\mu_k, \Sigma_k)}{\sum_{i=1}^{K} w_i \mathcal{N}(x|\mu_i, cov_i)} \tag{6.1}$$

where

$$\mathcal{N}(x|\mu_k,\, cov_k) = \frac{1}{\sqrt{(2\pi)^K |cov_k|}} \exp\big(-\frac{1}{2}(x-\mu_k)^T cov_k^{-1}(x-\mu_k)\big) \tag{6.2}$$

and $\sum_{k=1}^{K} w_k = 1$.

6.1.2 Sway/Gait Age Group Classification

The GMMs for the elder people are built in unsupervised manner using the EM approach. The age groups of the older individuals people are sorted based on their distance from the distribution of the ground truth GMM. The normalised Euclidean distance is used between the mean of the ground truth GMM component and the mean of each component of the elderly mixtures.

The testing is performed on the older participant sample by leave-one-subject-out (LOSO) for testing and merging the others with the ground truth signals for sake of training. The well-known leave-one-out scheme is used for training and evaluating the proposed models, which guarantees testing the models on unseen data for sake of generalisation.

Based on the sway or gait measurements, an elderly participant is classified to either the healthy athlete group or to one of the elderly age groups. The maximum probability of Equation 6.1 is used for this classification. Then, the estimated age group of each subject is compared with his/her chronological age to check whether the subject is classified in:

(1) *average risk* group, which the sway/gait age group is the same as the chronological age group,

(2) *decreased and low risk* group, which the sway/gait age group is less than the chronological age group, or

(3) *increased and high risk* group, which the sway/gait age group is higher than the chronological age group.

This will be discussed in more details in the experiments section.

6.2 Experiments

This section presents the experiments setup for using the sway and gait parameters that have been measured from the estimated sway and gait movements from vision data to define a reduced likelihood risk of having a fall.

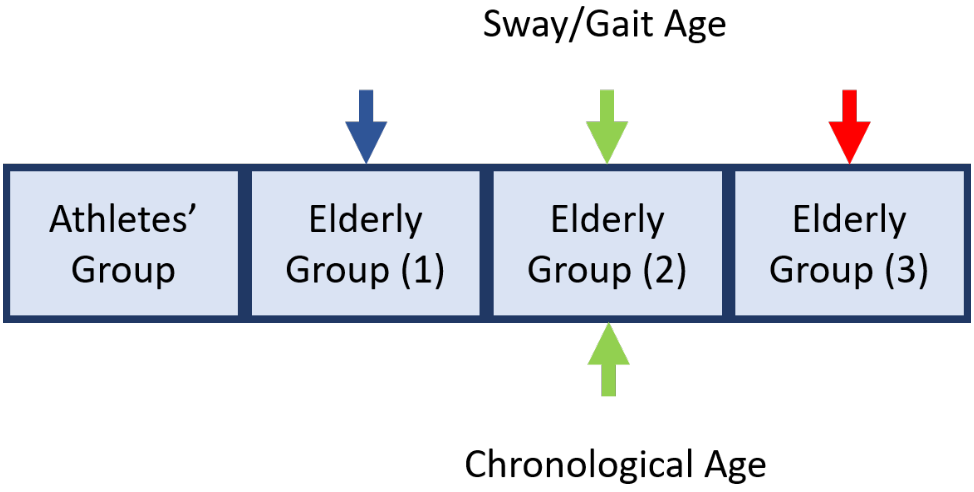


Figure 6.2: The risk analysis for a test subject is determined by comparing his/her actual age group with the predicted age group from estimated measurements. Higher predicted age group indicates higher risk of having a fall where lower predicted age group indicates lower risk

Based on participants' chronological ages, they have been divided into three age groups: fifty to sixty ($50 \leq$ age < 60), sixty to seventy ($60 \leq$ age < 70), and more than seventy (age ≥ 70) chronological-age groups.

Using calculated measurements from the estimated signals for the elderly participants, three gait/sway-age groups are identified based on the distance to the healthy athletes gait/sway-age group. Then, the risk analysis is performed based on the gait/sway-age group the test subject is classified into it. Classifying the participant into gait/sway-age group cluster that is lower than his/her chronological-age group indicates lower risk likelihood of having a fall as illustrated in Figure 6.2. On the other hand, having a gait/sway-age group higher than the chronological-age group indicates higher likelihood of having a fall.

Two groups of experiments are carried out using the proposed methodology investigating the ability to early detect the risk of having a fall in elderly people. The first experiment uses only the estimated postural sway signal from video recording to cluster the test participant into one of the age groups and build the risk analysis based on this classification, while the second experiment uses the estimated gait signal from the video recording for the risk detection.

6.2.1 Postural Sway

In the first experiment, with the proposed method, the age groups of elderly people are estimated based on the postural sway measurements from the extracted sway signal from the video recordings. These measurements are computed based on learning the postural sway signal from video footage only. Then, using the person's chronological age and the estimated age group to define the risk of a fall for the elderly people becoming more likely.

The proposed method to estimate and measure human postural sway in Chapter 4 is used on the elderly part of the dataset to estimate and measure postural sway from video recordings only. The sway measurement metrics, which are used to assess postural sway are presented briefly.

Sway Metrics

Postural sway is usually determined by measuring the bodys CoP displacements that are captured by the force plate. The area enclosed by the movements of the CoP in the $X - Y$ plane is known as the sway area, which is used as a basic measurement for the postural sway. Total path length, sway speed and frequency are other parameters that are commonly used to describe the amount of postural sway from force plate data. Applying the postural sway proposed method on the output of the frontal video camera to estimate the medial-lateral sway of the body movements, where medial-lateral sway is the main predictor for the increased postural sway that reflects the body balance while standing or walking.

For measuring postural sway from video recordings, two measurements are extracted and used in the experiments of this paper: maximum sway and sway frequency as explained next.

Maximum Sway

When one direction of the medial-lateral (side-to-side) sway is noted as d, the maximum sway, M, can be determined by the difference between the farthest reached points in both directions d and $-d$.

Sway Frequency

Within the specified ranges, a sway frequency f_r represents the number of times the direction of the medial-lateral sway changes within one of these ranges $r = (0.25, 0.50, 0.75, 1.00)$ of the maximum sway M in the balance test time period. Figure 6.3 shows the ranges, which are considered in this experiments. High maximum sway and sway frequencies close to the maximum sway range reflect the person's instability and indicate higher possibility to fall.

Sway Measurements

Using the ground truth part of the dataset, the proposed GRU-RNN model in Chapter 4 is trained on the force plate (as the target) signal and the corresponding tracked signal from the frontal view camera (as

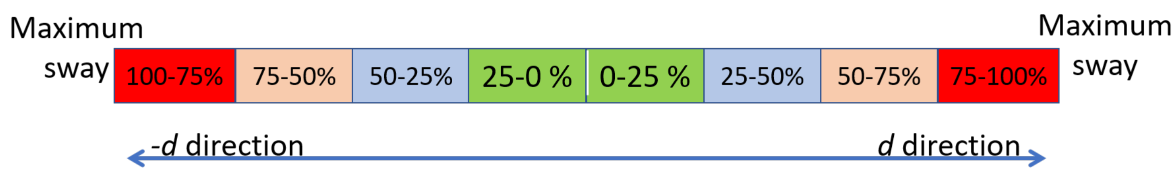


Figure 6.3: Proposed sway ranges used to calculate sway frequencies

the source signal) to transfer it to the force plate measurement (*i.e.*, in mm). Then, for each participant in the elderly part of the dataset, the trained GRU-RNN model is used to predict the sway signal for this participant. The proposed RNN model is composed of a GRU unit with 100 hidden units, followed by a 'time-distributed' fully connected layer with 100 units. The Stochastic Gradient Descent (SGD) with a learning rate of 0.1 and momentum of 0.9 is used to train the model.

