Novel Gait Models and Features for Gait Patterns Classification

Ronny Kurniawan Ibrahim
Supervisor: Prof. E. Ambikairajah

School of Electrical Engineering and Telecommunication
The University of New South Wales

2011
ORIGINALITY STATEMENT

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project’s design and conception or in style, presentation and linguistic expression is acknowledged.

Signed  

Date  
Acclerometry shows promise in providing an inexpensive but effective means of understanding the human gait. Accurate classification of everyday gait patterns could allow a monitoring system to exhibit greater ‘intelligence’, for example, improving the ability to detect and monitor the activities of a person, which would allow more accurate tracking of the health parameters associated with those activities in an un-supervised environment. This thesis develops an accurate gait classification algorithm using features derived from novel gait models.

The Linear Predictive (LP) model is proposed to model the gait with the basic assumption that the gait is a system that comprises impulsive inputs, which correspond to the footstrike. From the Linear Predictive model, the Linear Predictive Cepstral Coefficients (LPCC) were proposed as features, as they have better class separation compared to using LP coefficients directly. The filterbank energies were proposed to approximate the LPCC with a smaller number of parameters. Spectral Centroid Amplitude and Spectral Centroid Frequency features were also developed to integrate frequency information with the proposed filterbank features.

The second gait model that is proposed in this thesis is a harmonic model. The premise behind this model is that the accelerometer signal’s spectrum contains a fundamental frequency (which was found to be the walking stride rate) with multiple harmonics that fit a harmonic model. The first four harmonics were found to be a good approximation of the acceleration movement of the hip. The magnitudes of the harmonics were used for classification features and proved to be better features than the linear predictive filterbank features. Another advantage of the harmonic features is that they are independent of walking speed, which enables the extraction of features that are robust to the variations of speed.

Novel linear delta zero crossing counts regression features were used as complimentary features to the proposed static features from the model parameters. The assumption that the zero crossing counts provide a good characterisation of the amount of artifacts accelerations caused by the muscle movements was the motivation for using these features. Finally, the non-linear Empirical Decomposition (EMD) method was investigated to extract non-linear features for gait pattern classification.

The Bayesian adapted GMM classification system was used as a back-end system to further improve the classification accuracy of the system by removing the subject variation of the system. In addition, score level fusion was proposed to integrate the linear regression delta zero crossing features into the static features.

Declaration relating to disposition of project thesis/dissertation

I hereby grant to the University of New South Wales or its agents the right to archive and to make available my thesis or dissertation in whole or in part in the University libraries in all forms of media, now or hereafter known, subject to the provisions of the Copyright Act 1968. I retain all property rights, such as patent rights. I also retain the right to use in future works (such as articles or books) all or part of this thesis or dissertation.

I also authorise University Microfilms to use the 350 word abstract of my thesis in Dissertation Abstracts International (this is applicable to doctoral theses only).

..................................................................................................................

Signature         Witness         Date

The University recognises that there may be exceptional circumstances requiring restrictions on copying or conditions on use. Requests for restriction for a period of up to 2 years must be made in writing. Requests for a longer period of restriction may be considered in exceptional circumstances and require the approval of the Dean of Graduate Research.

FOR OFFICE USE ONLY

Date of completion of requirements for Award:

THIS SHEET IS TO BE GLUED TO THE INSIDE FRON’ COVER OF THE THESIS
Originality Statement

‘I hereby declare that this submission is my own work and to the best of my knowledge, it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked with at UNSW or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the design of the project, conception, style, presentation and linguistic expression acknowledged.’

Signed : 

Date : 

Name : Ronny Kurniawan Ibrahim
Copyright Statement

‘I hereby grant to the University of New South Wales or its agents the right to archive and to make available my thesis or dissertation in whole or part in the University libraries in all forms of media, now or hereafter known, subject to the provisions of the Copyright Act 1968. I retain all proprietary rights, such as patent rights. I also retain the right to use in future works for any articles or books wholly or partially of this thesis or dissertation. I also authorize University Microfilms to use the abstract of my thesis in Dissertations Abstract International. I have either used no substantial portions of copyright material in my thesis or I have obtained permission to use copyright material where permission to use copyright material; where permission has not been granted I have applied/will apply for a partial restriction of the digital copy of my thesis or dissertation.’

Signed  :

Date  :

Authenticity Statement

‘I certify that the Library deposit digital copy is a direct equivalent of the final officially approved version of my thesis. No emendation of content has occurred and if there are any minor variations in formatting, they are the result of the conversion to digital format.’

Signed  :

Date  :
Abstract

Accelerometry shows promise in providing an inexpensive but effective means of understanding the human gait. Accurate classification of everyday gait patterns could allow a monitoring system to exhibit greater ‘intelligence’, like, improving the ability to detect and monitor the activities of a person, in a more accurate tracking of the person health parameters in an unsupervised environment. This thesis develops a gait classification algorithm using features derived from novel gait models.

The Linear Predictive (LP) model is proposed to model the gait with the basic assumption that the gait is a system that comprises impulse trains input, which correspond to the footstrike. From the Linear Predictive model, the Linear Predictive Cepstral Coefficients (LPCC) were proposed as features, as they have better class separation compared to using LP coefficients directly. The filterbank energies were proposed to approximate the LPCC with a smaller number of parameters. Spectral Centroid Amplitude and Spectral Centroid Frequency features were also developed to integrate frequency information with the proposed filterbank features.

The second gait model that is proposed in this thesis is a harmonic model. The premise behind this model is that the accelerometer signal’s spectral contains a fundamental frequency found to be the walking stride rate with multiple harmonics that fit a harmonic model. The first four harmonics were found to be a good approximation of the acceleration movement of the hip. The magnitudes of the harmonics were used for classification features and proved to be better features than the linear predictive filterbank features. Another advantage of the harmonic features is that they are independent of walking speed, which therefore enables the extraction of features that are robust to the variations of speed. Novel linear delta zero crossing counts regression features were used as complimentary features to the proposed static features from the model parameters. The assumption that the zero crossing counts provide a good characterisation of the amount of artefacts caused by the muscle movements was the motivation for using these features. Finally, the non-linear Empirical Mode Decomposition (EMD) method was investigated to extract non-linear features for gait pattern classification.
The Bayesian adapted GMM classification system was used as a back-end system to further improve the classification accuracy of the system by removing the subject variation of the system. In addition, score level fusion was proposed to integrate the linear regression delta zero crossing features into the static features.

Keywords: Gait Classification, Harmonic Gait Model, Linear Predictive Gait Model, Temporal Gait features.
Acknowledgements

First and foremost, I would like to thank the Lord for His guidance and strength that He has provided me throughout my life. Secondly, I would like to express my sincere gratitude and appreciation to my supervisor Professor Eliathamby Ambikairajah for his insightful guidance, great encouragement, and endless support to me throughout the course of my PhD program. Whenever there were difficulties and obstacles in my research work, he always gave me advice to help me solve these hurdles. I have appreciated his constant encouragement and motivation, which I needed during my PhD journey; without him the accomplishments that I see today would not have been possible. I would like to express my deep appreciation and thank you to Dr. Julien Epps for his valuable feedback and tremendous advice on various topics related to this thesis.

It has been a great pleasure working alongside with dedicated people from the following two groups namely Biomedical and Signal Processing. I would like to thank the Biomedical System Laboratories: Prof. Nigel Lovell for his variety of help in proof reading several papers and publications, Dr. Ning Wang for his constructive feedback and valuable discussion of my work. I would like to thank members of the Speech Processing Research Group: Dr. Vidhyasaharan Sethu, Mr. Fendy Santoso and Ms. Stefanie Brown for proof reading my thesis. Many thanks to other members of both groups: Dr. Thamarajah Thiruvaran, Mr. Le Ngoc Phu, Dr. Hamid Teimoori, Mr. Tet Fei Yap, Ms. Karen Kua for their support and friendship throughout my life at the University of New South Wales. I would also like to thank my good friend Kaveh Fanian and my uncle Agung Setiana Ibrahim who has helped me in additional proof reading of this thesis.

This thesis is dedicated to my father, Dr. Agung B. Ibrahim and my mother Elizabeth Florentina, for their endless love, intellectual guidance, never ending support (through the hard times) and tremendous encouragement and support along the journey of my education. They have given me wonderful opportunities to further my overseas education and without them, all the achievements in my life would not be
possible. Also to my sister, Rachel Carolina for her support and endless love and last but not least my sweetheart Audrey, for not only her unyielding understanding, but also her support and companionship.
Contents

Chapter 1
Introduction
1.1 Motivation and Overview 1
1.2 Objectives of the Current Study 4
1.3 Organization of the Thesis 5
1.4 Major Contributions 6
1.5 Publications 7
Chapter 2
The Human Gait
2.1 Overview 8
2.2 Understanding the Gait 8
2.3 Walking on Different Terrains 11
2.4 Sensors for Gait Analysis 13
2.5 Gait Models 16
2.5.1 Inverted Pendulum Model 17
2.5.2 The Spring Mass Model 18
2.5.3 Complex Model 19
2.6 Triaxial Accelerometer Sensor and Signals 21
2.6.1 Feature Extraction 22
2.6.2 Classifiers 27
2.7 Summary 31
Chapter 3
Proposed Gait Models 32
3.1 Overview 32
3.2 Gait Data 32
3.2.1 Dataset of the 5 gait classes and analysis 32
3.2.2 Dataset of the variable walking speed and analysis 33
3.2.3 Dataset of the different foot-strike and analysis 34
3.3 Definition of Gait Models 36
List of Figures

Figure 1.1 Schematic Diagram of Gait Studies............................................................ 4

Figure 2.1 The three-dimensional plane of the human body adapted from [22] .......... 9

Figure 2.2 Phases of the Gait Cycle adapted from [23]............................................. 10

Figure 2.3 Electrogoniometers used at the ankle and knee (left) and hip and waist (right) adapted from [25] ......................................................................................... 13

Figure 2.4 Pressure Distribution Comparison between different types stages of walking using an insole shoe pressure sensors adapted from [25] ......................... 14

Figure 2.5 A Triaxial Accelerometer being worn around the waist area.............. 16

Figure 2.6 The Inverted Pendulum Model adapted from [14].............................. 17

Figure 2.7 Biomechanical model of muscles of a human, where M is the mass, k is the spring constant and c is the damping coefficient.................................................. 18

Figure 2.8 Schematic illustration of the effects of elastic and visco-elastic elements on ground reaction forces during impact and active phases of the gait adapted from [45] ............................................................................................................................. 19

Figure 2.9 Diagram of complex model diagram which consist of 23 degrees of freedom (Pandy, 2003).................................................................................. 21

Figure 2.10 (a) The TA unit, a push button and a wireless transmitter were contained in a small plastic case. (b) The TA unit transferred data via wireless (bluetooth) link to a bluetooth receiver unit and then to a personal computer for processing and storage. The direction of the three axes are shown .............................................. 21

Figure 2.11 Wavelet packet decomposition of a 50Hz time domain accelerometry signals. The shaded boxes are the target frequency band signals which were used for features extraction adapted from [20]. .............................................................. 25

Figure 2.12 Feature extraction which consisted of the EMD and the Hilbert Huang transform adapted from [21]. ................................................................. 27

Figure 2.13 Generic Gait Classification system ....................................................... 27

Figure 3.1 Time domain signal for five walking patterns (left to right : flat walking, slope down, slope up, stairs down and stairs up); (top to bottom : X-Axis, Y-Axis, Z-Axis)........................................................................................................ 33
Figure 3.2 Time-frequency plot for walking speeds between 3km/h and 7km/h on a treadmill, corresponding to slow walking up to very fast walking. .......................... 34

Figure 3.3 Z-axis signal of a foot-strike captured through the hip TA: .......................... 35

Figure 3.4 The foot-strike comparison plot (a) soft shoes (b) hard sole shoes. Blue, green, and red plots correspond to X,Y,Z axes respectively................................. 35

Figure 3.5 Gravity Acceleration vector (red vector) pointing down towards earth... 37

Figure 3.6 Body Acceleration and Velocity comparison over time of a walking person adapted from [71]......................................................................................... 38

Figure 3.7 The artefact acceleration of the Y-Axis for different gait patterns; left: flat walking; right: stairs up - right........................................................................... 38

Figure 3.8 Walking gait model system construction .................................................. 39

Figure 3.9 One full gait cycle (Z-Axis) signal reconstruction using a 30th order LP model (red solid line: generated signal from the LP model; blue dashed line: original signal). ........................................................................................................ 41

Figure 3.10 (a) The frequency response of the LP system of the hard foot strike shown in red solid line and soft foot-strike in blue dashed line and (b) The pole-zero plot of the hard foot-strike shown in red circles and soft foot-strike in blue crosses. 42

Figure 3.11 The gait speed frequency spectral (3km/h - solid line; 6 km/h – dotted line)... .......................................................................................................................... 43

Figure 3.12 The LP model’s pole zero plot comparison for 3km/h (blue) and 6km/h (red)... ...................................................................................................................... 43

Figure 3.13 Pole-zero plots of the LP model comparison for different gait patterns from one data set of a subject (from top to bottom: flat, slope down, slope up, stairs down, stairs up; left to right: X-Axis, Y-Axis, Z-Axis)............................................... 44

Figure 3.14 Magnitude spectral of a sample of flat walking from the TA signal placed on the right hip ........................................................................................................... 45

Figure 3.15 Comparison between the original signal (dotted - blue) and the harmonic generated signal (solid - red).................................................................................. 48

Figure 3.16 Normalized harmonic amplitude comparison between hard foot strike (squares) walking and soft foot strike (crosses) of the Z-Axis signal.................. 49

Figure 3.17 Signal reconstruction of the first four harmonics (dashed line) compared with the body and artefact signal (solid line). Region A: The swing leg lifts off the ground as the flexes moving the gait cycle into a single support phase. During this

xi
phase the waist moves in a shallow arc rising and then falling and the peaks shows the swing foot hitting the ground. Region B: In this phase the both feet are on the ground or it is more known as the double support phase.

Figure 3.18 Comparison of the Harmonic generated signal using the last eight harmonics (which represent the artefacts from the footstrike and muscles movements (blue - dotted)) with the original captured signal ((red - solid)).

Figure 3.19 Reconstructed signal using selected harmonic components: (dotted - reconstructed signal; solid - original signal) (a) even harmonics; (b) odd harmonics.

Figure 3.20 Comparison of the harmonic model across different speeds.

Figure 3.21 Harmonic model comparison for different gait patterns from one data set of a subject (from left to right: flat, slope down, slope up, stairs down, stairs up).

Figure 3.22 The Harmonic Model framework with TA signal.

Figure 4.1 Feature extraction roadmap.

Figure 4.2 Nonlinear mapping of ninety (30 from each of the axis) Linear Prediction Coefficients of the five different gait patterns (flat – dot; slope down – triangle; slope up - asterisk; stairs-down – rectangle; stairs up - star).

Figure 4.3 Nonlinear mapping of the LPCC of five gait pattern. (flat – dot; slope down – triangle; slope up - asterisk; stairs-down – rectangle; stairs up - star).

Figure 4.4 Magnitude spectral of Z-Axis flat gait pattern with different speeds (solid – 3km/h; dotted – 7km/h).

Figure 4.5 Bands grouping allocation for the antero-posterior (Z-Axis) acceleration.

Figure 4.6 Filterbank feature extraction diagram.

Figure 4.7 The Z-Axis filterbank energy features of the three bands (gravity acceleration – body acceleration – artefact) of a subject for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta crosses).

Figure 4.8 The Z-Axis filterbank energy features of the body acceleration vs. Artefact bands for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta)

Figure 4.9 The SCA and SCF values and how they relate to the frequency spectral of the X-Axis flat walking body acceleration signal.
Figure 4.10 The SCA and SCF feature extraction process. ................................. 63

Figure 4.11 The Spectral Centroid Features from one subject data being plotted (SCA on the Y-Axis and SCF on the X-Axis with the units of mg and Hz). (a) Body Acceleration of the X-Axis (BAx) (b) BAy (c) BAz (d) Artefact Acceleration of the X-Axis (Vx) (e) Vy (f) Vz. (circles – flat walking; crosses – slope down; dots – slope up; square – stairs down; triangle – stairs up). ............................................................ 65

Figure 4.12 Feature extraction of harmonic parameters. ................................. 66

Figure 4.13 Magnitude spectral of an example gait accelerometry signal, showing locations of the first 12 harmonics. ................................................................. 66

Figure 4.14 Signal reconstruction of the first four harmonics(dotted lines) compared to the original signal(solid line) ................................................................. 67

Figure 4.15 Grouping of harmonic amplitude spectra into harmonic features in the three axes (a) – antero-posterior; (b) – medio-lateral; (c) vertical, for an example frame of gait signal. ................................................................. 67

Figure 4.16 The Harmonic Features of the three axis (X-Axis –top; Y-axis – middle; Z-Axis - bottom) of a subject for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta). ........................................................................................................... 68

Figure 4.17 The ZCC of the Z-Axis for different gait pattern (top to bottom: flat; slope down; slope up; stairs down; stairs up). ......................................................... 70

Figure 4.18 Cross ZCC Linear Regression feature extraction diagram .............. 71

Figure 4.19 The Delta ZCC Regression diagram ............................................. 72

Figure 4.20 Comparisons between the mean (the bar value) and standard deviation (the small line on the middle of each bar) values of the ZCC and the ΔZCC features for five gait patterns within a subject. (F- Flat; SD – Slope Down; SU – Slope Up; StD – Stairs Down; StU – Stairs Up) ........................................................................................................... 73

Figure 4.21 A schematic representation of the EMD front-end feature extraction.... 75

Figure 4.22 The vertical acceleration signal is shown by the solid line, IMF 3 is shown by the dotted line and the threshold is shown by the bold line................. 76

Figure 4.23 The decomposition of the acceleration signal into nine IMFs with the residue for all gait patterns. .......................................................... 76

Figure 4.24 Non-linear Mapping of the IMF Features of five walking gaits........... 77
Figure 6.1 Complete Bayesian adapted GMM-based system for the classification of walking on various types of inclined slopes. ............................................................. 92

Figure 6.2 Classification employing score-level fusion using N different feature sets .................................................................................................................................... 94

Figure 6.3 Accuracies comparisons of non-adapted system, Bayesian adapted system, and score level fusion........................................................................................................... 97
## List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 4.1</td>
<td>The bandwidth specifications of the bandpass filters</td>
<td>60</td>
</tr>
<tr>
<td>Table 5.1</td>
<td>Confusion matrix of the linear prediction cepstral coefficients</td>
<td>80</td>
</tr>
<tr>
<td>Table 5.2</td>
<td>LPC features and LPCC features classification accuracy comparison</td>
<td>80</td>
</tr>
<tr>
<td>Table 5.3</td>
<td>Confusion matrix of the Filterbank features classification</td>
<td>81</td>
</tr>
<tr>
<td>Table 5.4</td>
<td>Overall classification accuracy of the SCA and SCF as features</td>
<td>82</td>
</tr>
<tr>
<td>Table 5.5</td>
<td>Confusion matrix of the spectral frequency centroid features for classification</td>
<td>82</td>
</tr>
<tr>
<td>Table 5.6</td>
<td>Confusion matrix of the harmonic model features classification</td>
<td>83</td>
</tr>
<tr>
<td>Table 5.7</td>
<td>Overall classification accuracy of various features derived from the harmonic model</td>
<td>84</td>
</tr>
<tr>
<td>Table 5.8</td>
<td>Classification accuracy comparison of various ZCC features</td>
<td>84</td>
</tr>
<tr>
<td>Table 5.9</td>
<td>Confusion matrix of the IMF Features for classification</td>
<td>85</td>
</tr>
<tr>
<td>Table 5.10</td>
<td>Comparison of classification accuracies using different feature sets</td>
<td>86</td>
</tr>
<tr>
<td>Table 6.1</td>
<td>Classification accuracy comparisons for Bayesian adapted systems vs. non-adapted GMM classification system</td>
<td>95</td>
</tr>
<tr>
<td>Table 6.2</td>
<td>Classification accuracy comparisons for the combination of ΔZCC Regression features and various static features combined through feature level fusion and score level fusion of Bayesian adapted systems GMM classifier</td>
<td>96</td>
</tr>
</tbody>
</table>
Chapter 1
Introduction

1.1 Motivation and Overview

Recent developments of small wearable sensors such as triaxial accelerometers and gyroscopes have made the unsupervised monitoring of human movements possible. The portability of these sensors with the aid of effective signal processing algorithms allows the possibility to monitor human movements in unsupervised environments. Such techniques open up the possibility of providing rapid assistance and of monitoring the health status at health care facilities and particularly among the elderly living on their own. This rapid assistance will prevent much of the morbidity, distress and socio-economic costs that are related to health care status.

Amongst numerous the physical daily activities, walking is one of the most typical movements encountered as it is the main source of locomotion in human beings. The gait is defined as the coordination of limbs’ movements to move the body from one place to another. Gait contains an abundance of information on a person’s ability to transport himself from one location to another. Having analysed gait in details, several important information can be derived as listed below:

- the stability during gait which can help determine the fall risk probability of a person[1],
- the impact of gait on a person’s health, for example, the harder the foot strikes the more prone to injuries that person may be[2].

Gait study is concerned with understanding the characteristics of walking, including the analysis of trips, slips and steps characteristics, and aims to help reduce falls or other incidents by analyzing the subject’s gait stability, and reduce injuries by designing specific footwear that reduces the impact of the foot strike motions. Gait studies can be subdivided into three major subclasses: gait analysis, gait recognition and gait classification. This leads to the necessity of rigorous gait studies to be carried out amongst the target population of interest.
Gait analysis is the study of how a person walks, which includes understanding the interaction of the muscles, joints and bones involved in walking. It analyses can be used to further assess how race walking athletes can improve their performance (fast walking). Yet another application of the gait analysis is the identification of abnormal gait characteristics (e.g. people with injuries). This can assist doctors/surgeons to make accurate decisions to fix gait abnormalities. Alkjaer et al., in [3] have analyzed the different gait patterns between a person walking with and without a rollator and found that the gait’s characteristic changes as a person uses a rollator. Winter et al., in [4] have discovered that the gait characteristics change as people age.

Gait recognition problem involves how to correctly identify a person by his/her gait patterns. Lie et al., [5] have tried to recognize the person’s gait by using the spectral characteristics of the foot motion (captured through video). Rajpoot and Massod [6] have used 3D wavelets and kernel based subspace projections for human gait recognition. Gafurov et al. [7] have used an accelerometer to perform authentication on biometric gait data.

Gait classification is the process of correctly determining a gait pattern and allocating it to a pre-specified class. Begg et al. in [8] have used support vector machines for automated gait classification. Sekine et al. in [9] have used wavelet coefficients and wavelet fractals to perform gait classification (walking on stairs, and flat walking) for elderly people, while in [10] have tried using a gyroscope to detect stair climbing motion.

Gait is a complex action which requires the integration of movement from multiple body segments. One gait cycle is understood to comprise a sequence of events, from the initial foot strike to the next strike of the same foot. It is generally assumed that all successions of the gait cycle are identical. Although this is not strictly true, it is a reasonable approximation for a limited time period of walking at a constant speed. Perhaps the simplest gait model comprises an inverted pendulum, in which the pendulum represents the movement of the body’s centre of mass [11]. In order to model the gait more accurately, Zajac et al. in [12, 13] have reviewed the biomechanics and muscle coordination of human walking. Subsequently, Pandy in [14] developed a complex gait model based on [12, 13] consisting of ten segments and 23 degrees of freedom. In their approach, the gait parameters are estimated using
an optimization technique which uses the metabolic energy as its cost function. Bessonnet et al., in [15] have tried to synthesize human gait using a parametric optimization method for a biped robot, while [16] have investigated the development of a 3-D tracking video for modeling the gait. These complex gait models have previously been used for gait analysis such as studying the abnormalities of the gait. However, these complex models are difficult and impractical to be used in a daily, physical, unsupervised monitoring environment as they require the attachments of many sensors to the subject’s body.

In this study, accelerometry has been proposed as a practical, inexpensive and reliable method for monitoring the ambulatory motions of humans. These features enable the implementation of gait and movement monitoring systems in an unsupervised environment. The only limitations of creating gait models from accelerometry data, is that analysis will not be as detailed as the complex models described by Pandy in [14] and Dockstader in [16].

All of the accelerometry gait classification studies in the past mainly focused on extracting features from the signal without any explicit linkage to the physiological parameters such as the gravitational acceleration, body acceleration artefacts and step rates being extracted [17-21]. Gait models have been investigated and developed in the past by Zijlstra et al. and Pandy in [11, 14] but they have not been adapted for use in gait classification. In this thesis, several gait models are being reviewed, proposed and compared, including the inverted pendulum model with its extensions, as well as more sophisticated complex models, such as Pandy’s complex muscle model [14], and Dockstader’s vision based gait model[16].

The use of simple pendulum model parameters are insufficient for gait classification using accelerometry because firstly the human leg consists of many joints, and secondly the gait patterns (flat, slope up and down and stairs up and down) studied in this thesis will be difficult to model using a single pendulum model. On the other hand, sophisticated biomechanical models such as that proposed by [14] are also difficult to be used for monitoring daily walking activities because of the implementation complexity of the model. This thesis will examine ways in which these limitations may be overcome by designing much less sophisticated models and incorporating the understanding from the complex muscle model system. A
A framework for the integration of gait models into the overall task of gait classification is illustrated in Figure 1.1.

In this study, the gait movements captured from the triax accelerometer are modeled by using models that closely resemble the characteristics of the signals captured from the sensor. The model parameters, extracted from the accelerometer, are then used to extract relevant and useful features. Furthermore, these sets of features are then used to determine the gait classification for tele-monitoring and energy expenditure calculations.

### 1.2 Objectives of the Current Study

The aim of the current study is to assess the feasibility of using a simple, low cost wearable accelerometer to classify gait patterns. The specific objectives of the studies can be listed as follows.

- To compare the existing gait feature methods used in gait pattern classification in terms of accuracy and robustness.
- To analyze the triaxial accelerometer (TA) gait data captured from the hip-worn TA sensor.
- To develop models which imitate the characteristics of the gait system.
- To develop features extracted from the gait models’ parameters to be used for gait classification.
- To develop and optimize a classification system for five gait patterns (which includes flat, slope down, slope up, stairs down, stairs up).
1.3 Organization of the Thesis

The remainder of the thesis is organized as follows:

**Chapter 2** discusses the physiology of human gait, including the different limbs involved in the gait cycle. The different gait parameters are also explained and then followed by a discussion of how different gait sensors can be used to analyze gait patterns. In addition, the advantages and disadvantages of each method are also discussed. Furthermore, the chapter describes various gait models used to model the traditional gait pattern (walking on flat surface). This includes the simplest gait models like the inverted pendulum and the biomechanical spring mass model, up to complex gait models. This is then followed by the description of different gait features which have been used in the past for gait classification. A proposed plan of this study is to integrate gait model information into gait pattern classification system.

**Chapter 3** firstly describes the database used for the whole thesis. It is then followed by the development of two new gait models which are the linear predictive model and the harmonic model for human gait classification. Furthermore, it analyses the performance of these proposed models, in particular how they will model the hip mounted TA signal.

**Chapter 4** describes six novel feature extraction algorithms for gait pattern classification. The first feature set is derived by transforming the linear predictive model parameters into the cepstral domain (LPCC). The second feature set provides an approximation of the LPCC features by using a set of filterbank energy features. The third feature set is the centroid features, which performs weighting on the filterbank energies. The fourth feature set is the harmonic features derived from the harmonic model. The fifth feature set investigates the use of ZCC(zero crossing counts) as a measure of muscle vibrations for discriminating the gait patterns. The sixth feature set incorporates the empirical decomposition method as a non-linear decomposition method to decompose the TA signal.

**Chapter 5** describes the experimental results and discussions of the proposed features in Chapter 4 and how these are compared to the existing well-known features used for gait classification.
Chapter 6 describes optimizing classification of the proposed system. The Bayesian adaptation technique is used to remove the subject’s variability. Furthermore, score level fusion is used to optimize the classification system for combining feature sets. Chapter 7 highlights the achievements of the thesis with respect to the gait models used to derive features for the classification system. Several problems that have not been addressed, as well as possible solutions that could guide future works, are also discussed.

1.4 Major Contributions

This research provides original contributions on the use of the harmonic model and the linear predictive model for gait pattern classification. The major contributions of the research can be summarized as follows:

- The Linear Predictor (LP) model is proposed as an approximation of the gait from the triaxial accelerometer. Linear Predictor model’s parameters were investigated for their suitability as features for gait classification. Transformed LP coefficients were found to be robust features for gait classification.

- A novel filterbank approach for analysing gait signals is proposed and cepstral coefficients are obtained from the filterbank energies as robust features.

- The spectral centroid features provides a weighting function to the filterbank features. It was found that spectral centroid features produce higher classification accuracy.

- Novel Zero Crossing Regression features are proposed for gait pattern classification. These features were found to be good, complimentary features for the filterbank features.

- The harmonic model is proposed to model the harmonics frequencies in the captured triaxial accelerometer signal as a result of the gait being a quasi-periodic signal.

- Novel gait features are derived from the harmonic model and they are found to be robust for classification.
• The Bayesian adaptation algorithm and score level fusion are proposed to optimise the gait classification and these combined methods were found to improve the classification accuracy of the gait classification system.

1.5 Publications

Journal Publication :


Conference Publications :

Chapter 2

The Human Gait

2.1. Overview

This chapter provides a literature review of the existing gait related studies. It starts with the discussion of the gait cycle that includes the gait parameters describing the gait, the phases resembling one gait cycle, body segments that mainly contribute to the gait cycle and how the gait characteristic changes with different terrains. In order to understand the nature of the gait in a simpler manner, gait models are developed and used to explain the characteristics of the gait. Several existing gait models are discussed in this chapter. Furthermore, several existing signal processing data analysis methods are also discussed. Gait classification systems, which include feature extraction methods and classifiers, are also discussed in this chapter.

2.2. Understanding the Gait

Prior to describing the gait in details, it is necessary to introduce the basic terminologies of the human body which are used to describe the gait. As illustrated in Figure 2.1, the human body can be divided into three planes which are:

- **The sagittal plane**: the plane which bisects the body into two symmetrical halves.

- **The frontal plane**: the plane which is perpendicular to the sagittal plane which separates the front part of the body and the back by the centre mass of an erect standing human body.

- **The transverse plane**: the plane dividing the upper body and lower body based on the location of the centre mass of an erect standing human body.

Walking is the repetition of a sequence of limb motions moving the body forward while simultaneously maintaining stance stability. As the body moves forward, one limb serves as a mobile source of support while the other limb advances itself to a new support location.
For the transfer of body weight from one limb to the other, both feet are in contact with the ground. A sequence of these functions by one limb is called a gait cycle [23]. Moreover, it can be quantified by using a series of parameters which measure the average timing, linear displacement and velocity. These parameters can be listed as follows.

- **Cadence:** the total number of steps divided by the time taken (steps/min). Thus cadence is half of the gait cycle.
- **Stride time:** the time measured to complete one gait cycle. This can be formulated as: \( \text{Stride time} = \frac{120}{\text{cadence}} \)
- **Step length:** The distance between the two heels during the double limb support phase.
- **Stride length:** The distance travelled between two successive foot strikes of the same foot.
- **Walking speed:** The average speed attained after 3 steps. The normal walking cadence for normal healthy subjects is approximately 115-150 steps/mins. Guinamraes [24] found that the frail elderly had an average walking cadence of around 95 steps/mins. This can also be formulated as
  \[
  \text{Walking speed} = \frac{\text{stride length} \times \text{cadence}}{120}
  \]

Each gait cycle is subdivided into two phases called stance and swing phase. The stance is the phase in which the observed foot touches the ground. The swing phase begins as the foot is lifted from the floor. The stance phase duration covers 60% of the total gait cycle and the swing phase covers 40%[23].
The stance phase is defined as including the following series of events (for example, if the right leg is considered as the observed leg):

- the initial contact,
- left toe off,
- left heel rise
- left foot strike

The swing phase is defined as the sequence of the following series of events:

- the right toe off,
- the foot adjacent,
- tibia vertical and
- the right foot strike

The stance phase itself is subdivided into three intervals which are the initial double limb stance, single limb stance and the terminal double limb stance. An illustration of the gait phases is shown in Figure 2.2

![Figure 2.2 Phases of the gait cycle adapted from [23].](image)

One complete set of these events is called a gait cycle. In order to understand the gait cycle thoroughly, it is necessary to investigate the body segments involved in the process. The main body segments involved in the walking process are the ankle, foot, knee and hip. The movement of these segments is dependent upon proper operation of the leg muscles.
In this section, the main walking segments are discussed. The main locomotor segments during walking are the ankle, the foot, the knee, and the hip. The function of these limbs and the connected muscles during gait is as follows:

- **The Ankle**: which is the junction between the leg and foot. The ankle is considered to be the location of all leg/foot interactions. As the ankle joint moves in a single plane, all the controlling muscles function either as dorsi-flexors or plantar-flexors. The plantar-flexors are active during the stance phase and the dorsi-flexors are active during the swing phase.

- **The Foot**: The foot consists of three sections which are the subtalar, midtarsal and metatarsophalangeal. The metatarsophalangeal is the section which has the main function of determining the progressional stability. The foot motion and its muscular control relates to three events namely, shock absorption, weight bearing stability and progression. These tasks occur sequentially as floor contact proceeds from initial heel contact to total forefoot support.

- **The Knee**: is the junction of the two long bones (tibia and femur) that constitute major segments of the lower limb. Small changes in the ankle position will result in significant changes in either foot or body position. During stance, the knee is the basic determinant of limb stability. On the other hand, during the swing phase, the knee is the primary factor in the limb’s freedom to advance.

- **The Hip**: The joint between the upper body and the lower body segments is called the hip. As a result, it is designed to provide three-dimensional motion with specific muscle control for each direction of activity. The functional focus of the hip also varies at different phases of the gait cycle. During the stance phase, the role of the hip muscles is to stabilize the upper body parts. In the swing phase, their role is to drive the body forward.

### 2.3. Walking on Different Terrains

Slopes and stairs are frequently encountered on walking terrains in daily living. Walking up/down either slopes or stairs requires different amounts of energy than level walking does. This can be related to the varying amount of potential energy that has to be produced (during ascent) or absorbed (during descent) by the muscles. The kinematics and kinetics of slope/staircase walking differ significantly from level walking.
• **Walking on a Slope**

It is noticeable that walking up an incline of increasing slope requires a change in walking pattern. The major change is that the leading foot does not land with the knee joint almost straight, as observed in level walking. A consequence of this change is that we cannot take advantage of the potential/kinetic energy conservation effect in level walking. Extra concentric contraction of the hip flexor muscles is needed, which represents extra work and costs more energy. Following the lead-foot landing, work is done concentrically by the hip and knee extensors to raise the centre of mass (COM). All of this concentric muscular work gives a continual increase in potential energy. The unfortunate fact is that the force available to us in concentric contraction decreases as the shortening speed increases such that concentric work is very costly when walking uphill.

A further requirement of walking uphill is an increased range of ankle joint angular motion. This means that the ankle extensors are lengthening and shortening over a great range than is observed on a horizontal surface. One might expect energy consumption of walking downhill to be the exact opposite of uphill walking. This would be true if it were a simple conservative mechanical system without energy dissipation. However this is not the case as one loses potential energy, one gains kinetic energy and the speed of the descent. In order to remain in control, one reduces the gain in kinetic energy by eccentric muscular contraction. In other words, one uses the same muscles to descend and ascend the slope. The difference is while descending the muscles are being stretched for developing force, whereas while ascending they are shortened.

• **Walking on Stairs**

A general rule in the construction of stairs is that the sum of the rise (vertical height of a step) and run (horizontal depth of step) should be within narrow limits. Departures from this rule make walking up stairs difficult because people have to shorten or lengthen their stride by an uncomfortable amount. A disadvantage of slope ascend compared to stairs ascend is that the subject may select his/her own comfortable stride length. On stairs, this is not possible as the
subject is forced by the structure of the stairs characteristics. Based on this knowledge, it can be hypothesised that there will be less variations in the anterior-posterior of the stairs gait patterns compared to the slopes gait patterns.

2.4. Sensors for Gait Analysis

Movement of the body during gait is commonly assessed in the clinic or the gait laboratory, often using multiple sensors technology. These sensors include electromyography, electrogoniometers, force pressure sensors, electromechanical switches, camera-based systems, and accelerometers. Each of these will now be discussed.

- **Electromyography (EMG)**
  EMG basically measures the muscle activity using electrodes that measures the potential differences between two points. Surface skin electrodes and intramuscular wire electrodes are used to measure the electrical activities of muscles. EMG is regularly used in gait analysis to identify the gait period and muscle activity during walking and also to examine various muscles which are active in different phases.

- **Electrogoniometers**
  Electrogoniometers are used to measure the angle of the joint segments during gait, most commonly the knee and the ankle (Figure 2.3). The parallelograms and a potentiometer are used to convert the movement captured and interpret them as electrical signals. This measurement system can be used to predict the gait parameters once the angles of each joint, and the length of the limb segments, are known.

Figure 2.3 Electrogoniometers used at the ankle and knee (left) and hip and waist (right) adapted from [25].
- **Force pressure sensors**
  The pressure sensors are mainly used to determine the pressure distribution of the foot during the gait cycle. This information can then be used to determine the stability during the gait. The most commonly used sensor types are capacitive and conductor based sensors.

  Fixed floor-mounted pressure sensors and pressure insoles are used to investigate the pressure distribution beneath the foot during gait. An illustration of an insole shoe fitted with pressure sensors during walking, at different health states, is shown in Figure 2.4.