In Figure 6.4, an example of the estimated sway signals from video and their corresponding target force-plate instances is shown. This qualitatively shows the robustness of the GRU based proposed method to estimate a force-plate likewise signals, only from video footage.

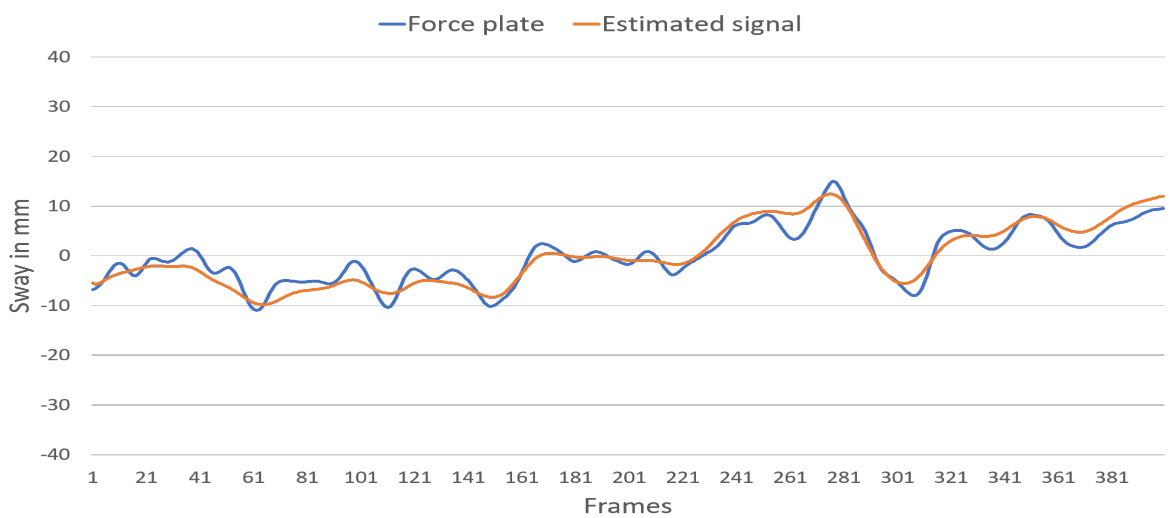


Figure 6.4: Example of estimated sway signal from video and the corresponding force plate signal.

Sway measurements, maximum sway M and sway frequencies in the different ranges f_r, are calculated for each subject in the two parts of the dataset, the ground truth and the elderly. These measurements, maximum sway and the four ranges of the sway frequency, will be the input for the GMM as $x = (M, f_{0.25}, f_{0.50}, f_{0.75}, f_{1.00})$.

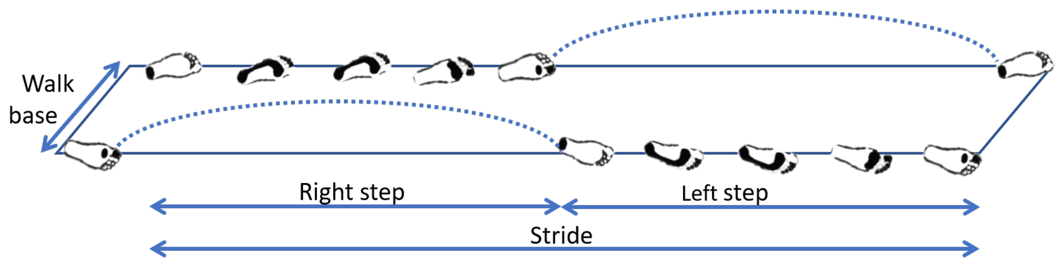


Figure 6.5: The selected spatial gait parameters (stride length, step length, and walk base) to be estimated and measured from video recording

6.2.2 Gait

Gait – walking style – is affected by the person's health status and aging process. Some changes take place on person's gait when aging to feel more secure and to have more control on his/her movements, such as, reducing gait speed, step length and/or increasing the walking base.

Gait can be measured using different parameters, such as, spatial, muscles action, and angles. and techniques and devices, such as, sensors, force plates, and different kinds of cameras. This study investigates measuring gait parameters from inexpensive devices, such as RGB cameras. To achieve that, some spatial gait parameters are considered, such as stride and step length and walk base. These parameters can be noticed in video recording and thus can be measured.

Using the proposed method in Chapter 5, the signals for feet, hips and upper body during walking are estimated from tracked joints over the video frames. Estimated signals are then used to calculate the selected spatial parameters. Next, in brief, the selected gait parameters are presented followed by measuring them. Results for risk analysis based on the estimated *gait-age* group using gait data are presented thereafter.

Gait Parameters

Stride length, *step length*, and *walk base*, illustrated in Figure 6.5, are examples of the spatial parameters that are considered in this work to be measured and analysed from video recordings. The stride length is the distance between successive points of heel strike of the same foot. In normal gait, the stride length is twice the step length, which is the distance between corresponding successive points of heel strike of one foot and the other foot. The walk base is the perpendicular distance between the two lines that pass through the heal strike points, respectively, for the two feet.

Gait Measurements

Using the ground truth part of the dataset, the proposed LSTM model is trained on the force plate (as the target) signal and the corresponding tracked signal from the frontal view camera (as the source signal) to transfer it to real world measurements (*i.e.* in mm). Then, for each subject in the elderly part of the dataset, the trained LSTM model is used to predict the feet, hips, and upper body signals for this participant.

Gait measurements:

(1) stride length for both left and right foot, $strd_l$ and $strd_r$,

(2) step length for both left and right foot, stp_l and stp_r, and

(3) walk base wb,

are calculated for each participant in the two parts of the dataset, the ground truth and the elderly. These measurements will be the input for the GMM as $x = (strd_l, strd_r, wb, stp_l, stp_r)$.

6.3 Results

In this sections, results of using the proposed method in Section 6.1 are presented on both sway and gait data. First, the defined risk group and how many elderly people are clustered into these risk groups are presented. Then, the link between the risk groups and the chronological-age groups is discussed. Lastly, an example of the movement pattern from each risk group is presented to illustrate the differences between them.

6.3.1 Postural Sway

The sway measurements are fed into GMMs to model the distributions of the sway signals for the healthy athlete group and the elderly groups. For the healthy athlete participants, they are considered as being in one group (reference group) and the elderly are considered to be in three risk groups (low risk, average and high risk). The first GMM for the athlete group has one mixture, while the second GMM for the elderly has three components, one for each age group.

Comparing the chronological-age group of an elderly participant with the sway-age group cluster, which this participant has been classified into, this participant can be identified as being at high risk, increased risk, normal, reduced risk, or low risk based on the distance to the healthy athlete sway-age group.

Double Leg Stance

Although the double leg stance in the balance test is considered to be the easiest stance, about 68% of the elderly people are classified in the increased and high risk groups as shown in Figure 6.6(a). This result can be referenced to the better control of the body balance in the athlete group which makes the sway excursions and frequencies in elderly people counted, which affect their ranking.