![Figure 2.4 Pressure distribution comparison between different types stages of walking using an insole shoe pressure sensors adapted from [25].](image)

- **Electromechanical switches**
  Foot switches are used to determine the timing of gait phase events precisely. The switches are placed on the heel and on the toe so that the heel strike and the toe land events can be determined.

- **Camera-Based Systems**
  Camera based systems offer a noncontact means of recording and reviewing motion of the entire body. Still photography uses a large frame camera to record motion by multiple exposures with interrupted light, commonly called strobe light photography. The number of pictures taken for gait analysis is usually 10-20
pictures per second [23]. The subject is usually dressed in black clothing and on
the clothing reflective markers are applied on the lateral sides of the thigh, leg
and foot. These markers are used to track the motion trajectories of the body
parts.

- **Accelerometers**

  There are two basic types of commercially available accelerometers. These
are the piezoelectric and the piezoresistive accelerometers. Piezoelectric
accelerometers are like damped mass spring systems in which a piezoelectric
element acts as a spring and a damper. An applied mechanical force generates an
electrical charge in the element from which the acceleration can be measured.

  Piezoresistive accelerometers use a silicon resistor whose electrical resistance
changes in response to a mechanical load. These sensors are made from a surface
micro machined polysilicon structure built on top of a silicon wafer. Polysilicon
springs suspend the structure over the surface of the wafer and provide a
resistance against acceleration forces. There are several ways in which the
acceleration can then be measured. One possibility is to connect the resistors in a
Wheatstone bridge configuration to produce a voltage proportional to the
amplitude and the frequency of acceleration of the small mass in the sensor.
Alternatively, a differential capacitor consisting of central plates attached to the
moving mass and the fixed external plates can be used. An applied acceleration
will unbalance the capacitor, resulting in an output wave with amplitude
proportional to the applied acceleration.

  Piezoresistive accelerometers are smaller than piezoelectric accelerometers.
Miniature piezoresistive accelerometers are sensitive to constant accelerations,
such as the acceleration due to gravity whereas piezoelectric accelerometers do
not have any D.C response. They are commonly used as tilt sensors while
piezoelectric accelerometers are commonly used for vibration monitoring. Recent
researches in human movement have favoured pizoresistive accelerometers
because the DC response helps in the calibration of the device by rotating the axis
within the gravitational field.

  Gage, et al., [26] has used accelerometers to determine the vertical and
horizontal accelerations of the trunk as well as the angular acceleration of the
shank analysing human gait. Researchers in the past [25] placed multiple accelerometers on different parts of the body (head, hip, shank) for measuring gait parameters, while [27] studied the effect of soft tissue vibrations on accelerometer measurements when mounted on skin. Shock foot impacts have also been studied using accelerometers with a force platform.

Because accelerometers have been found to be a compact and useful tool for human movement monitoring in an unsupervised environment, we decided to use a single waist mounted accelerometer in our studies. An example of a triaxial accelerometer being worn on the waist for daily physical activity classification is shown in Figure 2.5 [28].

![Figure 2.5 A triaxial accelerometer being worn around the waist area.](image-url)

### 2.5. Gait models

Gait models are developed to comprehend the complex nature of the gait. A wide range of mathematical gait models have previously been proposed to study human walking. Cavagna et al., [29]) developed the first and the simplest of all gait models, which is the inverted pendulum. It was found that the waist movement when walking on flat ground can be roughly approximated by the movement of an inverted pendulum. The model is used to study the changes in kinetic and potential energy during walking at natural speeds. While only a rough approximation, given its relative simplicity, the model has been used extensively in many areas such as:

- Explaining the observed changes in duty factor and ground force pattern with walking speed [30-32]
• Studying the dependence on leg stiffness of vertical movements of the centre of mass in walking and running [33]
• Simulating the time of swing in walking at normal speed [34]
• Studying stability of walking in the absence of active muscle control [35, 36].

The simple model has the advantage of having only a small number of variables and hence, the relationship between the cause and the effect is easier to understand. While the inverted pendulum predicts the fluctuations of kinetic and potential energy which oppose one another during normal walking [14], it does not produce real ground force pattern of the foot during gait.

Many scientists have also built models with multiple joints that are actuated by net moments rather than muscles [37-40]. Although these models have added insights of the mechanics of normal walking, they do not provide detailed information about the functional roles of individual muscles during the gait cycle. Nonetheless, simple models are helpful in identifying some basic features of muscle function. On the other hand, complex models have been built to explain muscle’s motion coordination [41-44]. One major difficulty with these models is the need of having many sensors attached to the subject’s body, which can be impractical in an unsupervised environment.

2.5.1 Inverted Pendulum model

![Figure 2.6 The Inverted Pendulum model adapted from [14].](image)

The inverted pendulum (Figure 2.6) is modeled by a stick and a mass which represents the leg and the centered mass of the body. The centre of mass is constrained to move on a circular arc, the radius of which is equal to the length of the
leg, \( l \). The vertical position of the centre mass can be written as a function of leg angle \( \theta \) as

\[ s = l \sin \theta \quad (2.1) \]

\[ \ddot{s} = l(\cos \ddot{\theta} - \sin \ddot{\theta}^2) \quad (2.2) \]

where, \( \ddot{s} \) is the second derivative of \( s \), which represents the vertical displacement of the hip, and \( \ddot{\theta} \) is the second derivative of leg angle. It was shown by Pandy [14] that the inverted pendulum is not an appropriate model for studying vertical movements of the centre of mass and ground reaction force in walking. This is because firstly, the inverted pendulum only models the swing phase and not the stance phase during gait. Secondly, the inverted pendulum model is not able to model the ground reaction force patterns correctly. Thirdly, the inverted pendulum model does not include the effect of the muscle’s vibration of the gait.

### 2.5.2 The Spring Mass model

Each of the human segments can be modeled as a spring, mass and dampener [25]. Each of the body segments could be formulated as:

\[ M \ddot{s} + c \dot{s} + ks = 0 \quad (2.3) \]

where, \( s \) is the displacement, \( M \) is the mass, \( c \) is the damping coefficient, and \( k \) is the spring coefficient. Each basic element can be cascaded to form a representation of a human body. This model can be illustrated in Figure 2.7.

![Biomechanical model of muscles of a human](image)

Figure 2.7 Biomechanical model of muscles of a human, where \( M \) is the mass, \( k \) is the spring constant and \( c \) is the damping coefficient.

Nigg and Herzog [25] have investigated the influence of the elastic and viscous properties of the heel pads, shoe soles and various surfaces on the energy demands.
during locomotion. In their experiments, they have used force plate sensors to determine the various models proposed as shown in Figure 2.8.

In order to provide an accurate description of the gait, each of the body segments’ mass has to be measured precisely, although it is difficult to determine the spring and dampener coefficients.

2.5.3 Complex model

A substantially complex 3D musculoskeletal model of the body was developed by Pandy in [14] to evaluate the contributions of individual muscles to the ground force pattern in normal walking. The model includes six determinants of normal walking: hip flexion, stance knee flexion, stance-ankle plantar-flexion, transverse pelvic rotation, pelvic list and lateral pelvic displacement [46].

The skeleton is represented as a mechanical linkage with 10-segments, 23-degrees-of-freedom (Figure 2.9). The first six degrees of freedom defined the position and orientation of the pelvis relative to the ground. The remaining nine segments branched out in an open chain from the pelvis. The head, arms and torso
are represented as a single rigid body articulated with the pelvis via a ball and socket joint located at the level of the third lumbar vertebra. Furthermore, each hip is modeled as a ball and socket joint having three degrees of freedom: hip flexional, internal-external rotation permitting transverse pelvic rotation and abduction-adduction permitting pelvic list. Each knee is modeled as a single-degree-of-freedom hinge joint allowing only flexion and extension. In addition, each ankle-subtalar complex is modeled as a universal joint with two degrees of freedom: ankle plantar flexion and subtalar inversion-eversion contributing to lateral pelvic displacement). Each foot is represented by two segments: a hind-foot and a toes segment, hinged together by a single degree-of-freedom metatarsal joint. Five damped springs were placed under each foot to model the interaction of the feet with the ground [47, 48].

The skeleton model is actuated by 54 muscles, and each muscle was represented by a contractile element with realistic force-length-velocity properties, and a combination of series and parallel-elastic elements with active and passive stiffness properties. Tendons were assumed to be elastic. Ligament action was also included by exerting torques at the joints to prevent anatomically-infeasible joint angles from arising in simulation.

Walking was simulated by solving a dynamic optimization problem which minimized the metabolic energy consumed by the muscle in the model, per unit distance traveled. Metabolic energy was calculated by summing the heat liberated during muscle contraction and the mechanical work done by the muscles to move the joints. Furthermore, the body’s consumed metabolic energy can be formulated as:

\[ \dot{E} = \dot{A} + \dot{M} + \dot{S} + \dot{B} + \dot{W} \] (2.4)

where \( \dot{A} \) is the activation heat rate, \( \dot{M} \) is the maintenance heat rate, \( \dot{S} \) is the shortening heat rate, \( \dot{B} \) is the basal metabolic rate, and \( \dot{W} \) is the work rate [47, 49-51]. The dynamic optimization problem is solved by using parameter optimization and high performance parallel computing.
Bessonnet et al., [15] have tried to synthesise human gait using a parametric optimization method for a biped robot. Dockstader et al., [16] developed a 3-D tracking system for feature extraction of human gait patterns using videography methods. However, these sophisticated models are difficult to be used for daily physical activity monitoring.

2.6. Triaxial accelerometer sensor and signals

The gait acquisition system used in this research consisted of a wearable Triaxial Accelerometer (TA) unit (Figure 2.10) connected by a wireless link to a receiver unit (the computer for recording) via bluetooth.

The TA unit contained a single Triaxial Accelerometer chip sensor, a push button, a Bluetooth transmitter and a rechargeable battery. The components were enclosed in a small case (71mmx 50mm x 18mm), which could be clipped to a belt. The recorded signal consisted of three data streams measured in mili-gravity (mg) scale where 1 g
corresponds to the earth’s gravity value of 9.87 m/s². The sensor was set to have a dynamic range of ±3g and it has a resolution of 0.003 g.

The idea of making a machine that is capable of recognizing gait patterns using a single TA sensor is not a very new idea [22]. However, the popularity of the research in this field has increased significantly in recent years, coinciding with the maturing of the development of faster Digital Signal Processors and also the portability of sensors.

A major motivation is the need for automated movement monitoring in unsupervised environments of an ageing population in order to reduce costs of health care. The TA sensor provides three data streams which correspond to acceleration along three orthogonal axes labeled X, Y, and Z. Based on the mounting on the right hip, the X-Axis is aligned to capture antero-posterior movements, the Y-Axis is aligned to capture the medio-lateral movements and the Z-Axis is aligned to capture the vertical movements.

A machine learning approach for gait classification can be generalized as a two stage process: extracting relevant features from the TA signal and classifying the extracted features into a pre-specified gait pattern class based on a pre-trained classification model.

2.6.1 Feature Extraction

In an automated classification system, the front end is as critical as the back-end and it will greatly affect the performance of the overall system. The front-end removes all the data redundancies and retains the discriminating features. Various feature extraction methods have been investigated from accelerometry data, some of these features includes temporal features [52-54], spectral features [55-57], and time-frequency features [18, 58, 59].

- **Time Series Analysis**

  Time series analysis is usually the first analysis which is performed on any time related signals as these analyses are usually easier to interpret and contains information that can be directly seen from the signals. In gait analyses, time series features are usually used to detect the amplitudes and timings of key events (foot-strikes) during the gait cycle. Many common statistical parameters are used for gait features such as the mean, standard deviation, local maxima and minima,
zero crossings. An advantage of using time series parameterization for gait feature extraction is the ease of understanding the actual gait events. On the other hand the time domain characterizations (features) are usually large in dimensions which can be a burden for simple signal processors [60, 61].

- **Spectral Analysis**

  Spectral analysis provides information of the frequency content of the signal. This analysis assumes that the signal is stationary. Spectral analysis is usually done by performing a Fourier Transform to the signal being analysed. Spectral analysis has been used extensively in gait analysis. Mostayed et al., [62] employed a DFT method to analyse the joint angle characteristics in the frequency domain by using the harmonic coefficients for abnormal gait recognition. In another example, Barton and Lees [63] obtained 128 Fourier coefficients by transforming the hip-knee joint angle diagrams and reducing the initial 128 coefficients to 8 coefficients only by selecting the lower band coefficients only. The reason of selecting the lower band frequency is that the gait is predominantly a low frequency activity.

The main limitations of the Fourier transform method for gait analysis nonetheless, can be summarised as follows:

- Fourier analysis loses the time domain information such as localising events at different gait phases and other temporal variations like the stride to stride variation.

- Both non-stationary and nonlinear properties of the time series data can induce harmonic components that will cause the spreading of energy across the whole frequency band, which in turn, will introduce misleading information.

- The gait is a non-stationary event, which means that the gait will vary slightly from stride to stride so therefore, it is not suitable to be analysed using the Fourier transform where the signal is assumed to be stationary.

In order to overcome the limitations of detecting the temporal changes in the signal in the spectral method and the stationarity of the signal, the spectrogram (also known as the short-time Fourier transform (STFT)) is used. The STFT is a Fourier Transform calculated over a short time period (window). During this
short time period (window), it is assumed that the signal characteristics remain stationary. The STFT uses a sliding window which moves along with time to create an overall analysis in the time and frequency domain. Window length selection needs to be adjusted to the signal event that needs to be captured.

- **Wavelet Decomposition**

  As an alternative to the STFT, the wavelet analysis that has been used as an analysis tool to derive time-frequency features in biomechanics and gait analyses [18, 58, 64], is attracting more attention over the last decade.

  The wavelet transform has offered a better time-frequency resolution as it has larger windows to capture the periodicity at the lower frequencies and smaller windows to capture the fast events in the high frequency. With wavelet analysis, the original signal is decomposed into a series of coefficients containing both spectral and temporal information about the original signal. It is possible to determine from these coefficients localized events at which there is a change in spectral characteristics of the original signal. This concept has been applied successfully to accelerometry signals [58] to determine the movement transitions from one event to another. Sekine et al., [64] have initiated the use of wavelet packets to decompose accelerometry based gait signals for gait classification purpose. Wavelet packets are a generalization of the concept of the wavelet transform in which an arbitrary time–frequency resolution can be chosen in conformance with the signal.

  In the discrete wavelet transform, the filtering is performed recursively only on the approximation signal. However, with wavelet packets, the filtering is performed not only on the approximation signal, but also on the detail signal. The means and the standard deviations of these wavelet coefficients are used as features in the past for a three gait pattern (stairs up, stairs down and flat) classification. They have reported that the values of the anterior-posterior (X-Axis) and the vertical (Z-Axis) can be used to discriminate the three gait patterns. Their algorithms are then further developed and used by Wang et al., [20] for a five gait pattern classification. The wavelet packet decomposition from a 50Hz accelerometry data is shown in Figure 2.11.
The sum of squared wavelet coefficients from level 2 to 6 (corresponding to 0.39Hz – 18.75Hz) were calculated from the anterior-posterior, medio-lateral and vertical axes. These frequency ranges were assumed to be the possible accelerations that came from the human gait when measured at the hip. Standard deviations and root mean square values of these bands are used as features. Wang et al., [20] reported that 33 features were selected and used for five gait pattern classification problems.

Although many previous wavelet based studies have investigated level walking, stair ascent, and stair descent [18, 58, 64], there has been lack of comparison of their performance with simple approaches. Recently, Preece et al., [65] have made a comparison of many previously reported time domain and frequency domain features (including the wavelet) and concluded that the accuracy were found to be similar. They have reported that the derived Fourier Transform (FT) features outperformed the wavelet derived features when the various characteristics of the activities can be distinguishable from the frequency signal. Furthermore, there are no references on how to select the mother wavelet.
• **Hilbert Huang Transform**

The Hilbert Huang transform has recently been proposed as a decomposition method to analyze gait signals [21]. The Hilbert-Huang transform is a two-step process namely:

1. Empirical mode decomposition (EMD)
2. Hilbert Transform

The EMD is an adaptive signal processing which are usually used to process non-linear and non-stationary signals. The EMD decomposes the signal into intrinsic mode functions (IMF) which reflects various intrinsic components and also signal dependence. The EMD differs from most decomposition methods because it adapts to the local characteristics of the data. The decomposed IMF’s can be transformed to an analytical time series using the Hilbert transform.

The EMD uses the envelopes defined by the local maxima and minima separately to derive the mean envelope adaptive to the highest intrinsic frequency trend of the signal. The intrinsic mode function is then defined as the highest mode function derived from the difference between signal and mean of the envelopes. At the decomposition stage, cubic splines are used to join the extrema (maxima and minima points) to create the envelopes. The difference between the sample data point and the mean of the envelope created gives the first component. The sifting process acquiring the extrema and interpolating the points and calculating the mean is repeated until the IMF conditions are fulfilled. It means that firstly the difference between numbers of extrema and zero crossing must be equal to zero or one; secondly the mean of the upper and the lower envelope is zero. When the component satisfies these two conditions mentioned, it is verified as an intrinsic mode function (IMF) and is noted by $c_1$. The difference between data and the first residue denoted by $r_1$ and treated as the signal for decomposing the signal to obtain the next IMF. The decomposition process can be repeated until the residue becomes monotonic.

Wang et al., [21] used the Hilbert Huang transform to decompose the accelerometry gait signals for the purpose of gait classification. They used of the root mean square values of the IMF and Instantaneous Frequency values for classification of five gait patterns. The instantaneous frequencies are defined as the derivative of the phase response Hilbert transformed IMFs. Their proposed feature extraction process is shown in Figure 2.12.
On the whole they have used a total of 20 features for five gait pattern classification problems.

2.6.2 Classifiers

The back-end system has the main task of making decisions of which class an incoming set of features belongs to. The backend is usually pre-trained using sets of training data to equip it with the required knowledge to make decisions. The following section will discuss several classifier systems used for gait pattern classification. A block diagram of the overall classification system is shown in Figure 2.13.
• **K Nearest Neighbour (K-NN)**

The basic K Nearest Neighbour algorithm classifies an example from the test data by finding the K examples in the training data to which it is most similar. The typical measure of similarity is the Euclidean distance metric, though other measures such as Mahalanobis distance can be used. The classification assigned to the test database example is based on which class a majority of these K Nearest Neighbours has in the training data.

There are many variants on the basic K-NN classifiers reported in the literature and a number of these have been investigated including:

- Weighting the contribution of each K-NN that makes a class score based on transformed versions of its similarity metric.
- Compensating the score calculated for each class based on the number of examples of that class in the training data.

• **Linear Discriminant Analysis**

Linear Discriminant Analysis (LDA) works based on the assumption that each class has a multi-variate normalized probability distribution function with the same covariance matrix. Under such assumptions, an optimum classifier (in the sense of minimizing the total number of misclassifications) can be determined. Further extensions of the LDA include Quadrature Discriminant Analysis (QDA) and Regularised LDA (RLDA). The QDA analyses assume that each class is normally distributed with different covariances matrices, while on the other hand the Regularised LDA creates a model based on covariances matrices which are weighted mixtures of those used in LDA and QDA. In general, the RLDA classification equation is a generalized equation which also describes both LDA and QDA cases.

• **Artificial Neural Networks**

An artificial neural network (ANN) is a computational system inspired by the learning characteristics and a structure of biological neural networks. ANN has been widely utilized as a pattern learning system or classification system. The fundamental computational unit in a Neural Network system is called the perceptron [66]. A perceptron consists of multiple weighted inputs with an
activation function which determines the values of the output. Generally a sigmoid function is used as the activation function as it provides continuous output which varies from 0 to 1 as the input ranges from \(-\infty\) to \(\infty\).

A single perceptron has limited linear decision boundaries which limits the differentiation capabilities in the pattern space. In order to overcome this issue, a multilayer perceptron is used. A multilayer perceptron is a cascade of multiple layers of perceptrons which enables the system to create complex decision boundaries. There are many algorithms which can be used to train the ANN; one of the simplest is the backpropagation algorithm which tries to adapt the weights by minimising the cost function. Aminian et al. [17] applied the ANN to estimate the slope of walking on inclined surfaces. Wang et al., [20] employed the ANN as a classifier to differentiate five gait patterns. Begg et al., [67] used the ANN to detect gait patterns changes due to ageing.

- **GMM Classifier**

In this study, the Gaussian Mixture Model (GMM) is applied as a statistical modeling tool to classify different gait patterns. For the purpose of the classification process, a GMM is trained for each class, so that it models the probability distribution function of the feature vectors representing that class. The classification process can be explained as follows.

Given an ensemble of training feature vectors \(X = [x_1, x_2, \ldots, x_L]^T\), where \(x_k \in \mathbb{R}^d\), and assuming that the \(L\) vectors are statistically independent and identically distributed, the likelihood that the entire ensemble has been produced by one walking class \(G_l\) is

\[
p(X = [x_1, \ldots, x_L]^T | G_l) = \prod_{k=1}^L p(x_k | G_l) \tag{2.5}
\]

If we assume that the probability density function of a vector can be expressed with a mixture of Gaussian distributions, then

\[
p(x_i | G_l) = \sum_{k=1}^L p(k | G_l) p(x_i | k, G_l) \tag{2.6}
\]

where \(P(k | G_l)\) is the prior probability of Gaussian \(k\) for walking class \(l\), \(p(x_i | k, G_l)\) is the likelihood of vector \(x_i\) being produced by Gaussian \(i\) within walking class \(G_l\), and

\[
p(x_i | k, G_l) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_{k,l}|}} \exp \left( -\frac{1}{2} (x_i - \mu_{k,l})^T \Sigma_{k,l}^{-1} (x_i - \mu_{k,l}) \right) \tag{2.7}
\]
is a multivariate Gaussian distribution. The parameters of this Gaussian distribution are the mean vector $\mu_{k,l}$ and the covariance matrix $\Sigma_{k,l}$, which we constrain to be a diagonal matrix.

During training, we extract all feature vectors from data belonging to a walking class $G_i$, and our task is to learn the parameters of each Gaussian mixture, i.e. the mixing weights, the mean vectors and the covariance matrices. We achieve this goal using the Expectation Maximisation (EM) algorithm. EM is an iterative algorithm that computes maximum likelihood estimates (Dempster, 1977). The initial Gaussian parameters (means, covariances, and prior probabilities) used by EM can be generated via the $k$-means method [68].

Once the Gaussian mixture model parameters for each walking class have been found, determining the class for a given test feature vector is straightforward. A test vector $x$ is assigned to the class that maximizes $p(G_i|x)$, which is equivalent to maximizing $p(x|G_i)p(G_i)$ using Bayes’ rule. When each class has equal a priori probability $p(G_i)$, the probability measure is simply $p(x|G_i)$. Therefore, the test vector $x$ is classified as the walking class $G_i$ that maximizes $p(x|G_i)$.

- **Support Vector Machine**

  Support Vector Machine (SVM) classification engines are an example of a linear classifier and as such share many fundamental characteristics with perceptron based neural networks. A linear SVM classifier determines a set of hyper-planes which implement a decision boundary in the K dimensional input feature space resulting in a 2 class classification system. SVMs differ from perceptron models in the criterion that it is used to determine the optimum position of the hyper-plane. In the case of a perceptron network, the optimization criterion is the minimization of mean squared error across the training set whereas with a linear SVM model the maximization of the “margin” (or “separation”) between classes is the criterion used. In practice, it is unlikely that a single set of hyper-planes will correctly separate the feature space so that all examples of the 2 classes in the training set are correctly classified and hence the concept of a “soft margin” was introduced to handle this likelihood. This effectively results in a “penalty” for each example in the training set that is
misclassified (which is represented by the constraint factor). The optimization criterion is altered to factor in consideration of this misclassification in addition to maximizing the margin.

An additional enhancement that is widely used with SVM is the use of the “kernel trick”. This is used to implement a non-linear classifier by transforming the input feature vector space into a higher dimensional space. In this way the resultant decision boundary implemented by the hyper planes in the higher dimensional space is likely to implement a nonlinear decision boundary in the original input feature vector space. The most commonly used kernel functions are polynomial and radial basis function (RBF) kernel function.

2.7. Summary

This chapter has reviewed the scenario of the overall problem of gait assessment. This includes the discussion of the various sensors for capturing and observing the gait, signal processing methodologies for analyzing the captured data, model development for providing a simpler characterization of the gait, and gait classification systems for determining various gait patterns. The chapter initially discussed the biomechanics and terminologies of human gait. It is then followed by the discussion of time-frequency signal analysis tools including the importance of each method in finding suitable features from the Triaxial accelerometer signal. Although these features reported in literature have been reported to produce reasonable gait pattern classification accuracies, they do not provide insights into what information has been extracted from the accelerometric signal.

Gait models have been developed to understand the mechanism underlying walking. In this chapter, several existing gait models have been discussed to outline their advantages and limitations. Although the simple gait models that have been developed are easy to understand, they are limited in their accuracy in describing gait. On the other hand, while complex models are accurate in describing gait, it may not be possible to implement them under all circumstances due to high system complexity. In this study two gait models, aimed to strike a balance between accuracy and simplicity, are proposed and investigated in the following chapter.
Chapter 3
Proposed Gait Models

3.1. Overview
As mentioned in Chapter 2, due its complexity, it is extremely challenging to understand the nature of the gait. In order to understand in detail the nature of the gait patterns, gait models are developed. Two gait models are developed to assist in simplifying the nature of the gait, namely the Linear Predictive model and the Harmonic model. Furthermore, the models’ parameters are investigated with the motivation of using them for classification features.

3.2. Gait Data
The gait database used for analysis has been collected by monitoring various conditions of 52 people’s movements by using the Triaxial Accelerometer (TA) Sensor and Signals. Each person was asked to repeat the task for 10 iterations for each dataset. Prior to the data collection, each subject’s age, height, and weight were recorded.

There were three types of datasets that were collected, namely:

- Dataset of the 5 gait pattern classes: flat, slope down, slope up, stairs down and stairs up.
- Dataset of various walking speeds.
- Dataset of different foot strikes.

3.2.1 Dataset of the 5 gait classes and analysis
The 5 gait class dataset was collected using a single waist-mounted accelerometer placed on the right hip. The data was collected from 52 subjects, 13 of whom were female and 37 males. Their ages were between 21 and 65 years old with a mean of 30 years old, heights between 1.52 and 1.83 m and weights between 42 and 94 kg as shown in Appendix A.
The subjects were asked to walk on a flat surface, a ramp going down, a ramp going up, stairs going down and finally stairs going up. Each subject was asked to perform 10 iterations, each of which was about 3-6 minutes in duration. A sample of these datasets can be seen in Figure 3.1.

Some of the observations of the five gait data from Figure 3.1 are as follows:

- The X-Axis acceleration signal of the stair walking signal (up and down) and slope up are small when compared to flat walking and slope down.
- The Y-Axis acceleration signals are similar in terms of amplitude however, the flat walking and slope down acceleration signals have more complex patterns when compared to the other three walking patterns (slope up, stairs down and stairs up).
- The Z-Axis acceleration signals of the flat walking, slope down and stairs down are higher in amplitude when compared to slope up and stairs up.

### 3.2.2 Dataset of the variable walking speed and analysis

The variable walking datasets were collected using a single waist-mounted accelerometer placed on the right hip. The subjects were asked to walk on a treadmill for the duration of 10 minutes at speed set by the treadmill. The treadmill was initially set at a low walking speed of 3km/h to represent a very slow walking speed.
This was then increased by 1km/h increments until 7km/h, which represents the fastest walking before the person actually starts to run. After each ten minutes, the subjects were given a day’s rest to avoid fatigue affecting the gait data. The time-frequency plots for the various speeds are shown in Figure 3.2.

Some observations that can be made from Figure 3.2:

- The gait signal has some harmonic components in its spectral. As the walking speed increases, the harmonics are more prominent and are shown by the red parts of the spectral. Furthermore, the harmonics shift to a higher frequency as the speed is increased.
- It is also observed that as the speed is doubled e.g. from 3km/h to 6km/h, the harmonic frequencies do not double. It is observed and investigated in [69] that a human tries to compensate for the increase of walking speed not only by increasing their step rate which relates to the frequency, but by increasing their step length as well.

### 3.2.3 Dataset of the different foot-strike and analysis

The various foot-strike walking datasets were collected using a single waist-mounted accelerometer placed on the right hip. The next experiment was performed to investigate the effect of different foot-strikes. Firstly, each of the subjects was
asked to perform a stomp motion with the aim of investigating the effect of the foot-strike motion towards the signal captured at the waist. A sample signal of the foot-strike motion is shown in Figure 3.3.

![Figure 3.3 Z-axis signal of a foot-strike captured through the hip TA: (a) time domain; (b) amplitude spectral.](image)

The foot-strike mostly involves that Z-Axis motion, but it was also found that the three axes of the TA are coupled and the other two axes were also affected. Furthermore, it can also be seen in Figure 3.3 (b) that the foot-strike acted like an impulse which ideally has a flat spectral. Due to the human body’s resonant vibration muscle frequency [70] which lies in the frequency range of 5-10Hz, the frequency response of the stomp motion of the human body peaks at the 5-10Hz frequency range.

To further investigate the foot-strike motion, the subjects were also asked to walk on flat ground using sport shoes, to imitate a soft strike and hard sole shoes to imitate hard strike. The effects of the foot-strikes are then compared and investigated as shown in Figure 3.4.

![Figure 3.4 The foot-strike comparison plot (a) soft shoes (b) hard sole shoes. Blue, green, and red plots correspond to X,Y,Z axes respectively.](image)
It can be seen from Figure 3.4 that walking with soft sole shoes has a lower acceleration amplitude than hard sole shoes. It can also be seen that the Y-Axis has the least acceleration because the human gait does not have large medio-lateral acceleration when compared to the anterior-posterior and vertical acceleration. The Z-Axis (vertical) acceleration has the highest values because it is directly aligned with direction of the foot-strike force.

3. 3. Definition of Gait Models

In order to model a gait, it is necessary to understand the physiological nature of the gait cycle. A gait is a combination of coordinated muscle movements which drives the joints and body segments. This enables the body to make a set of movements which form the gait cycle. In this study, gait is characterized by the output of a single Triaxial Accelerometer (TA). It is important to understand how the sensor actually captures the gait signal. Apart from measuring the acceleration due to body movements that affect the sensor, the TA piezoresistive sensor also measures gravity acceleration. Based on previous research [22], the gait’s TA signal can be subdivided into gravitational (orientation), body and artefact accelerations, which are the accelerations due to the earth’s gravitational field, body movements and a combinations of foot-strike impact forces and muscle vibrations respectively. This can be written as:

\[ a(n) = a_{gravity}(n) + a_{body}(n) + a_{artifacts}(n) \]  (3.1)

where \( a(n) \) is the overall accelerometry signal.

It is hypothesized that the gravitational acceleration, the body acceleration and artefact acceleration would be different for each type of walking pattern investigated.

Gravity Acceleration

The piezoresistive accelerometers respond to gravitational acceleration. This is the acceleration of the human body caused by gravity. On the surface of the earth, the human body falls with acceleration (G) between 9.78 and 9.82 m/s\(^2\) depending on latitude. The gravitational acceleration at a point in space is given by:

\[ a_{gravity}(n) = -\frac{GM}{r^2(n)} \]  (3.2)

where M is the mass of the earth, \( r(n) \) is the distance between the centre mass of the earth and the centre mass of the human body. This acceleration is also referred to as...
the D.C. response or the static component. When the accelerometer is rotated, the gravitational response measured by the sensitive axis will change. The gravity acceleration component reflects the orientation of the device. When the sensor is not moving and positioned such that its Z-axis is aligned with the vertical, the acceleration measured will be equal to 1 g. An illustration of how the TA sensor captures the gravity acceleration during motion is shown in Figure 3.5.

![Image](image.png)

**Figure 3.5 Gravity Acceleration vector (red vector) pointing down towards earth.**

**Body Acceleration**

The acceleration due to body movement is also referred as the A.C component or dynamic component. These names accurately reflect the behavior of this component: if there is no body movement then the body acceleration component goes to zero. The body acceleration refers to the acceleration of the TA sensor location; in this study this is the acceleration of the right hip during the gait. A moving person on the other hand experiences accelerations throughout the gait cycle, resulting in the up and down movement of the centre of mass, which manifests as body acceleration, even during steady state locomotion. A walking person only experiences significant surging or transient acceleration when increasing velocity. The body acceleration is shown by the solid grey line [71]. A schematic of the body acceleration is shown in Figure 3.6.
Artefacts

The gait is driven by the coordination of muscle movement which move the body segments and joints to transport the body from one place to another. These muscle movements are also recorded through the TA sensor. Apart from the generated internal muscle movements, the body also moves due to external forces such as the impact motions of a foot-strike event. The vibrations resulting from muscle and tissue movements due to external sources are called the artefact. An example of the medio-lateral artefact acceleration in the Y-Axis captured at the hip is shown in Figure 3.7.

It can be seen in Figure 3.7 that the Y-Axis flat acceleration has a larger peak acceleration when compared to the stairs up walking. This is because the step length is limited by the stairs step size when a person walks on stairs. The step length is shorter resulting in the reduced medio-lateral sway of the hip.
3.4. Proposed Linear Predictive model for gait analysis

The motivation for using a linear predictive (LP) model is to model the gait as an all pole model, similar to how the vocal tract is modeled in speech analysis. The input to the gait model is considered as a pulse train which corresponds to the series of foot strikes. Furthermore, the transfer function of acceleration at the hip is modeled as a series of cascaded system spring mass models [25] where each of the spring mass systems as discussed in Section 2.5.2, can be modeled as a second order linear differentiation system. These cascaded linear differentiation systems can be represented using an all pole model which can be written as:

$$\hat{a}(n) = G u(n) + K + \sum_{k=1}^{p} c_k a(n - k)$$

(3.3)

where $\hat{a}(n)$ is the predicted output, $G$ is an arbitrary gain constant representing the force exerted by the foot strike, $u(n)$ is impulse train of foot-strikes, $K$ is the acceleration due to gravity, $p$ is the order of the LP model, $c_k$ is the $k^{th}$ coefficient of the LP model and $a(n - k)$ is the previous outputs of the LP model. Once the LP coefficients are found, the transfer function between the foot and the waist can be written as:

$$H(z) = \frac{G}{1 + \sum_{k=1}^{p} c_k z^{-k}}$$

(3.4)

By treating the foot-strike as an impulse input to the model and the hip acceleration signal as the output, it is necessary to determine the period of impulse train (which determine the step rate to be generated). The period is extracted by applying the Average Magnitude Difference Function (AMDF) [72] on the vertical axis of the captured signal, because investigation by Mathie [22] shows that this axis provides the most accurate step rate estimation of the gait signal. A simplified diagram of the proposed/developed walking gait model system construction is described in Figure 3.8.

![Figure 3.8 Gait model system.](image)
3.4.1 Linear Predictive parameter estimation

The artefact is modeled using a 30th order Auto Regressive (AR) system as an approximation the spring mass model which, resembling the fifteen second order spring mass systems [25] see Figure 2.7. The estimated output sample of a linear predictive system can be written as

\[
\hat{a}(n) = \sum_{k=1}^{p} c_k a(n - k)
\]  

(3.5)

The derivations of the LP coefficients \( c_k \) can be determined using the least squares approach, assuming first that \( a(n) \) is a deterministic signal on a small time scale. Here it is assumed that the input \( u(n) \) corresponds to the impulse foot-strike. Therefore the signal \( a(n) \) can only be predicted approximately from a linearly weighted summation of past samples. The LP coefficients \( c_k \) are found by optimization with respect to the error, which is the difference between the original signal \( a(n) \) and the estimate \( \hat{a}(n) \). The optimization is done by using the sum of the error squared as the cost function, written as:

\[
E = \sum_{n=1}^{N} e^2(n) = \sum_{n=1}^{N} \left( a(n) - \sum_{k=1}^{p} c_k a(n - k) \right)^2
\]  

(3.6)

Differentiating the cost function with respect to \( c_k \) and setting the result to zero to find the maxima yields:

\[
\frac{\partial E}{\partial c_i} = 2 \sum_{n=1}^{N} \left( a(n) - \sum_{k=1}^{p} c_k a(n - k) \right) (-a(n - l)) = 0
\]  

(3.7)

which for \( 1 \leq l \leq p \), will result in

\[
\sum_{k=1}^{p} c_k \sum_{n=1}^{N} (a(n - k)a(n - l)) = \sum_{n=1}^{N} (a(n)a(n - l))
\]  

(3.8)

where
\[ \sum_{n=1}^{N} (a(n-k)a(n-l)) = R(k-l) \quad (3.9) \]

and

\[ \sum_{n=1}^{N} (a(n)a(n-l)) = -R(l) \quad (3.10) \]

and the LP coefficients are found from

\[ C = -R_l R_{k-l}^{-1} \quad (3.11) \]

where \( R_l \) is the autocorrelation matrix, and \( R_{k-l}^{-1} \) is the inverse of the autocorrelation matrix.

Once, the LP coefficients were found, they were used to determine the goodness of fit of the model by using them to reconstruct the gait signal. The reconstructed signal was formed by passing an impulse train with the same period as the foot strike to the AR system formed by the LP coefficients. A sample result of a reconstructed flat walking gait cycle Z-Axis signal is shown in Figure 3.9.

Figure 3.9 One full gait cycle (Z-Axis) signal reconstruction using a 30th order LP model (red solid line : generated signal from the LP model; blue dashed line : original signal).