The majority of the elderly people with chronological-age $\geq$ 70 years are classified into increased and high risk based on their sway in the double stance as shown in Figure 6.6(b). Elderly participants in lower chronological-age groups are classified more into average and decreased and lower risk groups.

An example of the double stance sway signal from each risk group is shown in Figure 6.6(c). The differences in the maximum sway and the sway frequencies can be easily seen between the the examples from the different risk groups.

Single Leg Stance

Balancing on a single foot, especially with closed eyes, is considered a challenge posture even for young adults. The body sways in the single leg stance more frequently and with a bigger sway distance trying to keep the body's CoP in a smaller base of support (the one foot). In elderly people, balancing on one foot with closed eyes becomes harder as a natural sequence of aging. More than a half (64%) of the elderly people are classified into increased and high risk groups as shown in Figure 6.7(a).

Based on the sway signals for the single leg stance, more than 80% of the elderly people with chronological-age $\geq$ 70 year are classified into the increased and high risk group. Elderly people in younger chronological-age groups ($<$ 70) are classified more into the average, decreased, and low risk groups as shown in Figure 6.7(b).

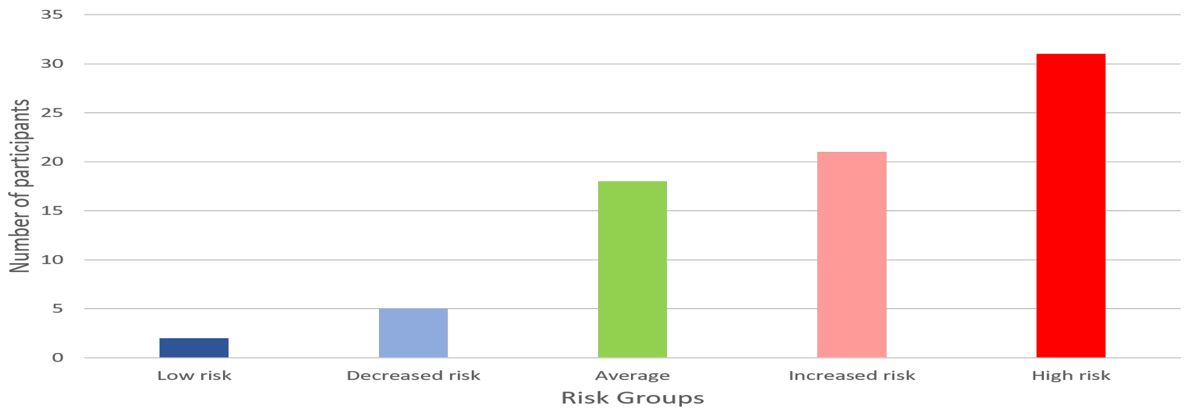
An example of the single leg stance sway signal from each risk group is shown in Figure 6.7(c). Bigger maximum sway distance and more sway frequency can be seen in the example of increased and high risk group compared to the example of the decreased and low risk group.

Tandem stance

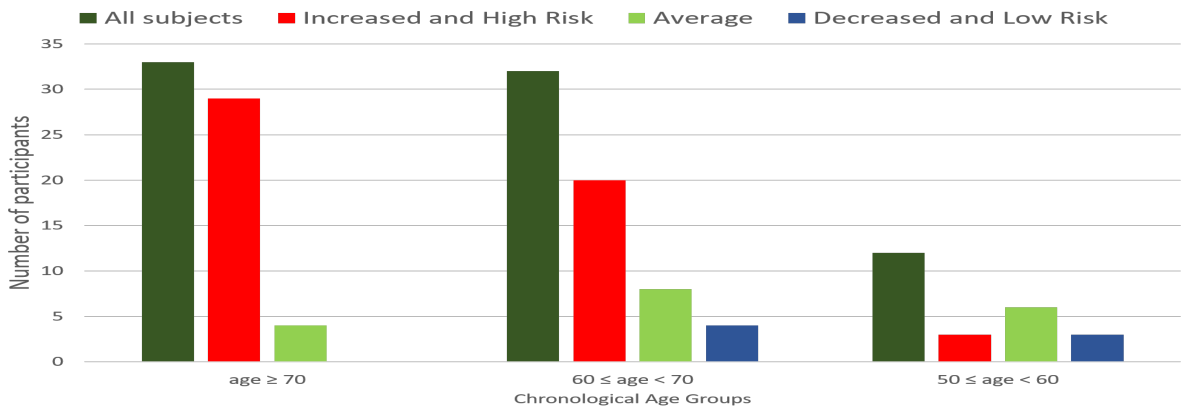
Another challenging stance in the balance test even for younger adults, tandem stance while eyes are closed. The body's base of support in this stance is narrow because of the position of the feet (toe-to-heel one foot in front of the other). That makes it harder to control the body balance. More than half (62%) of the elderly people are classified into increase and high risk groups, while only 28% of the elderly people are classified into decreased and low risk groups based on the tandem stance sway signals.

The majority of the elderly people from the chronological-age group ≥ 70 (78%) are classified into the increased and high risk group. More elderly people are classified into the average, decreased, and low risk groups when they are in younger age groups as shown in Figure 6.8(b).

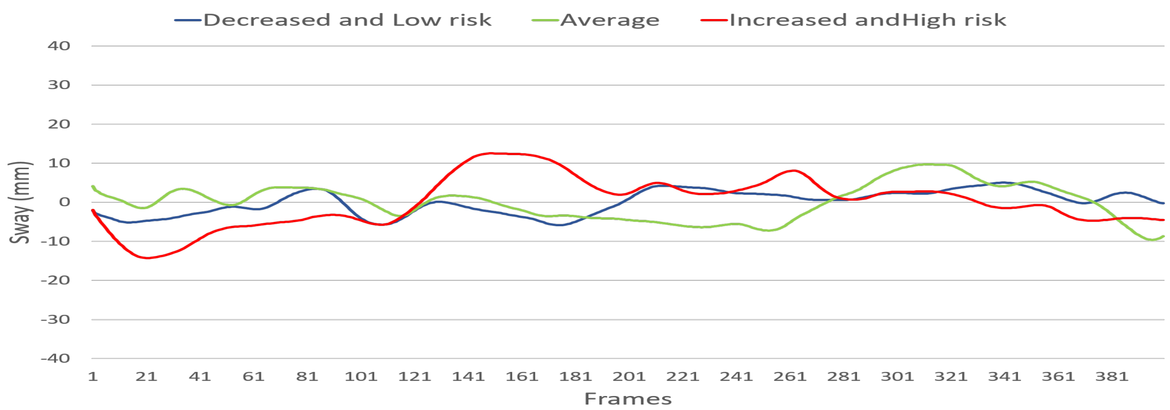
An example of sway signals for the tandem stance from each risk group is shown in Figure 6.8(c). Sway signal from the higher risk group shows bigger maximum sway distance and more sway frequency compared to the sway signal from the lower risk group.



(a)

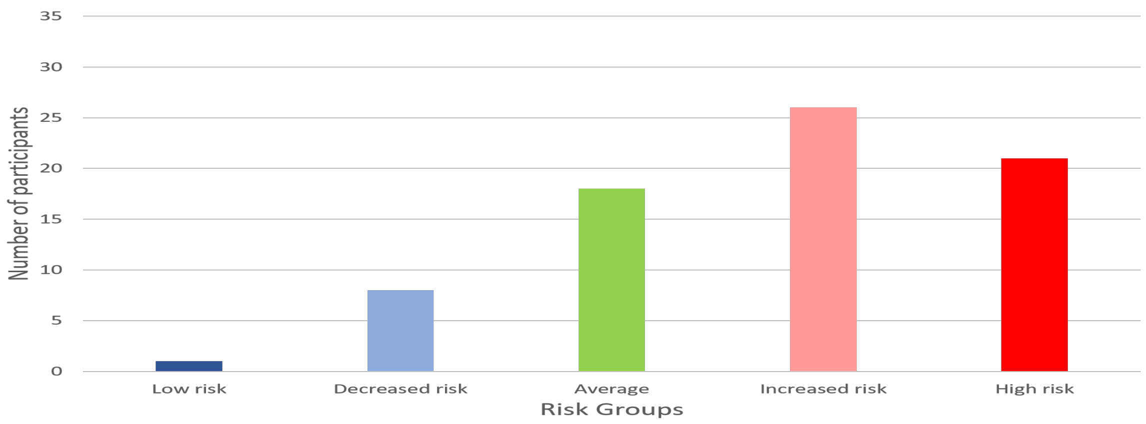


(b)

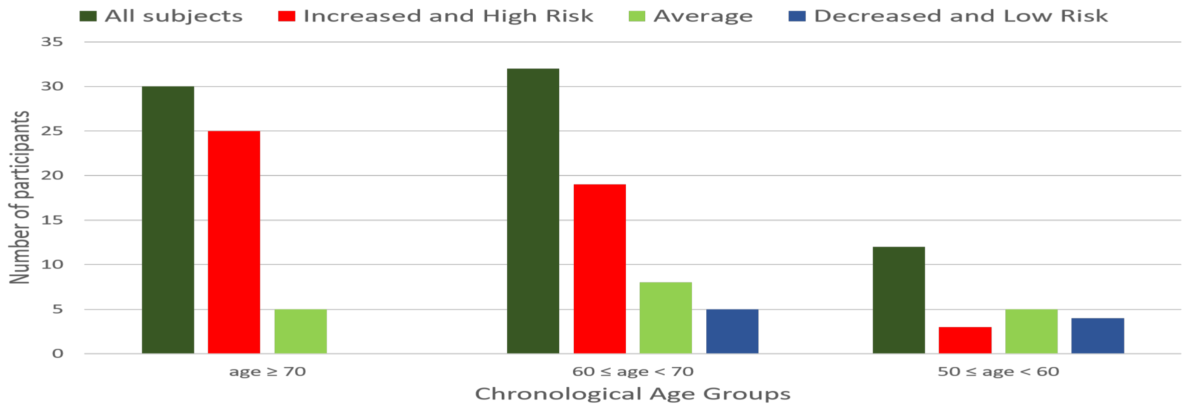


(c)

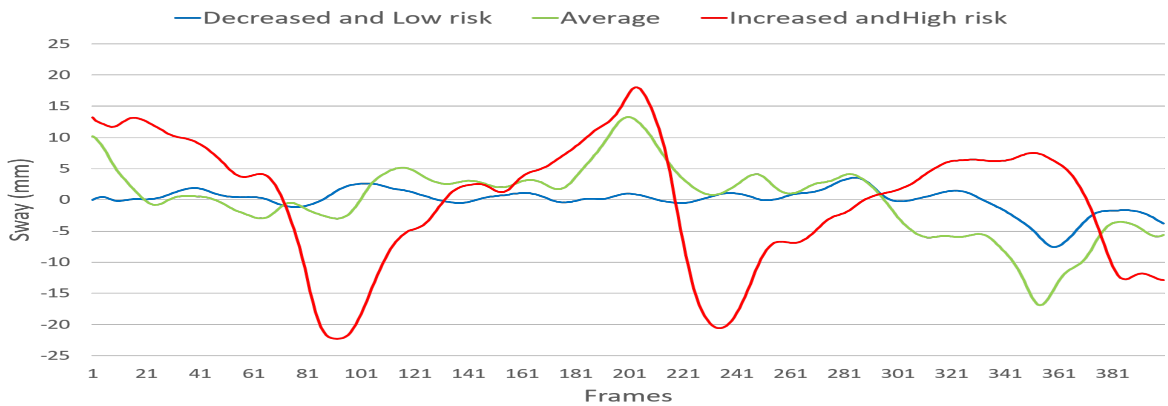
Figure 6.6: For the **double leg stance**, (a) Elderly subject classification over the different risk groups based on the measured sway parameters from the estimated sway signal from the video and the chronological-age of the subject. (b) Risk groups analysis based on elderly age groups. (c) Example of double sway signal from the different risk groups. High risk group shows higher sway frequencies and greater sway distances.



(a)

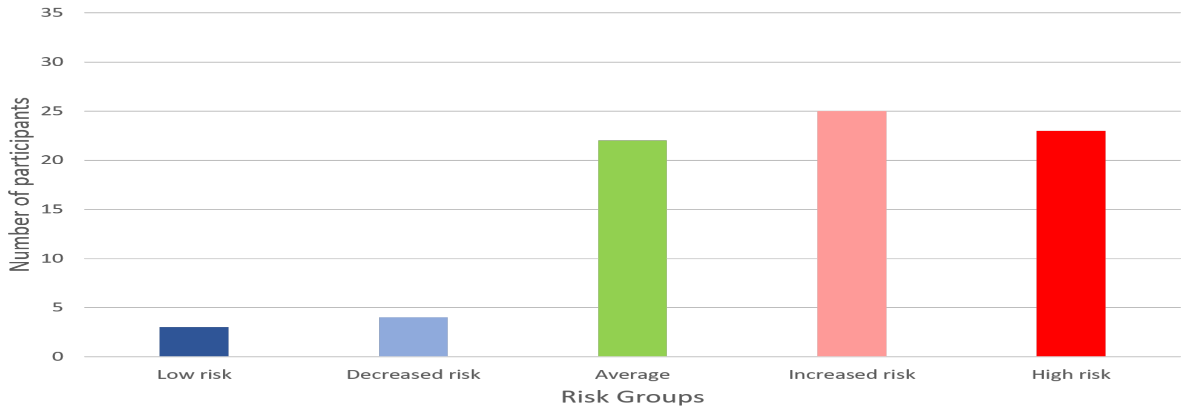


(b)

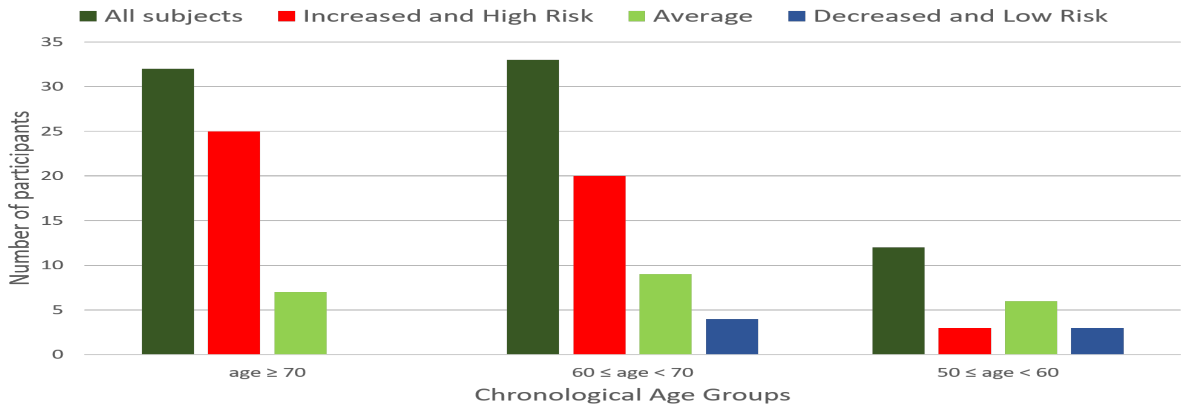


(c)