It can be seen from Figure 3.9 that the reconstructed signal shows a good fit to the original acceleration signals captured at the hip. This shows that the LP model is an appropriate model with which to characterise gait.

Another investigation on the effect of different foot-strikes (hard foot-strike VS soft foot-strike) was made using the foot-strike data described in Section 3.2.3. The
motivation of the comparison was to observe and investigate on how the different foot-strikes would affect the model’s parameter. The frequency response and the pole-zero plot of the foot-strikes (hard and soft) are shown in Figure 3.10.

![Figure 3.10 (a) The frequency response of the LP system of the hard foot strike shown in red solid line and soft foot-strike in blue dashed line and (b) The pole-zero plot of the hard foot-strike shown in red circles and soft foot-strike in blue crosses.](image)

It can be seen from Figure 3.10 (a), that the hard foot-strike system response provides higher peaks at frequencies up to 5 Hz. There are also variations in the higher frequencies in the frequency response of the model. This result agrees with the earlier investigations where the harder foot-strike would have resulted in higher energies as described in Section 3.2.3.

Furthermore, the LP model can also be analysed from the pole-zero plot. It can be seen from Figure 3.10b, that the poles magnitude of the soft foot-strike gait model are smaller than that of the hard foot-strike model in the lower 5-12Hz frequency region.
3.4.2 Variations of the Linear Predictive model to walking speed

The objective of this experiment was to investigate how speed affects the characteristic of the LP model’s parameters. The experiment was performed using the speed dataset described in Section 3.2.2. Based on visual observations, it was noticed that as people walked faster, they had a tendency to take larger steps instead of more steps to accommodate for the faster treadmill speed. In Figure 3.11, the frequency spectral of a subject’s 3 km/h walk is compared with that of their 6 km/h walk.

Figure 3.11 The gait speed frequency spectral (3km/h - solid line ; 6 km/h – dotted line).

In Figure 3.11, it is seen from the frequency spectral that the frequency components are not simply scaled up, but that the relative amplitudes of the different harmonics are changed, indicating that the walking style has also been affected.

Figure 3.12 The LP model’s pole zero plot comparison for 3km/h (blue) and 6km/h (red).

Furthermore, the LP parameters for different walking speeds are investigated and the plots are shown in Figure 3.12. It can be seen that pole positions have in general
shifted to a higher frequency position as a result of the subject taking more number of steps within a specific time period to compensate for the increase in speed. Furthermore, the locations of some poles have moved closer to the unit circle as a result of walking faster which would normally result in harder foot-strikes and higher energy and also more hip movement.

3.2.4 Comparisons of the five walking patterns

Further investigation on the LP model was carried out. This time, five gait patterns were observed; flat walking, slope down, slope up, stairs down and stairs up walking. The pole-zero plots for the five gait LP model are shown in Figure 3.13.

Figure 3.13 Pole-zero plots of the LP model comparison for different gait patterns from one data set of a subject (from top to bottom: flat, slope down, slope up, stairs down, stairs up; left to right: X-Axis, Y-Axis, Z-Axis).
It can be seen from Figure 3.13 that the location at the low frequency poles of the X-Axis flat walking, slope down and slope up are closer to the unit circle when compared to both up and down stairs gaits. This is because forward the motion of stair walking is limited due to the stairs’ step size.

Movement in the direction of gravity i.e. slope and stairs down, shows increased muscle artefact, which is located in the higher frequency poles, when compared with movement opposing gravity i.e. slope and stairs up, on all three axes. This is because as the body accelerates faster due to the addition of gravitational acceleration, a larger impact force is required to counteract the velocity gained. On the other hand, the upwards movement that opposes gravity has a slower acceleration so that when the foot strikes the ground impact forces will be smaller. This artefact acceleration is smaller.

3.5. Proposed Harmonic Model for Gait Analysis

In this study, the use of a harmonic model to describe the gait signal was motivated by the strong periodicity observed in gait patterns. Figure 3.14 shows the captured spectral of a TA gait signal. From this is can be seen that the gait signal contains harmonic patterns which suit the harmonic model.

![Figure 3.14 Magnitude spectral of a sample of flat walking from the TA signal placed on the right hip.](image)

Clearly, in any automatic analysis of gait signals it is desirable to model the signal as accurately as possible because accurate estimates of model parameters will contain characteristic information about the gait. Having said this, a model may be considered too detailed for classification purposes if its parameter estimates exhibit
too much variability, when applied to real data, to offer consistent characteristic information, since this is a prerequisite for a successful classification feature. The measured waist displacement of a gait cycle during walking on a flat surface can be approximated using the Fourier series [11]. This can be formulated as:

$$s_{\text{axis}}(n) = A_k + \sum_{k=1}^{N} A_k \cos(2\pi k f_0 + \phi_k)$$  \hspace{1cm} (3.12)

where $A_k$ is the $k$th harmonic amplitude, $f_0$ is the fundamental frequency which corresponds to the stride frequency, $\phi_k$ is the phase of the $k$th harmonic, $N$ is the total number of harmonics needed for the reconstruction of the displacement signal and the axis subscript refers to the direction of the displacement.

The fact that acceleration is the second derivative of displacement motivates the use of the harmonic model for gait pattern classification. Thus, the harmonic model for acceleration signal on the waist can be formulated as

$$a_{\text{axis}}(n) \approx \sum_{k=1}^{N} A'_k \cos(2\pi k f_0 + \phi_k)$$  \hspace{1cm} (3.13)

where $A'_k$ is the $k$th harmonic amplitude, $f_0$ is the fundamental frequency, $\phi_k$ is the phase of the $k$th harmonic, $N$ is the total number of harmonics extracted, and the axis subscript refers to the accelerometer axis. The parameters of greatest interest for classification purposes are $A'_k$ and $f_0$. The phase term $(\phi_k)$ would be needed only for reconstructing the gait signal from its parameterisation. In applications such as monitoring daily physical gait activities, classification is required to be performed independently of the stride cycle rate, in which case:

- $f_0$ is needed only to allow accurate estimation of $A'_k$.
- the $A'_k$’s are then independent of $f_0$ which is the fundamental period. It is a reasonable assumption that the harmonic frequency components of the various gait patterns investigated are different.

A harmonic model offers two advantages over other possible models for feature extraction:

- although it is not generative, it is demonstrated herein that its parameters can be reliably and usefully extracted. This is a more challenging problem for generative models; and
- unlike other features such as the Empirical Mode Decomposition (EMD) features [21, 73], wavelet-based features [20, 58, 59], spectral features [73],
the harmonic amplitudes are independent of the stride cycle rate i.e. they are normalised with respect to the walking rate.

3.5.1 Harmonic Parameter Estimation

The model is constructed by first estimating the fundamental frequency from the z-axis of the captured acceleration signal, since the z-axis contains the most reliable information about the stride cycle rate [22]. The fundamental frequency can be extracted in many different ways. Here, the signal is first filtered using an 8th order elliptical low pass filter with a cut-off frequency of 4 Hz. This is just larger than the fastest practical stride cycle rate which has been determined experimentally to be around 1-2 Hz). A period estimation method is then applied to the filtered signal on a frame by frame basis. The Average Magnitude Difference Function (AMDF) method [72] is used to estimate the fundamental period of the signal. The AMDF can be formulated as

\[
AMDF(n) = \frac{1}{N} \sum_{i=1}^{N} |a(n) - a(n - i)|
\]

from which the fundamental period \( f_0 = \frac{2\pi}{\omega_0} \) is given as

\[
f_0 = \frac{1}{(\arg\min_{n \in [n_{\min}, n_{\max}]} (AMDF(n)))},
\]

where \( n_{\min} \) and \( n_{\max} \) are limits on the range of the search for the fundamental period and are determined empirically.

Another way of estimating the fundamental frequency is from the maximum amplitude of the spectral. The frequency component with maximum amplitude corresponds to the step rate of the gait. With the assumption that the gait is symmetric, the fundamental frequency can be calculated by halving the step rate frequency.

Once the fundamental frequency is obtained, the \( A_k \) values are estimated from the gait signal using a harmonic extraction algorithm similar to that used by Paul [74]. Following the Discrete Fourier Transform (DFT) of \( a(n) \), harmonic peaks are found by searching within a specified interval around frequency multiples of the fundamental \( (f_0) \) for the largest peak value. The search is conducted over all bins in the intervals given by \([f_{k-1} + \alpha, f_{k-1} + \frac{3}{2} \alpha]\), where \( k \) ranges from 1 to 11, \( \alpha \) is \( f_0/2 \) and \( f_k \).
is the \((k-1)^{\text{th}}\) harmonic component obtained. For cases where no peaks are found within the searched region, the maximum of the endpoints is used.

### 3.5.2 Signal reconstruction using the Harmonic model's parameters

In order to determine the goodness of fit of the model, the Harmonic’s parameters were used to reconstruct the original signal gait signal. The phase and the amplitude of the first 12 harmonics were used for the signal reconstruction as there were little energy beyond the 12\(^{\text{th}}\) harmonics as seen in Figure 3.14.

![Figure 3.15 Comparison between the original signal (dotted - blue) and the harmonic generated signal (solid - red).](image)

The comparison between the original signal and reconstructed signal can be seen in Figure 3.15. It can be seen that the signal can be well reconstructed using the harmonic model, showing that it provides a good fit for the original walking signal. Therefore the harmonic model is an appropriate model to be used to characterize the gait.

### 3.5.3 Variations in the foot-strike

In observing the foot-strike event in detail, the effects on the harmonic model of hard and soft foot strikes more typical of normal walking were compared. In doing so, an experiment was conducted where the subject was asked to walk using hard soled shoes and also sport shoes with the assumption that a hard sole would provide a greater force as the foot strikes the ground compared to cushioned sport shoes as described in Section 3.2.3. Figure 3.16 shows the comparison between the harmonic amplitudes normalised with respect to the energy of the signal of hard soled shoes and sport shoes. In addition, the differences between the foot-strike energy can clearly be seen in the 5\(^{\text{th}}\) to 12\(^{\text{th}}\) harmonic. It can be seen that the 5\(^{\text{th}}\) harmonic onwards have higher amplitudes for hard soled shoes when compared to the soft
soled shoes. The more ideal impulse-like hard soled foot strike signal is more
spectrally flat than that of the soft soled foot strike, as would be expected. This
suggests that the harmonic components from these range (5 to 12) would be
important for classification.

![Graph showing normalized harmonic amplitude comparison between hard foot strike (squares) walking and soft foot strike (crosses) of the Z-Axis signal.](image)

Figure 3.16 Normalized harmonic amplitude comparison between hard foot strike (squares) walking and soft foot strike (crosses) of the Z-Axis signal.

3.5.4 Investigation of the harmonics

With the motivation of linking the gait characteristics such as the waist
movement and the muscle artefact shown in Equation 3.1 with the harmonic
parameters, the harmonic components were divided into two groups.
The first group is composed of the first four harmonics to determine the hip
movement (Figure 3.17, dashed line) or the body movement described in Equation
3.1. This assumption was made based on a study that was conducted by ([69]; [75])
who showed that the first four harmonics were sufficient to form a good
approximation for hip movement during a gait.

Based on the foot-strike investigation on the harmonic model, it can be seen that
the hard foot strike created by hard soled shoes has the impact of the spectral having
larger magnitudes in the region of 5-12 Hz. These assumptions suggest that the first
four harmonics are sufficient to model the hip movement signal. The first four
harmonics of the model were then used to reconstruct the signal and the comparison
result is shown in Figure 3.17.
Figure 3.17 Signal reconstruction of the first four harmonics (dashed line) compared with the body and artefact signal (solid line). Region A: The swing leg lifts off the ground as the flexes moving the gait cycle into a single support phase. During this phase the waist moves in a shallow arc rising and then falling and the peaks shows the swing foot hitting the ground. Region B: In this phase the both feet are on the ground or it is more known as the double support phase. Region C: In this phase the stance leg lifts off the ground and becoming the swing leg. Region D: This is the final cycle that ends with the double support phase.

It can be seen from Figure 3.17 that the first harmonic aligned well with the raw acceleration signal. This plot is similar to the hip movement curve that was reported by [69] where the author used markers to investigate the vertical displacement of the hip. Furthermore, this explains why the variation of the first four harmonics is lower when compared to the 5th to 12th range (Figure 3.16).

The second group is composed of the last 8 harmonics and is used to characterise the muscle artefact. This allocation is based on the understanding that the resonant frequency of the human body lies between 5-10Hz [70] and therefore these last 8 harmonics are used to capture this information. The result of harmonic signal reconstruction using the last eight harmonics representing the artefact from the foot-strike and muscles movements can be seen in Figure 3.18.

Figure 3.18 Comparison of the Harmonic generated signal using the last eight harmonics (which represent the artefacts from the footstrike and muscles movements (blue - dotted)) with the original captured signal ((red - solid)).
Motivated by the works of past researchers [76-80] who used the harmonic ratios i.e. between the even and odd harmonics, to measure trunk acceleration for gait stability studies, in this study the even and the odd harmonics are used to reconstruct the signal separately with the aim of investigating the contributions of the various harmonics of the signal. These results are shown in Figure 3.19.

They results are shown in Figure 3.19. The result showed that the odd harmonics have the same characteristics as the stride cycle (Figure 3.19b), whereas the even harmonics provide information on step rates (Figure 3.19a).

![Figure 3.19 Reconstructed signal using selected harmonic components: (dotted - reconstructed signal; solid - original signal) (a) even harmonics; (b) odd harmonics.](image)

The results from Figure 3.19 show that the alternate right and left swing of the gait phase are different from the odd harmonics signal reconstruction. This information could be useful in detecting swing and stance phases during the gait cycle. However, the even harmonics reconstructed signal does not differentiate between the left and the right swing. Thus the even harmonics can be used to determine the walking steps. The intention of the odd and even harmonics separation was to assess their relative performance as features for classification.

### 3.5.5 Variations of the harmonic model parameters to walking speed

The harmonic model is used for investigating a comparison and variation of different walking speeds. The objective of this comparison was to investigate how speed affects the characteristics of the harmonic model’s parameters. The speed
dataset as described in Section 3.2.2 was used for this experiment. As mentioned in Section 3.4.2, subjects had tendency to take larger steps and also more frequent steps to accommodate the increasing treadmill speed. In Figure 3.11, a subject’s 3 km/h frequency response is compared with that from a 6 km/h walk. It is seen from the frequency spectral that the frequency components are not simply frequency scaled to speed, but affect the relative amplitudes of the different harmonics, indicating that the walking style is also affected.

![Figure 3.20 Comparison of the harmonic model across different speeds.](image)

Furthermore, the harmonic parameters at different speeds are investigated and the plots are shown in Figure 3.20. It can be seen that most of the harmonic components normalised with respect to the total amount of energy of the spectral are very similar in value except for the second harmonic and the fourth harmonic where their variations are up to 0.08. The rest of the harmonics only have variations of 0.01. The main reason for this is the fact that as the speed is increased, the foot strikes the ground harder. This conclusion is based on observations during the data collection process. It can also be seen that this harmonic result is consistent with the flat walking (Z-Axis) result shown in Figure 3.21.

### 3.5.6 Comparison of the five gait patterns

Further investigation on the harmonic model was made by using the five gait pattern dataset as described in Section 3.2.1. This time five gait patterns were observed. These are flat walking, slope down, slope up, stairs down and stairs up.
walking. The five gait harmonic models for the named five gait patterns are shown in Figure 3.21.

![Figure 3.21 Harmonic model comparison for different gait patterns from one data set of a subject (from left to right: flat, slope down, slope up, stairs down, stairs up).](image)

From the harmonic model parameters, it can be seen that there is increased antero-posterior (X-Axis) movement in the flat and sloping gaits when compared with stairs because the stairs impose a fixed step size which is usually smaller than the step size used for slope and flat walking. Apart from that, movement in the direction of gravity i.e. slope and stairs down, shows increased muscle artefacts (harmonics five to twelve) when compared with the movement opposing gravity i.e. slope and stairs up. This occurs on all three axes because as the body accelerates faster due to the addition of gravitational acceleration, a large impact force is required to stop the extra velocity gained. On the other hand, movement opposing gravity i.e. upwards, has a slower acceleration because the muscle forces are being opposed by gravity. Thus the impact forces of the foot striking the ground will be smaller. From the Z-Axis, it can be seen that body acceleration is relatively increased (harmonics one to four) in the movements aligned with the gravitational direction when compared with movements which are opposing gravity. A schematic showing the relationship between the harmonic model and the gait’s captured TA signal is shown in Figure 3.22.
Figure 3.22 The Harmonic Model framework with TA signal.

There are several key gait parameters which can be found from the harmonic model. These include the step rate which can be found using the second harmonic frequency and also the timing of the gait cycle phases that can be determined from the odd harmonics signal reconstruction. In addition to this, the first four harmonics are shown to represent the body acceleration of the hip while the last eight harmonics determine the hardness of the foot strike.

3.6. Summary

In this chapter, the linear predictive and harmonic models of gait have been developed and analysed. The LP model is intended to model the transfer function between the acceleration of the foot and the acceleration of the hip with the foot-strike as input. The LP model is characterized by the pole zero plot, and several investigations have indicated that the poles shift to a higher frequency as the subject increases their walking speed. Results from this study showed that the poles move closer to the unit circle with a harder foot-strike.

The harmonic model tries to model the gait signal by exploiting its strong periodicity. From the investigation of the captured signal spectral, it was found that only twelve harmonics have significant values. It was also found that the even harmonics can be used to determine the number of steps that the subject has taken while the odd harmonics carry information about the differences between the left and right legs and can be used to determine the swing and stance phases.
The first four harmonics of the harmonic model can also be used to approximate the movement of the hip leaving the last eight harmonics to model the artefacts. The 5\textsuperscript{th} - 12\textsuperscript{th} harmonic magnitudes increase as the subject alters their foot-strike intensity from soft to hard strikes.

Both of these models can be used to extract features that may be useful for discriminating between different gaits. Various feature extraction techniques are outlined in Chapter 4.
Chapter 4

Proposed Features

4.1. Overview

In order to develop an optimal classification system, it is critical that the feature extraction stage is able to extract class specific information, or features, from the signal and remove redundant information which can confuse or degrade the classification system performance. This chapter proposes six novel feature extraction processes which could be used for gait pattern classification. Several of these features are derived from the gait models proposed in Chapter 3 namely the Linear Predictive Cepstral Coefficients (LPCC), the Filterbank and the Harmonic features. Other feature extraction methods are also proposed which are the spectral centroid features, the delta Zero Crossing Counts (ZCC) regression features and the Intrinsic Mode Function features. An overall overview of the feature extraction work in this chapter is shown in Figure 4.1.