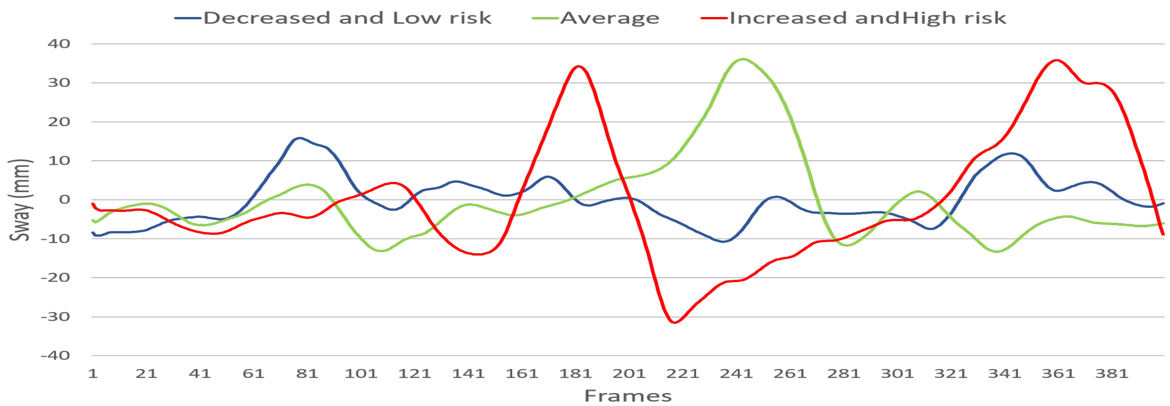
Figure 6.7: For the **single leg**, (a) Elderly subject classification over the different risk groups based on the measured sway parameters from the estimated sway signal from the video and the chronological-age of the subject. (b) Risk groups analysis based on elderly age groups. (c) Example of double sway signal from the different risk groups. High risk group shows higher sway frequencies and greater sway distances.



(a)



(b)



(c)

Figure 6.8: For the **tandem stance**, (a) Elderly subject classification over the different risk groups based on the measured sway parameters from the estimated sway signal from the video and the chronological-age of the subject. (b) Risk groups analysis based on elderly age groups. (c) Example of double sway signal from the different risk groups. High risk group shows higher sway frequencies and greater sway distances.

6.3.2 Gait

The gait measurements are fed into GMMs to model the distributions of the gait signals for the athlete group and the elderly groups. The healthy athlete participants are considered to be in one group (healthy young adults) and the elderly are considered in three gait-age groups based on the distance between them and the healthy athlete gait-age cluster. The first GMM for the healthy group has one mixture, which the second GMM for the elderly has three components, three age groups.

Comparing the chronological-age group of the elderly participant with the gait-age group cluster, which this subject has been classified into, this subject can be identified as high risk, increased risk, normal, reduced risk, or low risk based on the distance to the athlete age group.

Figure 6.9 illustrates the risk analysis applied on the gait measurements for stride length, step length, and walking base. A number of participants reported having an active life style including walking, swimming, horse riding, and other activities that optimised their walking style. Most of the participants who were in the increased and high risk clusters are over seventy years.

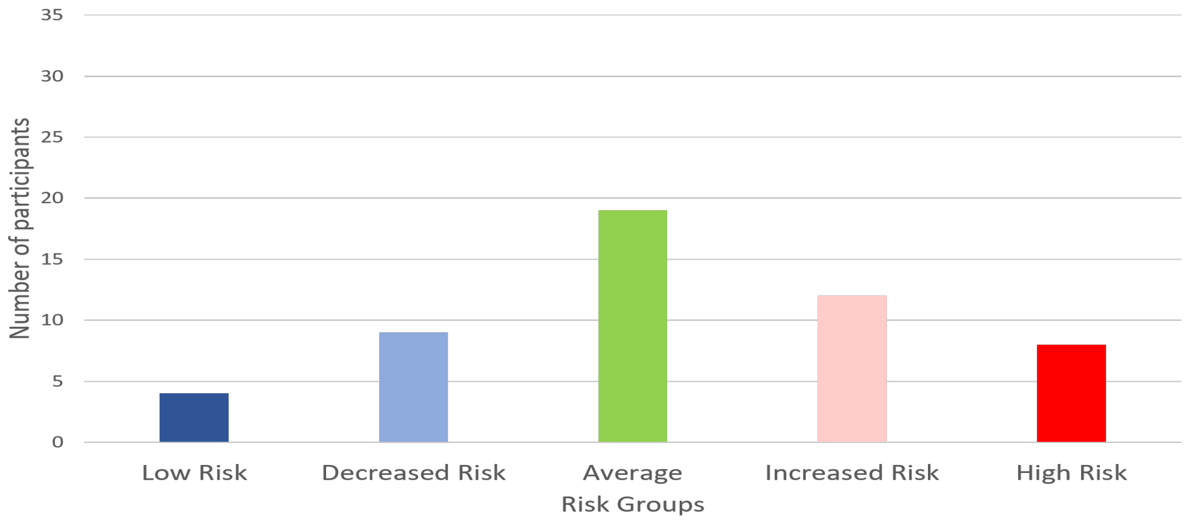


Figure 6.9: Risk analysis based on the gait measurements from estimated gait signal.

An example of walk base measurements for the three risk clusters, low risk, average, and high risk is shown in Figure 6.10. The figure shows that a walk base for the high risk cluster is much wider than the walk base in the average cluster. The figure also shows that the walk base for a subject in the low risk cluster is the narrowest.

Analysing the participants clustered into the three gait-age groups based on the gait parameters measurement supports the hypothesis that getting older increases the likelihood of having a fall. Figure 6.11 shows that 65% of the elderly people with chronological-age > 70 years are classified into increased and

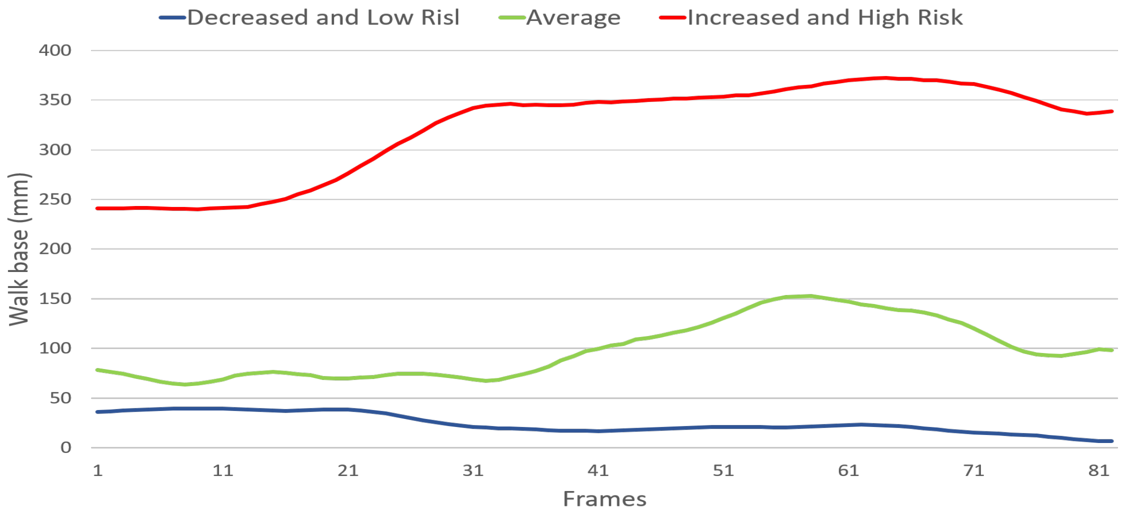


Figure 6.10: Example of walk base measurements for the three risk clusters: decreased and low, average, and increased and high risk. Higher risk group shows wider walk base.

high risk, while 70% of elder people with $50 \leq$ chronological-age < 60 are classified into decreased and low risk group.

6.4 Discussion

Applying the presented methodology in this chapter, Section 6.1 after using the previous presented methodologies in Chapters 4 and 5 on the collected data, a likelihood risk of having a fall is predicted for the elderly subjects. This risk analysis for an elderly person is based on the comparison between the gait/sway age group that person is classified to and the chronological age group for that elderly. Postural results show that getting older affects the reaction speed to be taken to maintain body balance within the base of support. On the other hand, although the gait in the elderly people is affected by the aging process, participating in different activities in the daily life can move the gait style into younger gait age group.

Sway and gait results are displayed in Figure 6.12. These results show that the majority of the elderly people in the collected dataset, who are classified into increased and high risk groups,their chronological age is ≥ 70 years. More than 80% of $70+$ years elderly people are classified into increased and high risk groups based on the sway signal for the three balance test stances, double leg, single leg, and tandem stances. The rest of the people in the $70+$ years age are classified into the average risk group.

For $60 \leq$ chronological-age < 70 years, the percentage of elderly people classified into increased and high risk groups is around 60% for the three stances. A higher percentage of elderly people in this

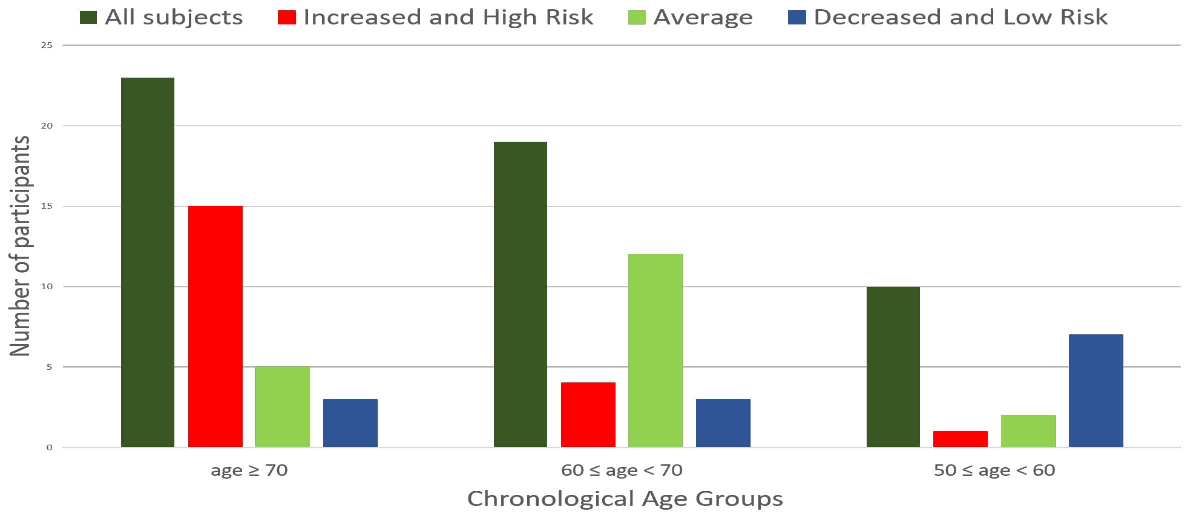


Figure 6.11: Number of subject in each age group classified into the three risk groups.

age group are classified into the average risk group with 25% for both double leg and tandem stances and 27% for the single leg stance. 12% of the elderly in this age group are classified into decreased and low risk groups have for the double and tandem stances and 16% for the single stance.

The youngest elderly age group, $50 \leq$ chronological-age < 60 years, has the lowest percent of classified elderly people in the increased and high risk groups based on the sway age, 25% for the three stances. The average risk group has 50% of the elderly people classified into it from this age group in the double leg and tandem stances and 40% of the elderly people in the single leg stance. A higher percentage of elderly people in this age group are classified into the decreased and low risk groups with 25% for the double and tandem stances 33% for the single stance.

In the gait results, a lower percentage of the elderly people are classified into the increased and high risk groups for the three gait-age groups compared to the sway-age results as seen in Figure 6.12. 65% of the elderly people are classified into increased and high risk groups from the 70+ years chronological age compared to 21% from the $60 \leq$ chronological age < 70 years, and 10% from the $50 \leq$ chronological-age < 60 years. The percentage of the classified elderly people in the decreased and low risk groups is higher to 70% of the elderly in the youngest age group, $50 \leq$ chronological-age < 60.

6.5 Summary

Although most of the elderly participants in the collected dataset have an active life style, some differences have been noticed in their walk styles and their postural sway, which are related to their age.

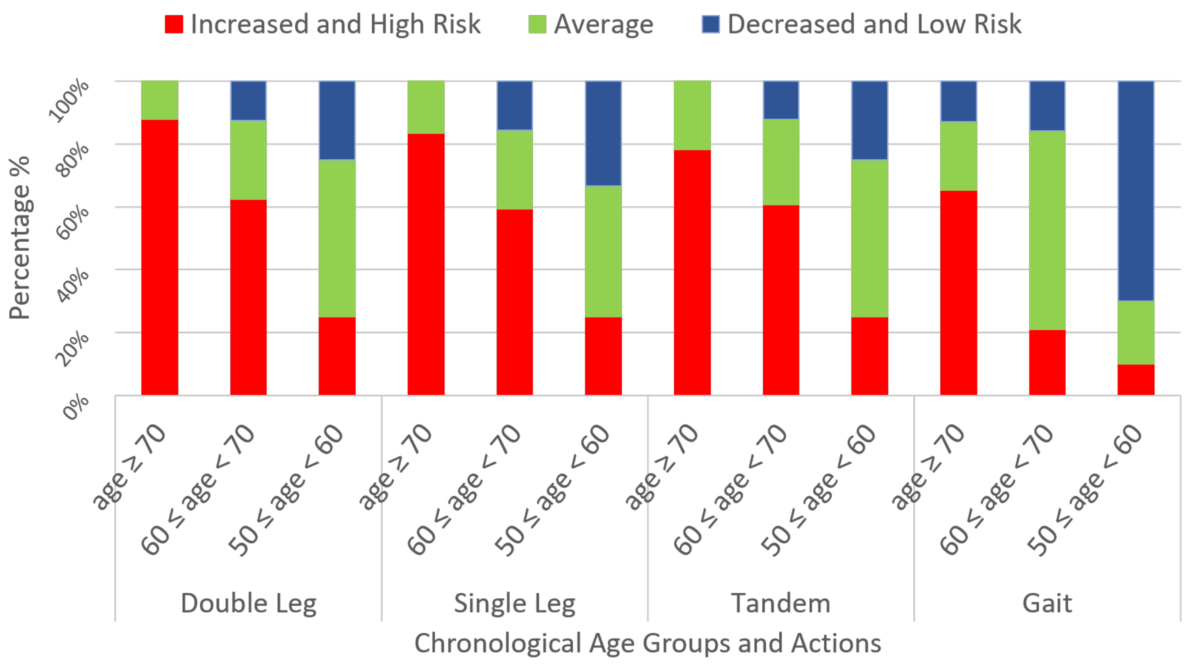


Figure 6.12: Risk analysis results percentage in each age group for the three stances of the balance test and the gait.