Figure 4.1 Feature extraction roadmap.
Linear predictive cepstral coefficients are proposed instead of direct LP coefficients because they provide more robust features. This is due to the nature of the transformation which decorrelates the LP coefficients from each other. The filterbank features are proposed for gait pattern classification with the aim of providing an approximation of the LPCC features with a lower dimension. The spectral centroid features were then developed with the intention of adding frequency information into the filterbank features. Furthermore, the harmonic features are proposed with the aim of removing the speed variability from the filterbank features. The delta regression features are then proposed to capture dynamic variations from the gait signal. Lastly, as the gait has been identified as a non-linear process overall, the non-linear Empirical Mode Decomposition (EMD) method was used to extract IMF features for classification.

4.2. Proposed linear prediction cepstral coefficient features

As discussed in Chapter 3, the location of the poles of the LP system showed promising discrimination abilities between the five gait patterns observed. In this section the LP coefficients are investigated by mapping them onto a 2D plane using the Sammon non-linear mapping algorithm [81] to observe the class separation between the gait patterns. Using this mapping, it can be seen in Figure 4.2 that the LPC points for the five gait patterns are scattered all over the two dimensional plane. Therefore it can be concluded that the LP coefficients are not robust enough to be used directly for classification.

Figure 4.2 Nonlinear mapping of ninety (30 from each of the axis) Linear Prediction Coefficients of the five different gait patterns (flat – dot; slope down – triangle; slope up - asterisk; stairs-down – rectangle; stairs up - star).
As a result of this, LPCC were proposed as these cepstral coefficients have been successfully reported to provide better and more robust features than the LP coefficients (speech related classification systems). The reason is because the transformation provides decorrelation on the LP coefficients. These LPCC, are defined by the DCT of:

\[ d_0 = \ln(c_0^2) \]

\[ d_m = c_m + \sum_{k=1}^{m-1} \left( \frac{k}{m} \right) d_k c_{m-k} \]  

for \( 1 \leq m \leq p \), where \( c_m \) is the \( m^{th} \) LP coefficient, \( c_0 \) is the LP gain, \( p \) is the LP order and \( d_m \) is the \( m^{th} \) cepstral coefficient.

The discrete cosine transform (DCT) is a convenient approximation to the optimal decorrelating transform, the Karhunen-Loeve Transform. This transformation aims to at reducing the dimension of the features used for classification. This is possible because of the nature of the DCT, which transforms the original cepstral coefficients (Equation 4.1, 4.2) and compacts their energy into the first few basis functions. The resulting DCT coefficients are then analysed and a non-linear mapping of the LPCC features is created to determine the separation between the five gait patterns. The non-linear mapping is shown in Figure 4.3, from which it can be seen that the filterbank features within each gait class are grouped nicely. Thus the classes are more separable using LPCC features.

![Figure 4.3 Nonlinear mapping of the LPCC of five gait pattern. (flat – dot; slope down – triangle; slope up -asterisk; stairs-down – rectangle; stairs up - star).](image)

The LPCC features are derived from the LP model, and these features try to model the transfer function from the foot to the waist. It can be seen by comparing the Sammon nonlinear mapping of the LP coefficients (LPC) and LPCC that the gait
classes were more separable when the LPC were transformed into the cepstral domain.

4.3. Proposed filterbank features

Filterbank features are proposed for gait pattern classification with the aim of providing an approximation of the LPCC features with lower dimensionality. Three filterbanks for each of the axes were proposed to approximate the LPCC. The three bands correspond to the gravity acceleration, body acceleration and artefacts as shown in Equation 3.1. The energies within these three bands are hypothesized to be different for the various gait patterns studied.

The gravitational band was selected as 0-0.5Hz consistent with previous researchers [22]; [82] who used bands with upper cut off frequencies values between 0.25 and 0.5Hz. The main body acceleration band was selected to range from 0.5 Hz to 3.5 Hz. The basis for selecting this bandwidth was a separate experiment where the subjects were asked to walk at various speeds from 3km/h (which was considered as slow walking) to 7km/h (fast walking) on a treadmill where it was found that the stride frequency lies between 1 Hz to 3 Hz as shown in Figure 4.4. The artefacts bandwidth was selected as 3.5 Hz to 13.5 Hz because it was seen in Figure 4.4, that there is little energy beyond 13.5 Hz.

![Figure 4.4 Magnitude spectral of Z-Axis flat gait pattern with different speeds (solid – 3km/h; dotted – 7km/h).](image)

![Figure 4.5 Bands grouping allocation for the antero-posterior (Z-Axis) acceleration.](image)
Figure 4.5 shows an example of the filterbank grouping which consisted of the gravity acceleration, body acceleration and artefact. The bandwidth specification is listed in Table 4.1.

**Table 4.1 The bandwidth specifications of the bandpass filters**

<table>
<thead>
<tr>
<th>Feature Number</th>
<th>Axis</th>
<th>Bandwidth no.</th>
<th>Bandwidth (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>X</td>
<td>1(gravitational)</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>2(body)</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>3(artefact)</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>Y</td>
<td>1(gravitational)</td>
<td>0.5</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>2(body)</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>3(artefact)</td>
<td>10</td>
</tr>
<tr>
<td>7</td>
<td>Z</td>
<td>1(gravitational)</td>
<td>0.5</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>2(body)</td>
<td>4</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>3(artefact)</td>
<td>10</td>
</tr>
</tbody>
</table>

The overall signal processing algorithm of the filterbank feature extraction is illustrated in Figure 4.6. Furthermore, [82, 83] suggested that the body acceleration during walking can be approximated from the first few harmonics which lie between 0.5-4.5Hz. Lastly the artefact band is selected between 3.5-13.5Hz because [70] suggested that the resonance frequency of the human body lies in the 5-10Hz range while [84] mentioned that the resonance frequency may lie in the region vicinity of 20Hz. With this in mind and also observing Figure 4.4, the artefact band is selected as 3.5-13.5Hz as it can be seen that there are not much energy beyond the 14Hz region.

![Figure 4.6 Filterbank feature extraction diagram.](image-url)
The three axes accelerations are firstly windowed with the intention of processing the gait signal for a short enough duration that the signal can be assured to be stationary within the window. The magnitude spectral of the windowed signal is then obtained by taking the absolute value of the Fourier transformed window signal. The FFT magnitudes from each individual band (gravitational, body and artefact) and axis (X,Y,Z) are then grouped and appended. This process created a total of nine features (3 from each axis corresponding to the gravity acceleration, body acceleration and the artefact acceleration). The three energy bands are plotted against one another in Figure 4.7 and the two dimensional version of the Body Acceleration and the Artefact band are shown in Figure 4.8.

Figure 4.7 The Z-Axis filterbank energy features of the three bands (gravity acceleration – body acceleration – artefact) of a subject for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta crosses).

Figure 4.8 The Z-Axis filterbank energy features of the body acceleration vs. Artefact bands for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta).
The filterbank features were derived based on the assumption that the TA signals were composed of the gravitational acceleration, body acceleration and artefact acceleration. From the filterbank feature plot in Figure 4.7, it can be seen that the gravitational acceleration of the stairs up and slope up in the Z-Axis is smaller when compared to the other three gait patterns (flat walking, slope down and stairs down). This is because they are inhibited by the gravity acceleration. Furthermore, it can be seen that the acceleration along the Z-Axis for a person walking down is larger due to the gravity assisting the person’s acceleration.

In addition, the artefact acceleration of the walking down gait patterns are larger when compared to the walking up and flat walking because they are being assisted by gravity resulting in a faster walking speed. In order to avoid walking at a faster and potentially uncontrollable speed, they would use the braking motion of the feet and ankles (stomping motion) causing greater impact on the body. This results in having more energy in the artefact band.

On the other hand, the movement which opposes gravity the subject has a tendency to walk at a slower pace. No braking motion is required and therefore the artefact energy is small.

4.4. Proposed Spectral Centroid Frequency features

The spectral centroid is an alternative way to condense the information contained in the frequency spectral. It is a measure of the weighted mean frequency, using the spectral magnitudes as weights. Spectral centroid features are proposed for the application of gait pattern classification. These features are named Spectral Centroid Amplitude (SCA) and Spectral Centroid Frequency (SCF) and are extracted for both body acceleration and artefacts subbands. The spectral centroid amplitude (SCA) is then formulated as

$$SCA = \frac{\sum_i f_i K_i}{\sum_i f_i}$$  \hspace{1cm} (4.3)

Where $M$ is the number of sample points within the DFT subband, $f_i$ is the frequency and $K_i$ is the magnitude corresponding to the $i^{th}$ DFT coefficient. The SCF can be formulated as

$$SCF = \frac{\sum_i f_i K_i}{\sum_i K_i}$$  \hspace{1cm} (4.4)
An illustration of the SCA and SCF values and how they relate to the frequency spectral of the gait signal is shown in Figure 4.9.

![Figure 4.9 The SCA and SCF values and how they relate to the frequency spectral of the X-Axis flat walking body acceleration signal.](image)

It can be seen that the SCA value closely approximates the mean value of the subband energy while the SCF closely approximates the frequency corresponding with peak energy. The SCA and SCF are applied to the body and artefact bands of the TA signal. The feature extraction process is set out in Figure 4.10

![Figure 4.10 The SCA and SCF feature extraction process.](image)

The mean is removed from each of the axes and then the three axial signals are windowed. The magnitude spectral of the windowed signal is then obtained using the FFT. From the Z-Axis magnitude spectral, the step rate of the gait signal can be found by finding the frequency with maximum magnitude, $2f_0$. This information is then used to calculate the bandwidth of the body acceleration and artefacts bands of the signal. The body acceleration band is set as $0-4f_0$ Hz and the artefact band is set at...
The spectral centroid features can also be considered as transforming the magnitude spectral into a 2-dimensional feature space which incorporates frequency and magnitude information. Figure 4.11 shows the six SCA being plotted against their corresponding SCF values. It can be seen from Figure 4.11 (a) that the X-Axis SCA values of the stair walking body acceleration are lower when compared to the other types of walking. This is because of the stairs limit the forward acceleration of the subject as they are limited to taking one step at a time.

The SCA value of the flat walking X-Axis body acceleration has the highest value among the other walking patterns. This is due to the tendency of people to take longer steps which leads to higher acceleration in the anterior-posterior body acceleration. Furthermore the artefacts on X-Axis of the flat walking, slope down and stairs down are higher (see Figure 4.11(d)) when compared to the other walking patterns. This is because of the impact forces required to brake motion while walking with gravity which in muscles produces large vibrations. Due to flat walking having the largest foot step among the five gait patterns, it has the largest instability of gait motion. The foot tries to keep the body in control using a wobbling motion which leads to the generation of artefacts.

Furthermore, it can also be seen from Figure 4.11 (c) that the SCA values in the Z-Axis of the walking downwards patterns are large when compared to the other walking patterns. The reasoning for this is because when a person is walking with gravity, he/she will gain acceleration. In order to gain control of the body motion, the body will try to counter this motion by producing a large force braking motion.

Another useful piece of information that can be extracted from this figure is that the gait patterns oppose gravity have lower SCF values. This is because while walking against gravity, the body consumes more energy and has a tendency to reduce its walking rate.

Furthermore, the SCF body accelerations of the downward walking patterns is higher, which implies that a person would normally move at a faster rate when walking with gravity. Movements with gravity have a higher artefact SCF because the braking motion adds vibrations which leads to energy being concentrated at higher frequencies.
4.5. Proposed harmonic features

In this feature extraction method, the harmonic model amplitudes’ are proposed for classification features. The features for gait classification are extracted directly from the harmonic amplitude described in Chapter 3. The motivation for using the harmonic model parameters is that they can be easily extracted from the model as well as easily referred back to the model. Furthermore, harmonic components have been used in the past for gait stability analysis [80]. A schematic of the feature extraction process can be seen in Figure 4.12.
Figure 4.12 Feature extraction of harmonic parameters.

The vertical acceleration is used to find the step rate of the signal by using the AMDF signal. The period of the stride rate can be found, enabling the fundamental frequency of the model to be found. Once the fundamental frequency is found, the other eleven harmonics are searched for using the method described in Chapter 3. The search is limited to 12 harmonics in total within each axis, which includes the fundamental frequency because there is little energy beyond the 12th harmonic as seen in Figure 4.13.

Figure 4.13 Magnitude spectral of an example gait accelerometry signal, showing locations of the first 12 harmonics.
With the motivation of linking the body movement and the artefacts with the harmonic parameters, the harmonic amplitudes are categorized into two groups by assigning the first four harmonics to characterize the body movement and the last eight harmonics to characterize the artefacts, as discussed in Chapter 3. A signal reconstruction using the first four harmonics can be seen in Figure 4.14 and an illustration of the band grouping mechanism is shown in Figure 4.15.

![Figure 4.14 Signal reconstruction of the first four harmonics (dotted lines) compared to the original signal (solid line).](image)

![Figure 4.15 Grouping of harmonic amplitude spectra into harmonic features in the three axes (a) – antero-posterior; (b) – medio-lateral; (c) vertical, for an example frame of gait signal.](image)

Band grouping is carried out according to the following procedure:

\[
G_{\text{axis,low}} = \sum_{k=1}^{4} H_{\text{axis}}(k) \quad (4.5)
\]

\[
G_{\text{axis,high}} = \sum_{k=5}^{12} H_{\text{axis}}(k) \quad (4.6)
\]
where $H_{\text{axis}}(k)$ is harmonic $k$ for each axis, $G_{\text{axis, high}}$ is the total sum of harmonic amplitude for the artefact band and $G_{\text{axis, low}}$ is the sum of the harmonics within the body movement band. The $G_{\text{axis, high}}$ and $G_{\text{axis, low}}$ from the five gait patterns flat, slope down, slope up, stairs down and stairs up are compared and plotted in Figure 4.16.

![Figure 4.16 The Harmonic Features of the three axis (X-Axis – top; Y-axis – middle; Z-Axis – bottom) of a subject for the five gait patterns observed (flat – red dots; slope down – green square; slope up – blue star; stairs down – black triangle; stairs up – magenta).](image)

Since the spectral envelope is not similar across different walking speeds as seen in Figure 3.2, methods described by [18, 20, 21, 58, 85] which extract features from fixed bandwidths would encounter problems as the person walks at different pace because the frequency components shift with speed. It can also be seen from the speed data in Section 3.4.2 that as a person walks faster, the frequency components are not simply frequency-scaled according to the speed; the harmonic amplitudes and hence the walking style also change with walking rate. This is seen from the time-frequency spectral shown in Figure 3.2. However the harmonic model can resolve this problem by capturing the components (peaks) which are essential in the frequency spectral. From the $G_{x,\text{low}}$, it can be seen that walking flat, slope down and slope up have higher values when compared to the stairs up or stairs down. The reason for this is that the other two stair walking patterns are limited by the stair size. Furthermore, the $G_{x,\text{low}}$ of slope down has the highest value because the person is assisted by gravity in accelerating downward.

The $G_{x,\text{high}}$ values of slope down and flat walking are higher than the other walking patterns because for slope down, the person will try to maintain control of their walking by using a braking motion. This braking motion uses the feet and the ankles to create a jerking foot-strike motion which would act as an inhibitor to the
acceleration increase due to gravity. This motion increases the artifact acceleration which is translated from the feet to the TA sensor at the hip.

The $G_{y,low}$ parameter has the least magnitude when walking on stairs both up and down. This is because as a person walks on stairs with limited forward acceleration due to the stair size, the hip does not sway as much when compared to other walking patterns.

The $G_{y,high}$ values of the walking slope down and flat walking are larger compared to the other walking movements. This is because while using these gaits people have a tendency to take larger steps which results in a more unstable movement. Normally the feet would try to stabilise the body through sideward oscillatory movements. These oscillatory movements cause the artefacts in the slope down and flat walking to be high in magnitude.

The $G_{z,low}$ has higher values for walking flat, slope down and stairs down when compared to the stairs up and slope up. The reason for this is that the upwards two walking patterns are movements which require more energy and there is a tendency to move slower when moving against gravity. In addition, because they require more energy, the fatigue factor would also slow the acceleration of these gait patterns.

The $G_{z,high}$ of the slope down and stairs down are higher because as a person walks downwards with gravity, they experience additional acceleration. Their foot will make harder contact with the ground due to the increased velocity. Thus, the resulting impact impulse would be greater than walking upwards and this force would generate a larger vibration source at the feet which is then propagated throughout the whole body.

4.6. Proposed Linear Regression based ΔZCC features

As previously discussed in Section 2.6, the TA signal can be subdivided into three categories namely gravitational acceleration, body acceleration and artefacts. It is hypothesized that the different gait patterns contain different artefact patterns
It can be seen from Figure 4.17 that ZCC patterns between the five gait patterns have are quite different. The flat walking pattern and slope up have more rapid by varying ZCC values (standard deviation) compared to the other gait patterns on a frame by frame basis. Furthermore, flat and slope down walking have larger mean ZCC values when compared to the other three walking patterns. The reasoning of the large standard deviation of flat walking ZCC values is because the flat walking gait cycle has the largest variation in step length. Typically, a person would take larger steps while walking on flat surfaces when compared to the other four gait patterns. This results in a less stable motion which the foot has to stabilize in order keep the body in a controlled motion, which created artefacts resulting in higher ZCC values. Slope down walking also has large mean ZCC value because during this gait the person will try to avoid walking faster leading to instability created by the use of a braking motion of the feet and ankles which produces a large impact force. This impact force generates large vibrations in the body which leads to the high amount of ZCC.

The artefact acceleration is extracted by subtracting the low-pass filtered signal ($f_c = 4\text{Hz}$) from the original TA signal from each of the axis. An example of the ZCC signal of the Z-Axis TA is shown in Figure 4.17. ZCCs are proposed to characterize the artefact signal. The ZCC can be formulated as:
\[
ZCC_{axis} = \frac{1}{2} \sum_{m=1}^{N} |\text{sign}(\hat{a}_{axis}(m)) - \text{sign}(\hat{a}_{axis}(m-1))| 
\]  

(4.7)

where \( \hat{a}_{axis} \) is the artefact acceleration signal within an axis and \( N \) is the frame size. The artefacts patterns are affected by the number of gait cycles (stride). In order to normalize the ZCC over the number of strides, the number of strides per frame is calculated using the Average Magnitude Difference Function (AMDF) \[72\] from the filtered vertical acceleration (Z-Axis) signal. Instead of using the ZCC as features directly, the linear regression parameters of the cross difference of the ZCC values from two adjacent axes is used instead. The cross difference helps to remove any artefact vibrations caused by muscle movement and can be formulated as:

\[
\Delta ZCC_{ij} = ZCC_i - ZCC_j
\]  

(4.8)

where \( i \) and \( j \) correspond to the acceleration axes X, Y, or Z.

The main reason for using the cross difference is because the ZCC within a single axis has large variations due to different walking speeds and other causes when compared to the difference between the axis. The \( \Delta ZCC \) would also be more robust to unwanted noise artefacts such as bumps on the sensor because the three axes are mechanically linked, meaning that when one axis vibrates, so do the others.

The linear regression parameters are used instead of the \( \Delta ZCC \) value because it is hypothesised that the regression parameters characterise how the \( \Delta ZCC \) values changes over time. The gradient and the DC constant are used as features for classification. The gradient tracks how \( \Delta ZCC \) evolves over time and the DC constant provides an indication of its mean value. A block diagram of the \( \Delta ZCC \) regression feature extraction process is shown in Figure 4.18.

![Figure 4.18 Cross ZCC Linear Regression feature extraction diagram.](Image)
The linear regression $\Delta ZCC$ parameters consisted of the gradient $a$ and the DC component $b$ shown in Figure 4.19.

![Figure 4.19 The Delta ZCC Regression diagram.](image)

Actual regression parameters will be written as $\Delta ZCC_{ij}(n)$ and estimates of these parameters as $\hat{\Delta ZCC}_{ij}(n)$. The optimal parameters can be found by minimizing the error $e(n)$ which can be formulated as

$$e(n) = \Delta ZCC_{ij}(n) - \Delta \hat{ZCC}_{ij}(n) \quad (4.9)$$

Thus the mean square error can be written as

$$E = \frac{1}{2N+1}\sum_{m=-N}^{N} e^2(m) \quad (4.10)$$

Thus, to find the optimal gradient value $a$, $E$ is minimized by differentiating it with respect to the gradient and setting it to zero:

$$\frac{\partial E}{\partial a_{ij}} = 2\sum_{m=-M}^{M} \left(\Delta ZCC_{ij}'(m) - am\right)(-m) = 0 \quad (4.11)$$

this results in

$$\text{Grad}_{ij} = \frac{\sum_{m=1}^{N}(\Delta ZCC_{ij}(m) - \Delta ZCC_{ij}(-m))}{2\sum_{m=1}^{N}(m^2)} \quad (4.12)$$

Once the gradient parameter $Grad$ is found, the DC component DC is derived in the same way and is presented by
Figure 4.20 shows the comparison of $\Delta ZCC$ and $ZCC$ based on the five gait patterns data from the 52 subjects, described in Section 2.8.

These novel linear regression $\Delta ZCC$ features were proposed as temporal features to model the variations of signal in the artefact band. By looking at the values shown in Figure 4.20, the $\Delta ZCC$ has a smaller standard deviation when compared to $ZCC$. This is because the vibrations within each individual axis differ as the person walks at different paces but as one axis vibrates more, the other axis will also tend to vibrate more. This is the idea behind using the $\Delta ZCC$ instead of the $ZCC$.

![Figure 4.20 Comparisons between the mean (the bar value) and standard deviation (the small line on the middle of each bar) values of the ZCC and the $\Delta ZCC$ features for five gait patterns within a subject. (F – Flat; SD – Slope Down; SU – Slope Up; StD – Stairs Down; StU – Stairs Up).](image-url)

$$DC_{ij} = \frac{\sum_{m=1}^{N}(\Delta ZCC_{ij}(m)-am)}{N} \tag{4.13}$$
4. 7. Proposed Intrinsic Mode Function features

Recent research in the area of biomechanics [86] has led to the conclusion that
the human gait is a non-linear system which produces non-stationary signals.
Empirical Mode Decomposition (EMD) is proposed due to its non-linear and non-
stationary decomposition characteristic. This section explores gait feature extraction
and classification methods using EMD to analyse, characterise and classify the five
walking patterns.

The aim of this section is to investigate the possibility of using the EMD to
extract novel features for gait classification. The EMD extracts functions which form
a complete and nearly orthogonal basis for the original signal and these extracted
functions are known as Intrinsic Mode Functions (IMFs). The normalised energy
Intrinsic Mode Function (IMF) features per step cycle are proposed for gait pattern
classification.

IMFs are hypothesised to be sufficient to describe the signal, even though they
are not necessarily orthogonal. Obtaining IMFs from real world signals is important
because natural processes often have multiple causes and each of these causes may
happen at specific time intervals. This type of data is evident in an EMD analysis, but
quite hidden in the Fourier domain or in wavelet coefficients. Here, the EMD
approach is used to decompose the TA signal.

The three streams of TA signal (X, Y and Z axes) are first low pass filtered at 17
Hz. The signal is then decomposed into nine IMFs using a sifting process. Each axis
of the triaxial accelerometer signal can be decomposed as:

\[ a_{\text{axis}}(n) = \sum_{i=1}^{m} IMF_{i,\text{axis}}(n) + r_{m,\text{axis}}(n) \]  \hspace{1cm} (4.14)

where \( IMF_{i,\text{axis}} \) is \( i^{th} \) the Intrinsic Mode Function (IMF), \( r \) is the residue, \( \text{axis} \) is the
axis index corresponding to the three TA axes (X, Y or Z) and \( m \) is the
decomposition level.

The sifting process is explained as follows:

- Two smooth splines are constructed by connecting all the maxima and the
  minima of the acceleration signal to obtain the upper envelope
  \( a_{\text{max,\text{axis}}}(n) \) and lower envelope \( a_{\text{min,\text{axis}}}(n) \).
- The mean of the two envelopes is subtracted from the data to get a difference
  signal \( a_{1,\text{axis}}(n) = a_{\text{axis}}(n) - \frac{(a_{\text{max,\text{axis}}}(n) + a_{\text{min,\text{axis}}}(n))}{2} \).
The process is repeated for $IMF_{1,\text{axis}}(n)$ until the resulting signal satisfies the criterion for an intrinsic mode function (the mean of the upper and lower envelope is zero). The first three IMFs and the residue are chosen and used for features. The energy $E_{i,\text{axis}}$ of each IMF is then calculated as follows:

$$E_{i,\text{axis}} = \frac{1}{S_t} \sum_{k=1}^{N} [IMF_{i,\text{axis}}(k)]^2$$

(4.15)

where $i$ is the mode number, $N$ is the total number of samples in the frame and $S_t$ is the number of walking steps in that frame. After computing equation (4.15) for X, Y and Z-Axis signals, we obtain a 12-Dimensional Energy vector as shown in Figure 4.21.

As an example, the EMD of the vertical acceleration signal for one subject is shown in Figure 4.22. It can be seen from Figure 4.22 that the number of walking steps can be easily calculated by finding the peaks of the third level IMF and setting a threshold. Setting the threshold too high would miss some foot-step counts and setting it too low would pick up false counts. Thus the threshold value was determined empirically to be one third of the maximum peak within that frame. The energy of the decomposed IMF is then transformed into the cosine basis functions using the DCT.
Figure 4.22 The vertical acceleration signal is shown by the solid line, IMF 3 is shown by the dotted line and the threshold is shown by the bold line.

The decomposed signal of the different walking patterns of the vertical axis is shown in Figure 4.23.

Figure 4.23 The decomposition of the acceleration signal into nine IMFs with the residue for all gait patterns.
In order to investigate the separation of the five gait classes, Sammon non-linear mapping was performed on the IMF features and the result is shown in Figure 4.24.

![Figure 4.24 Non-linear Mapping of the IMF Features of five walking gaits.](image)

The IMF features were proposed to differentiate between the five gait patterns. It can be seen from the non-linear mapping in Figure 4.24 that the slope up and stairs up IMF features are of a relatively close to each other. The same applies for the slope down and stairs down gaits. The main reason for this is that the pairs of gait movements are either moving against gravity or with gravity. Gaits moving against gravity will have lower energies compared to gaits with gravity. It can be seen from Figure 4.23 that the higher IMFs order do not have substantial information and they therefore have not been included as features. The third IMF has also been shown to represent the walking’s step rate. The biggest shortcoming of the EMD features is that they cannot be calculated in a near real-time. This is because the algorithm needs to decompose the whole signal, which can only be done offline. This restriction is required due to the boundary problems of framing the signal prior to the EMD.

4.8. Summary

This chapter proposed six feature extraction algorithms for gait pattern classification. While all the feature extraction techniques described in Section 3.3 are reported to be able to classify gait patterns with reasonable accuracies, they do not have the theoretical explanations of how the parameters are linked to any gait models.
The LPCC were derived from the LP model and were shown to be promising features for classification. Due to their large dimension of the LPCC features, the filterbank features were developed in order to reduce the feature set dimension while maintaining the information contained in the LPCC. Further development of the filterbank features was done by incorporating the frequency information; this resulted in the development of the spectral centroid features. Further investigation of the gait characteristics lead to the conclusion that gait patterns vary with speed, therefore the harmonic features were proposed as a solution to remove the speed variability. Finally, the gait was assumed to be a non-linear process, and therefore empirical mode decomposition of the signal was proposed and the resulting IMF features were used for classification. All of the above-mentioned proposed features predominantly determine the gait’s static information. Further to this dynamic features such as the ΔZCC were proposed to enhance the classification system.
Chapter 5

Experiments and Results

In this chapter, all of the features proposed in Chapter 4 are tested. Several experiments were performed in order to compare the effectiveness of the proposed features. For each of the features proposed, the GMM back-end classifier was trained using data from 40 of the 52 subjects' from the classification dataset as described in Chapter 3. The other 12 subjects was used for testing the trained GMM system. The 12 testing subjects' age varied from 24 years to 59 years old with a mean of 33 years old. The results of the tests on the proposed features are presented herein. Furthermore, other well known existing features such as the statistical features, DFT features and wavelet features are also tested using the classification dataset.

5.1. LPCC experiment

The first experiment was performed in order to test the performance of the proposed LPCC features as described in Section 4.2. Each axis of the data stream was divided into 2.5 second frames to ensure that the subject had completed one full gait cycle or one stride. The LP coefficients are calculated for each 2.5 seconds frame are then transformed into LPCC using the method described in Section 4.2. The LPCC features from each of the gait patterns were then used to train the five GMM classes which correspond to the five gait patterns. Once the GMM classifier was fully trained, the classification system was tested using the testing dataset. The testing data was divided into frames and processed similarly to the training data set.
Each of the test feature sets is then fed into the trained GMM systems where the likelihood score for each class is obtained. The maximum score of the likelihood is chosen as the decision output of the classification system. This output is then tallied and compared to the known gait type of the test data. The result of the classification system using the LPCC features is shown as confusion matrix in Table 5.1.

An additional experiment was conducted to compare between the effectiveness of the LPCC and the LPC. This time round, the GMM was trained using the above mentioned procedure but used the LPC features instead of the LPCC. The comparison of the overall classification accuracy between the LPCC and the LPC features is presented in Table 5.2.

Table 5.2 LPC features and LPCC features classification accuracy comparison.

<table>
<thead>
<tr>
<th>Features</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPC</td>
<td>61.7</td>
</tr>
<tr>
<td>LPCC</td>
<td>83.1</td>
</tr>
</tbody>
</table>

5.2. Filterbank experiments

The first experiment tested the performance of the proposed Filterbank features which were described in Section 4.3. As seen in Section 5.1, each axis of the data stream is divided into 2.5 second frames and a DFT of each frame is taken. The DFT points from each of the three axes are then grouped into three bands as specified in Section 4.3. The grouped DFT magnitudes are then summed up and these values were used as features.

The Filterbank features from each of the gait patterns are then used to train the five GMM classes which correspond to the five gait patterns. The classification
system was then tested using the testing data set. The testing data was divided into frames and processed similarly to the training data set. It was fed into the trained GMM systems and the likelihood score for each class was obtained. The maximum score of the likelihood is chosen as the decision output of the classification system. This output is then tallied and compared to the known existing test features. The overall accuracy of the classification system using the Filterbank features is shown as a confusion matrix in Table 5.3.

<table>
<thead>
<tr>
<th></th>
<th>Flat</th>
<th>Slope Down</th>
<th>Slope Up</th>
<th>Stairs Down</th>
<th>Stairs Up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat</td>
<td>81.1%</td>
<td>3.6%</td>
<td>2.7%</td>
<td>7.9%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Slope Down</td>
<td>0.6%</td>
<td>87.2%</td>
<td>1.2%</td>
<td>7.3%</td>
<td>3.7%</td>
</tr>
<tr>
<td>Slope Up</td>
<td>3.6%</td>
<td>5.9%</td>
<td>78.8%</td>
<td>4.2%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Stairs Down</td>
<td>2.7%</td>
<td>2.9%</td>
<td>1.4%</td>
<td>90.5%</td>
<td>3.3%</td>
</tr>
<tr>
<td>Stairs Up</td>
<td>1.2%</td>
<td>1.3%</td>
<td>9.4%</td>
<td>3.5%</td>
<td>84.8%</td>
</tr>
</tbody>
</table>

Overall Accuracy = 84.5%

### 5.3. Spectral Centroid experiment

The following experiment tested the performance of the proposed spectral centroid features which were described in Section 4.4. The spectral centroid features are extracted by firstly windowing the signal using a 2.5 second frames ensuring sufficient samples to capture one stride cycle. A DFT is then performed and the step rate is approximated using the maximum value of the DFT magnitude in the Z-Axis. Once the step rate \((2f_0)\) is found, the body acceleration is approximated by band-limiting the DFT from \(f_0\) to \(5f_0\) times the step rates while the artefact vibrations are extracted by band-limiting the DFT from \(4f_0\) to \(12f_0\). This process is to accommodate for the fact that the frequency components of the gait shift according to the walking speed as shown in Figure 3.2. The Spectral Centroid Amplitude and Frequency (SCA and SCF) are then calculated using Equation 4.3 and Equation 4.4 to each of the band-limited DFT outputs.

Three tests were performed in this experiment. In the first part of the experiment, the GMM is trained and tested using the SCA features. In the second, the GMM is trained and tested using the SCF features only. In the last experiment, the GMM is trained and tested using both SCA and SCF combined through concatenation. Each
of these experiments was performed by using the specified features to train the five GMM classes corresponding to the five gait patterns. The classification system was tested using the testing data set. The testing data sets were divided into frames and processed similarly to the training data set similar to the method described in Section 5.2. The maximum score of the likelihood is chosen as the decision output of the classification system. This output is then tallied and an overall classification accuracy is calculated. The overall classification accuracies of these experiments are presented in Table 5.4.

<table>
<thead>
<tr>
<th>Features</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Centroid Amplitude</td>
<td>83.1</td>
</tr>
<tr>
<td>Spectral Centroid Frequency</td>
<td>80.4</td>
</tr>
<tr>
<td>Spectral Amplitude + Frequency</td>
<td>86.7</td>
</tr>
</tbody>
</table>

In addition, a confusion matrix of the combined SCA and SCF features are presented in Table 5.5.

<table>
<thead>
<tr>
<th></th>
<th>Flat</th>
<th>Slope Down</th>
<th>Slope Up</th>
<th>Stairs Down</th>
<th>Stairs Up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat</td>
<td>85.1%</td>
<td>3.6%</td>
<td>2.7%</td>
<td>7.9%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Slope Down</td>
<td>0.6%</td>
<td>87.2%</td>
<td>1.2%</td>
<td>7.3%</td>
<td>3.7%</td>
</tr>
<tr>
<td>Slope Up</td>
<td>3.1%</td>
<td>5.9%</td>
<td>84.1%</td>
<td>0.4%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Stairs Down</td>
<td>2.7%</td>
<td>2.9%</td>
<td>1.4%</td>
<td>90.5%</td>
<td>2.5%</td>
</tr>
<tr>
<td>Stairs Up</td>
<td>4.2%</td>
<td>3.3%</td>
<td>2.4%</td>
<td>3.5%</td>
<td>86.6%</td>
</tr>
</tbody>
</table>

**Overall Accuracy = 86.7%**

5.4. Harmonic experiment

This experiment tested the performance of the proposed Harmonic features as described in Section 4.5. The TA training data stream from each axis was divided into 2.5 second. The step rate was then estimated using the Average Magnitude Difference Function shown in Equation 3.14 from the Z-Axis signal. A DFT of each frame for each of the three axis (X,Y,Z) was taken. The harmonic magnitudes were
determined from the DFT signal using the algorithm described in Section 3.5. The magnitude peaks were then grouped into two bands, the body acceleration band (harmonics one to four) and the artefacts bands (harmonics five to twelve). This was done by summing into the $1^{\text{st}}$ harmonic until the $4^{\text{th}}$ harmonics to be grouped into the body acceleration band and summing up the $5^{\text{th}}$ harmonics until the $12^{\text{th}}$ harmonics to be grouped into the artefacts band.

Once these features were formed, they were used to train the five GMM classes which correspond to the five gait pattern classes. The classification system was tested using the testing data set. The maximum score of the likelihood is chosen as the decision output of the classification system. This output is then tallied and the overall classification accuracy is calculated. The result is shown in Table 5.6.

<table>
<thead>
<tr>
<th></th>
<th>Flat</th>
<th>Slope Down</th>
<th>Slope Up</th>
<th>Stairs Down</th>
<th>Stairs Up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat</td>
<td>85.1%</td>
<td>3.6%</td>
<td>2.7%</td>
<td>7.9%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Slope Down</td>
<td>1.6%</td>
<td>86.2%</td>
<td>1.2%</td>
<td>7.3%</td>
<td>3.7%</td>
</tr>
<tr>
<td>Slope Up</td>
<td>3.6%</td>
<td>1.9%</td>
<td>86.8%</td>
<td>1.2%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Stairs Down</td>
<td>1.7%</td>
<td>2.9%</td>
<td>1.4%</td>
<td>92.5%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Stairs Up</td>
<td>1.2%</td>
<td>1.3%</td>
<td>9.4%</td>
<td>0.5%</td>
<td>87.8%</td>
</tr>
</tbody>
</table>

In addition, other harmonic properties are investigated for use as classification features. The 12 extracted harmonics can be categorised into two other groups which are odd and even harmonics. The ratio of the even to the odd harmonics has previously been used as a measure of gait stability [80]. Using similar testing procedures, the odd and even harmonic features were used individually as classification features. Furthermore, the harmonic ratios were also calculated and tested for then classification ability.

In addition to the body component and muscle artefacts features, an investigation into incorporating the fundamental frequency as feature was performed. The body and muscle artefact features from the harmonic model were compared to the features developed from the LP model. The aim was to compare the features which contained the walking rate variability with features which had the walking rate variability removed. As a comparison measure, the classification results are used to
compare the feature sets. A similar testing procedure was performed and the classification results are shown in Table 5.7.

Table 5.7 Overall classification accuracy of various features derived from the harmonic model.

<table>
<thead>
<tr>
<th>Features</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Body + Muscle Artefacts</td>
<td>87.7</td>
</tr>
<tr>
<td>Odd Harmonics</td>
<td>84.7</td>
</tr>
<tr>
<td>Even Harmonics</td>
<td>85.1</td>
</tr>
<tr>
<td>Harmonic Ratios</td>
<td>79</td>
</tr>
<tr>
<td>Body + Muscle + ( f_0 )</td>
<td>85.7</td>
</tr>
</tbody>
</table>

5.5. Linear Regression based \( \Delta \text{ZCC} \) experiment

The sixth experiment was performed to test the performance of the proposed dynamic linear regression \( \Delta \text{ZCC} \) features which was described in Section 4.6. The linear regression \( \Delta \text{ZCC} \) features are extracted by firstly filtering each axis using a filter which has a cut-off frequency of 4Hz. This was performed to extract the artefacts. The artefacts component is then processed in frames of 256 samples. The \( \text{ZCC} \) values are then normalised by the number of strides per frame. Furthermore, \( \Delta \text{ZCC} \) values were calculated for the different axes. Linear regression parameters were calculated over a frame of five \( \Delta \text{ZCC} \) values. Once the regression parameters were found, these features are then used to train the five GMM classes which correspond to the five gait patterns. Once the GMM classifier was fully trained, the classification system was tested using the testing data set. The testing data sets were divided into frames and processed similarly to the training data set. The classification comparisons of various investigated \( \text{ZCC} \) features are shown in Table 5.8.