Participants are more able to control their walk style if they are undertaking activities, such as walking and going to the gym. On the other hand, age effects may impact on postural sway where the muscle reaction speed to the different sensory systems is affected by the ageing process, which results in more frequent and/or wider postural sway.

In this chapter, a method is proposed and presented to estimate the *gait/sway* age groups of elderly people based on the extracted sway and gait measurements separately. These measurements are computed based on the postural sway and gait signals derived from video data. Then, the person's chronological-age group and the estimated gait/sway-age group are used to analyse the risk of a fall for the elderly people. The experiments show the effectiveness of the proposed method to detect an increased risk for elderly based on their estimated sway and gait signals. This study has presented an automated approach to detect the risk of fall from video data based on postural sway and gait measurements. This work can be extended by tracking more body joints to be more representative for the body movements. Also, repeated recordings (every three months) of the elderly participants in the dataset could be used to study the changes of the sway and gait measurements over time.

Chapter 7

Conclusions and Future Work

In this thesis, estimating human gait and postural sway from vision data has been studied. This thesis starts by studying the literature of the human gait and sway for the sake of identifying the research gaps in these areas. To fill some of these gaps, a dataset for gait and postural sway has been recorded, where one part of this recording was allocated to a group of healthy athletes and the other part of the recording was for elderly people. Then, the parameters to study the gait and the sway from video data have been defined. Machine learning methods have been proposed to estimate the postural sway and gait movements from videos. These estimations have been correlated with the corresponding measurements from force plate devices to validate these proposed methods. Then these estimations have been used to measure the defined parameters. As an application for using the estimated parameters, the classification of the *sway-age* and *gait-age* groups for the elderly people has been provided to estimate the likelihood of the fall risk. In the next sections, the contributions of this thesis are summarised and then followed by the future directions of research in this area.

7.1 Summary

The contributions of the work presented in this thesis can be summarised as follows:

(1) Reviewing the current research for gait and postural sway:

A comprehensive literature review has been presented in Chapter 2 including a general view about gait and postural sway, the defined parameters to measure and analyse them, and devices and techniques that have been used to that end. Gait and postural sway have been specially reviewed from a clinical perspective as it is considered to be the original domain that initiated such studies.

Gait and postural sway have been also reviewed from a computer vision perspective as the point of interest of this research is to utilize computer science techniques on vision data to measure and analyse human gait and postural sway. Moreover, research that discuss fall and risk of fall with gait and sway, specially related for elderly, have been presented.

(2) Dataset: Due to the lack of available datasets that contains vision data for gait and sway, especially for elderly people, a dataset has been collected during this research, (Chapter 3). This dataset has been collected in two parts:

(I) Ground truth part, which contains collected data for healthy athlete subjects performing the Balance Error Scoring System (BESS) balance test and walk. Vision data (from video recording), Centre of Pressure (CoP) displacements that represent postural sway movements (from force plate), and body joint movements in the 3D space (from a motion capture system, Vicon) have been recorded in this part of the dataset.

(II) Elderly part, which contains data for elderly subjects over fifty years performing the BESS balance test and walk. In this part, vision data as well as CoP have been collected. Elderly part of the dataset has been collected in three stages three months apart for the same elderly subjects to assess potential changes over time.

(3) Human postural sway from vision: Based on the ground truth part of the data set, a method investigates using TGPR and RNN as regression methods to estimate postural sway from vision data has been proposed in Chapter 4. Force plate and Vicon data have been used to validate the estimated postural sway from vision data. While both regression methods have been shown close results in the estimated movements, RNN has shown better estimation for sudden movements in the body sway.

(4) Human gait from vision: Based on the ground truth part of the dataset, a regression method based on Long-Short Term Memory to estimate gait movements from vision data has been proposed in Chapter 5. Gait parameters have been measured from estimated movements and compared with measured gait parameters from Vicon for validation. An acceptable measurements for right foot stride and step lengths with MSE 0.036 m and 0.040 m, respectively and MSE 0.044 m and 0.047 m for left foot stride and step lengths.

(5) Vision-based gait and sway risk analysis: After the proposed methods for estimating and mea-

suring postural sway in Chapter 4 and gait in Chapter 5 were verified, they have been used on the elderly part of the dataset in Chapter 6 to estimate postural sway and gait movements for elderly people from vision data. Gait and postural sway parameters have been measured on the corresponding estimated movements.

A model for clustering elderly people into three *sway-age* groups has been built based on their estimated postural sway and measured parameters from vision. Based on the difference between the *sway-age* group, which the elderly person has been classified to, and the *chronological-age* group that elderly person belongs to, each elderly person has been classified into one of the defined risk group: decreased and low risk, average risk, and increased and high risk.

A similar clustering model, based on estimated gait and measured parameters from vision has been built to cluster elderly people into three *gait-age* groups. Based on the difference between the *gait-age* and the *chronological-age* group for each elderly person, he/she has been classified into one of the risk groups: decreased and low risk, average risk, and increased and high risk.

7.2 Limitations

Though this thesis produces valuable impact on studying the risk of falling for elderly people, there are number of limitations, which are summarised as follows:

- The dataset has been collected for around 50 elderly subjects in three phases, three months apart. Studying the increasing likelihood of having a fall for elderly people may require more subjects with different falling history, more phases and with longer time differences between the phases to capture the changes in the sway and the gait of the participants.

- While standing, all body parts participate in producing the body sway. This thesis has studied the sway estimation from parts of the upper body only. While this has shown reasonable correlation with the measured sway from the force plate, incorporating other body parts may produce more robust postural sway estimation.

- This study focused on measuring maximum medial-lateral sway and frequencies while standing and also, on measuring three of the gait spatial parameters, stride, step length and walk base, from video recording. There are some other sway and gait parameters that can be added to analyse the risk of falling, which are not used in this thesis. Some of these parameters have been mentioned in Section 2.1. Adding these parameters to the proposed framework in Section 6.1 may result in more accurate risk analysis system.

7.3 Future Work

Based on the contributions of this thesis, multiple future directions can be explored as follows:

(1) Expanding the dataset: In this research, the elderly part of dataset has been collected in three phases separated by three months. Follow up recordings are suggested to cover a longer period of time as changes to gait and sway are often manifest themselves over a long period of time. Moreover, expanding the number of participants for each phase would be beneficial in order to improve the representativeness of the dataset.

(2) Estimating the 3D of the human poses: In all of our experiments, the gait and postural sway parameters are estimated by handling the cameras individually and estimating the 2D human poses from each camera independently. However, this can be extended by estimating the 3D poses from the two views of the body movements at the time. Estimating the 3D poses may result in improving the estimation of the gait and sway parameters, which may lead to more accurate risk analysis.

(3) Including more gait and sway information: Analysing the human gait movements and postural sway can be extended by considering more information from the body parts, such as, estimating the angles between the body parts. This may open the door for estimating other sway and gait parameter,s such as kinematics motion based parameters. Also, the recorded information about the participants, such as their age, gender, and history of disease and falls can be used to guide the analysis.

(4) Introducing a multi-modal risk analysis model: In this thesis, risk analysis has been conducted based either on the estimated gait parameters or on the estimated sway parameters. However, fusing these two parameters can be used to build a multi-modal risk analysis model. Different parameters measure different strength and weakness factors in maintaining body sway. Combining more factors might lead up to more accurate risk analysis.

(5) Developing a self-monitoring system: The underpinning research in this thesis can be extended to build a self-monitoring system, for example using the camera of the smart phones, to enable the people to check their movement changes over time based on their gait and postural sway and

to facilitate predicting the risk of fall well before it occurs. This would allow countermeasures to be put in place, such as particular exercises. Such a monitoring system could also be useful in aged-care facilities.

(6) Investigating other applications: The focus in this thesis has been to estimate the likelihood of risk of fall for the elderly people based on the estimated gait and sway parameters. However, this can be extended to other applications such as injury prediction and intervention for the players by analysing their video recordings and estimating their gait and sway parameters on a regular basis, then comparing these parameters over time to check for the risk of injury.

Appendices

Appendix A: Ethical Approval – Ground Truth

UNIVERSITY OF CANBERRA
AUSTRALIA'S CAPITAL UNIVERSITY

7 October 2015

APPROVED - Project number 15-193

Professor Roland Goecke
Faculty of Education, Science, Technology & Maths
University of Canberra
Canberra ACT 2601

Dear Roland,

The Human Research Ethics Committee has considered your application to conduct research with human subjects for the project titled **Computational Modelling of Sway and Movement Patterns, Ground Truth.**

Approval is granted until 6 October 2018.

The following general conditions apply to your approval.

These requirements are determined by University policy and the ***National Statement on Ethical Conduct in Human Research*** (National Health and Medical Research Council, 2007).

Monitoring:	You must assist the Committee to monitor the conduct of approved research by completing and promptly returning project review forms, which will be sent to you at the end of your project and, in the case of extended research, at least annually during the approval period.
Discontinuation of research:	You must inform the Committee, giving reasons, if the research is not conducted or is discontinued before the expected date of completion.
Extension of approval:	If your project will not be complete by the expiry date stated above, you must apply in writing for extension of approval. Application should be made before current approval expires; should specify a new completion date; should include reasons for your request.
Retention and storage of data:	University policy states that all research data must be stored securely, on University premises, for a minimum of five years. You must ensure that all records are transferred to the University when the project is complete.
Contact details and notification of changes:	All email contact should use the UC email address. You should advise the Committee of any change of address during or soon after the approval period including, if appropriate, email address(es).

Yours sincerely
Human Research Ethics Committee

Hendryk Flaegel
Research Ethics & Compliance Officer
Research Services Office
T F (
E

www.canberra.edu.au

Postal Address:
University of Canberra ACT 2601 Australia
Location:
University Drive Bruce ACT

Australian Government Higher Education Registered Provider Number (CRICOS): 00212K

Appendix B: Ethical Approval – Elderly

UNIVERSITY OF CANBERRA
AUSTRALIA'S CAPITAL UNIVERSITY

4 June 2015

APPROVED - Project number 15-122

Professor Roland Goecke
Faculty of Education, Science, Technology & Maths
University of Canberra
Canberra ACT 2601

Dear Roland,

The Human Research Ethics Committee has considered your application to conduct research with human subjects for the project titled **Smartphone accelerometer measures as a feedback tool in maintaining healthy movement in community dwelling older Australians: The "Healthy Movement Data Set" normative data set.**

Approval is granted until 3 June 2018.

The following general conditions apply to your approval.

These requirements are determined by University policy and the ***National Statement on Ethical Conduct in Human Research*** (National Health and Medical Research Council, 2007).

Monitoring:	You must assist the Committee to monitor the conduct of approved research by completing and promptly returning project review forms, which will be sent to you at the end of your project and, in the case of extended research, at least annually during the approval period.
Discontinuation of research:	You must inform the Committee, giving reasons, if the research is not conducted or is discontinued before the expected date of completion.
Extension of approval:	If your project will not be complete by the expiry date stated above, you must apply in writing for extension of approval. Application should be made before current approval expires; should specify a new completion date; should include reasons for your request.
Retention and storage of data:	University policy states that all research data must be stored securely, on University premises, for a minimum of five years. You must ensure that all records are transferred to the University when the project is complete.
Contact details and notification of changes:	All email contact should use the UC email address. You should advise the Committee of any change of address during or soon after the approval period including, if appropriate, email address(es).

Yours sincerely
Human Research Ethics Committee

Hendryk Flaegel
Research Ethics & Compliance Officer
Research Services Office
T [redacted] F ([redacted]
E [redacted]

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Postal Address:
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Appendix C: Consent Form

Consent Form

Computational Modelling of Sway and Movement Patterns in Elderly People

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PURPOSE OF THE STUDY
The primary aim of this project is to develop a database of normal walking movement patterns for healthy community dwelling individuals 60 years and over using a smart phone based data collection system across 10-year age groups in males and females.

I, (print your name) ________________________________ have read the information contained within this consent form and any questions I have asked have been answered to my satisfaction.

- I agree to participate in this project, realising I am free to withdraw my participation at any time without being subject to any penalty or discriminatory treatment.
- I have been given the opportunity to ask questions about the research and received satisfactory answers.
- I agree that the purpose of this research and potential risks or discomforts involved with the testing procedures have been sufficiently explained to me, with the opportunity to ask questions.
- I understand that any information or personal details gathered in the course of this research about me is confidential and that neither my name nor any other identifying information will be used or published without my written permission.
- I give ☐ permission for photographs and video footage to be taken during my data collection session. I understand that photographs will be used at a later date for academic presentations (i.e. conferences), however, all persons will be de-identified.

The University of Canberra's Human Research Ethics Committee has approved this study. I understand that if I have any complaints or concerns about this research I can contact a member of the research team as detailed above or:

University of Canberra's Human Research Ethics Officer
Mr Hendryk Flaegel
02 6201 5220
hendryk.flaegel@canberra.edu.au

____ ____________
Signature of participant (and parent/guardian if under 18 years of age) **Date**

____ ____________
Signature of investigator **Date**

Appendix D: Information sheet

Computational Modelling of Sway and Movement Patterns in Elder People - Information Form

CODE:	
Surname:	**First name:**
Contact number:	
Email:	
Age:	
Gender: M / F	

HISTORY OF FALLS

Falls prior to this admission during current stay ☐

If ticked, detail most recent below)

CIRCUMSTANCES OF RECENT FALLS:

Last fall: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

Previous: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

Three months later

Falls prior to this admission during current stay ☐

If ticked, detail most recent below)

CIRCUMSTANCES OF RECENT FALLS:

Last fall: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

Previous: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

Six months later

Falls prior to this admission during current stay ☐

If ticked, detail most recent below)

CIRCUMSTANCES OF RECENT FALLS:

Last fall: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

Previous: _____ Time ago, ☐ Trip ☐ Slip ☐ Lost balance ☐ Collapse ☐ Leg/s gave way ☐ Dizziness

(Where? / Comments) ____

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