Table 5.8 Classification accuracy comparison of various \( \text{ZCC} \) features.

<table>
<thead>
<tr>
<th>Features</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{ZCC} )</td>
<td>55.9</td>
</tr>
<tr>
<td>( \Delta \text{ZCC} )</td>
<td>67.3</td>
</tr>
<tr>
<td>( \Delta \text{ZCC} ) regression</td>
<td>71.9</td>
</tr>
</tbody>
</table>

5.6. IMF experiment

This experiment tested the performance of the proposed IMF features which were described in Section 4.7. The whole data stream is decomposed into IMF’s using
Empirical Mode Decomposition. These decomposed modes were then divided into 2.5 second frames. It was found that the step rate can be extracted from the third mode of the Z-Axis. The walking rate was approximated by applying a threshold at 2/3 of the maximum peak value of the third Z-Axis mode. Once the number of steps was known, the energy from the first three IMF modes and the residue from each axis were calculated within the frame. They were then normalized by the calculated step rate. These twelve energy values are then transformed into the cosine domain using the DCT. Only the first eight DCT coefficients were used as features for classification. These features are then used to train the five GMM classes which correspond to the five gait patterns. Once the GMM classifier was fully trained, the classification system was tested using the testing data set. The testing data sets were divided into frames and processed similarly to the training data set.

<table>
<thead>
<tr>
<th>Flat</th>
<th>Slope Down</th>
<th>Slope Up</th>
<th>Stairs Down</th>
<th>Stairs Up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat</td>
<td>81.1%</td>
<td>3.6%</td>
<td>6.7%</td>
<td>4.9%</td>
</tr>
<tr>
<td>Slope Down</td>
<td>3.1%</td>
<td>87.2%</td>
<td>1.2%</td>
<td>5.1%</td>
</tr>
<tr>
<td>Slope Up</td>
<td>5.6%</td>
<td>4.6%</td>
<td>80.1%</td>
<td>5.2%</td>
</tr>
<tr>
<td>Stairs Down</td>
<td>1.7%</td>
<td>9.1%</td>
<td>1.4%</td>
<td>85.5%</td>
</tr>
<tr>
<td>Stairs Up</td>
<td>4.2%</td>
<td>0.1%</td>
<td>5.4%</td>
<td>3.5%</td>
</tr>
</tbody>
</table>

Overall Accuracy = 84.1%

Each of the test feature sets was then fed into the trained GMM systems where the likelihood score of the testing feature vector belonging to each of the trained class was obtained. The maximum score of the likelihood is chosen as the decision output of the classification system. This output is then tallied and the overall classification accuracy is calculated. The classification result using the IMF features is presented in Table 5.9.

5.7. Comparisons with existing features experiment

A comparison of the proposed features with the existing features described in Chapter 2 was performed. The existing features investigated were the statistical features, spectral features and the wavelet features.

The first subsection of the sub-experiment was to use the statistical features from the TA data to classify the five walking patterns. The TA data from the sensor is firstly
framed using a 2.5 second window and the mean and standard deviations of the three axes \((X,Y,Z)\) were taken to be used for classification.

The second sub-experiment was to use the DFT spectral points for classification. The TA signal is firstly framed and then the DFT of each of the axes was taken. It is then followed by using these magnitude points as features for the gait classification.

Table 5.10 Comparison of classification accuracies using different feature sets.

<table>
<thead>
<tr>
<th>Features</th>
<th>Feature Dimension</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical Features</td>
<td>6</td>
<td>66.9</td>
</tr>
<tr>
<td>DFT features</td>
<td>75</td>
<td>74.1</td>
</tr>
<tr>
<td>Wavelets</td>
<td>32</td>
<td>80.3</td>
</tr>
<tr>
<td>LPCC</td>
<td>75</td>
<td>83.1</td>
</tr>
<tr>
<td>Filterbank</td>
<td>9</td>
<td>84.5</td>
</tr>
<tr>
<td>Centroid (SCA+SCF)</td>
<td>18</td>
<td>86.7</td>
</tr>
<tr>
<td>ΔZCC</td>
<td>6</td>
<td>71.9</td>
</tr>
<tr>
<td>Harmonic</td>
<td>6</td>
<td>87.7</td>
</tr>
<tr>
<td>IMF</td>
<td>9</td>
<td>84.1</td>
</tr>
</tbody>
</table>

The third subsection of the experiment was to extract the wavelet transform features, which were described in Chapter 2, where each frame of the TA gait signal is decomposed into bands as shown in Figure 2.12. The root mean values of the decomposed bands are then used as features for classification. These features are then used to train the five GMM classes which correspond to the five gait patterns. Once the GMM classifier was fully trained, the classification system was tested using the testing data set. The testing data sets were divided into frames and processed similarly to the training data set. Each of the test feature sets is then fed into the trained GMM systems where the likelihood score of the testing feature vector belonging to each of the train classes is obtained. The class with maximum score is chosen as the decision output of the classification system. This output is then tallied and the overall classification accuracy is calculated. The classification accuracies using the existing features are shown in Table 5.10.
5.8. Discussion and Summary

This chapter presents the accuracies of the proposed features for gait pattern classification. In the first experiment, the LPCC features were tested and found to be able to classify the five gait patterns with an accuracy of 83%. In order to justify that the cepstral transformation was useful for classification, the LPCCs were compared to the LP coefficients and proved that the LPCCs outperform the LPC features by a 21%.

The filterbank features are then developed with the aim of reducing the dimensions of the LPCC features results show that the filterbank features have a 1.4% higher classification accuracy compared to the LPCC. This may be due to the LPCC having a large number of features which may lead to degradation in robustness and which not contribute significantly towards the class separation of the gait patterns.

The centroid features add frequency information to the filterbank features. The combined SCA and SCF features outperform the classification accuracy of either SCA or SCF features being used individually. The combined SCA and SCF features shows a 3% improvement in classification accuracy when compared to the filterbank features.

The harmonic features are then developed to remove the variations due to the speed variation of the gait. By using the harmonic energy features, an overall classification accuracy of 87.7% was achieved. This is an improvement of 3.2% over the filterbank and 1% over the combined centroid features. There were several other harmonic features such as the harmonic ratio, odd harmonics and even harmonics which were also tested. Amongst the features tested, the proposed harmonic energy features set has the highest classification accuracy of the five gait patterns. Based on harmonic feature classification experiments, it can be seen that the fundamental harmonic $f_0$ does not contribute towards improving the overall classification accuracy.

Although, the proposed delta regression features did not perform as well as the proposed static features such as the LPCC, Filterbank, Centroid and Harmonic features, they did perform better when compared to the ZCC and $\Delta$ZCC features.
The IMF features were tested and they were shown to perform better than the Filterbank features with an accuracy of 84% though this is slightly lower than the Centroid and Filterbank features.

Based on the comparison result between the proposed features and the existing features, it can be seen that the proposed features results have better classification accuracies and it can be concluded that the proposed features derived from the proposed models are better suited to the classification of these five gait patterns.
Chapter 6

Adapted Bayesian Back-End Classification System and Score Level Fusion

6.1. Overview

Many difficulties are encountered in gait patterns classification due to a loss in accuracy. This is caused by either:

- Training the system with data from multiple subjects (‘individuals’) because of differences in the characteristics of walking mechanics [87].
- Limited availability of data from an individual subject.

If the system is trained on data from a particular training subject, the system will typically be under-trained. It will not be robust to variation in movements, since gathering sufficiently large training data sets from a particular subject is impractical. On the other hand, if the system is pre-trained on a larger set of data taken from multiple training subjects, the models may not be specific enough to the final user for accurate classification. In order to overcome these difficulties, the Bayesian adaptation approach for GMMs is proposed.

Furthermore, different types of features can be complementary which would help improve the classification system. As such, score level fusion methods are investigated in this chapter.

6.2. Bayesian Adaptation

The Bayesian estimation framework provides a way of incorporating prior information into the training process which is particularly useful for dealing with problems posed by sparse training data, for which the Maximum Likelihood (ML) approach gives inaccurate estimates. Bayesian adaptation was initially used for speech recognition and was introduced to create a robust gait pattern model by
adapting the statistics from a generalised gait pattern model. This adaptation includes updating mixture components’ mean, variances and weights. However, research has shown that the best performance can be achieved by updating the mean vectors only [88]. In this section, the iterative Bayesian adaptation is discussed as follows.

Let the sample \( X = (x_1, ..., x_T) \) denote a given set of \( T \) observation vectors, where \( X = (x_1, ..., x_T) \) are either independent and identically distributed or are drawn from a probabilistic function of a Markov chain.

The difference between Bayesian adaptation and ML estimation lies in the assumption of an appropriate prior distribution of the parameters to be estimated \( (\lambda) \) from the sample \( X \) with probability density function \( p(X|\lambda) \). If \( p \) is the prior p.d.f of \( \lambda \) then the Bayesian estimate \( \hat{\lambda} \) is defined as the posterior p.d.f. of \( \lambda \) and is denoted as \( p(\lambda|X) \):

\[
\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} \frac{p(X|\lambda)p(\lambda)}{p(X)} \quad (6.1)
\]

Since the likelihood of \( X \) is independent of the speaker model parameters, the parameters may be determined as the following

\[
\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} p(X|\lambda)p(\lambda) \quad (6.2)
\]

Given a non-informative prior likelihood of the model parameters, e.g. all prior probabilities equal \( p(\lambda) \), Bayesian adaptation becomes equivalent to the ML algorithm.

Since there is no sufficient statistic for the p.d.f \( p(X|\lambda) \), the Bayesian solution is given by maximizing \( p(\lambda)p(X|\lambda) \) through an Expectation-Maximisation (EM) algorithm [89], like the ML case. This is achieved by maximizing the auxiliary function \( \psi(\lambda, \tilde{\lambda}) \), whereby given the old parameters \( \lambda \) the likelihood of the new set of parameter estimates \( \tilde{\lambda} \) is greater than or equal to the previous estimates. The details of obtaining the auxiliary function can be found in [90, 91].

\[
\psi(\lambda, \tilde{\lambda}) \propto p(\lambda) \prod_{t=1}^{N} w_{t}^{i} \left| \Sigma_{t}^{-1} \right|^{\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\mu_{i} - \tilde{x}_{i})' \Sigma_{i}^{-1} (\mu_{i} - \tilde{x}_{i}) - \frac{1}{2} tr(s_{i}\Sigma_{i}^{-1}) \right\} \quad (6.3)
\]

where

\[
c_{it} = P(i|x_{t}, \tilde{\lambda}) \quad (6.4)
\]

\[
c_{it} = \frac{w_{it}g(x_{t}|\mu_{i}, \Sigma_{i})}{\sum_{j=1}^{N} w_{ij}g(x_{t}|\mu_{j}, \Sigma_{j})}
\]
Since the EM algorithm is iterative, the Bayesian estimation for GMM parameters is also iterative and the new estimates are obtained by replacing the old estimate parameters $\lambda$ by $\tilde{\lambda}$ like in the EM procedure. The first set of $\lambda$ parameters can be determined from the GMM parameters of the general trained GMM.

\[
\hat{w}_i = \frac{v_i + \sum_{t=1}^{T} c_{it}}{\sum_{j=1}^{N} [v_j + \sum_{t=1}^{T} c_{jt}]} 
\]

\[
\hat{\mu}_i = \frac{\tau_i m_i + \sum_{t=1}^{T} c_{it} x_t}{[\tau_i + \sum_{t=1}^{T} c_{it}]} 
\]

\[
\tilde{\Sigma}_i = \frac{\mu_i + \sum_{t=1}^{T} c_{it} (x_t - \bar{x}_i)(x_t - \bar{x}_i)'}{[\alpha_i - \tau_i + \sum_{t=1}^{T} c_{it}]} 
\]

where the parameters $(\tau_i, \alpha_i, v_i, m_i, \mu_i)$ are the set of hyper-parameter vectors with $\tau_i > D - 1, \tau_i > 0$. $m_i$ is a D-dimensional vector and $\mu_i$ is a $D \times D$ positive definite matrix. These parameters are obtained from a large universal gait pattern model trained from a large population of gait data.

In this thesis, the Bayesian adaptation equations are limited to updating the means only. When no adaptation data is available, the generalized gait pattern GMM parameters can be considered as the prior information:

\[
\mu_i^{\text{prior}} = m_i^{\text{init}} 
\]

This will give the following iterative solution to the adaptation of component means

\[
\mu_i = a_{\mu_i} \tilde{x}_i + (1 - a_{\mu_i}) \mu_i^{\text{prior}} 
\]
The new complete Bayesian adapted classification system can be seen in Figure 6.1.

6. 3. Score Level Fusion

The fundamental assumption behind performing fusion is that different feature sets can contain complementary information. The fusion of such information provides additional input which can be substantially decisive for the classification. Fusion can be categorized into three main categories:

(a) sensor data fusion,
(b) feature-level fusion and
(c) score level fusion.

For fusion at the prior classification/matcher stage, integration of information from several sources can take place either at the sensor level or at the feature level. Sensor level fusion entails the integration of the data from different sources before
they are subjected to feature extraction or selection. This supposes that the compatibility and the correspondence within points in the raw data is either known in advance or reliably estimated.

Feature level fusion refers to combining different feature sets extracted from several sources. In fact, the raw data, e.g. hyperspectral data, represents the richest source of information content and subsequent processing, such as feature extraction and feature selection, compresses the amount of information that is available to the fusion process. When the feature sets are homogeneous i.e. features of same nature of data, a single resultant feature vector can be calculated as a weighted average of the individual feature vectors. When the feature sets are non-homogeneous i.e. features issued from data with different natures, they can be concatenated to form a single feature vector. Feature extraction and feature selection schemes are used to reduce the dimensionality of the resulting feature vector [92]. The concatenation of different feature vectors associated with the same frame of the gait signal, prior to classification, is known as feature-level fusion. Although feature-level fusion may improve recognition accuracy, it has several shortcomings [93]. Firstly, fusion requires the individual feature vectors be available at the same frame rate i.e. the multiple feature extraction must be synchronous. Secondly, the number of training vectors needed for robust density estimation increases exponentially with the dimensionality. Thirdly, a problem caused by the concatenation operation is the significant differences in the range as well as distribution of the individual feature vectors.

Score-level fusion is proposed here as an alternative to feature level fusion. It models each feature set separately. A specialised classifier is trained for each feature set and then each classifier output score is then combined for the final decision. Simply put, each of the different feature sets acts as an independent “expert”, giving its opinion about the unknown class. The structure of score level fusion is shown in Figure 6.2. Each of the weights shown is found from the algorithm developed by [94].
Figure 6.2 Classification employing score-level fusion using N different feature sets

The Bayesian method for decision level fusion uses more information on classifiers in combination of their results than the majority voting methods. To make the application of the Bayesian combination method more coherent with its theoretical foundation, the two following hypotheses must be respected [95]: the combination of classifiers ignores their internal characteristics and what is actually important in combination, is the classifier outputs or the class labels. Consequently, this method of combination is generally applicable to all types of classifiers.

6.4. Experiments and Results

There were several initial experiments conducted to investigate the characteristics from the signal captured and to validate the hypothesis made.

Adaptation Experiment

The adaptation experiment involves using Bayesian adaptation techniques in trying to remove inter-subject variability. The aim was to improve the classification system accuracy by adapting the classifier to the subject’s specific walking style using Bayesian adaptation as described in Section 6.2. In the adaptation experiment, the classification system was trained using the features described in Chapter 4. Once the GMMs were fully trained similar to the fourth experiment, they were then adapted using the Bayesian adaptation described in Section 6.2 before the testing was performed. The classification system was trained using 40 subjects of the 52 subjects. The evaluation subset, comprising data from the 12 remaining subjects, was then used to assess the performance of the classification system for the five gait
patterns. Ten percent of each subject’s evaluation data is used to adapt the GMM prior to testing. The data was divided into frames, and a single decision was made for each movement in each frame. The optimal number of mixtures was determined empirically to be four as such as four mixtures were used to model each of the GMM classes for all classification experiments. The accuracy of the classification result is then computed. This initial system is then compared to the classification accuracy of the Bayesian adapted system with the same configuration. The performance of the Bayesian adapted classification system is then compared to the non-adapted system.

Table 6.1 Classification accuracy comparisons for Bayesian adapted systems vs. non-adapted GMM classification system.

<table>
<thead>
<tr>
<th>Feature Sets</th>
<th>Classification Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-adapted</td>
</tr>
<tr>
<td>LPCC</td>
<td>83.1%</td>
</tr>
<tr>
<td>Filterbank</td>
<td>84.5%</td>
</tr>
<tr>
<td>Centroid (SCA + SCF)</td>
<td>86.7%</td>
</tr>
<tr>
<td>ΔZCC Regression</td>
<td>71.9%</td>
</tr>
<tr>
<td>Harmonic</td>
<td>87.7%</td>
</tr>
<tr>
<td>IMF</td>
<td>84.1%</td>
</tr>
</tbody>
</table>

The features extracted in Chapter 4 are used to assess the performance of the Bayesian adapted system. The results of the overall classification accuracy of the Bayesian adapted system and the non-adapted GMM systems are presented in Table 6.1.

Fusion Experiment

The fusion experiment was conducted by comparing the effectiveness of fusing additional information into the classification system. Most of the proposed features were static features and it is hypothesized that the dynamic information (trend information between successively analysed frames) would complement the existing static features. Therefore, the integration of the dynamic ΔZCC regression features was proposed. In the score level fusion experiment, two classifier systems were trained. The first is intended for the various feature sets discussed in Chapter 4 and
the other is trained using the ΔZCC Regression features. Once the GMM was fully trained -similar to the fourth experiment - they were then adapted using the Bayesian adaptation described in Section 6.2 prior to testing. For this experiment, the features extracted as described in Chapter 4 were used and classification system was trained using 40 subjects of the 52 subjects. The evaluation subset, comprising data from the 12 remaining subjects, was then used to assess the classification performance of the classification system for the five terrains. The data was divided into frames, and a single decision was made for each movement in each frame. Four mixtures were used to model each of the GMM classes for all classification experiments. The optimal number of mixtures was determined empirically. The weights all set to be 1/2 except for the centroid features experiment where in this instance there were three classifiers that were used including one for SCA, one for SCF, and one for ΔZCC.

The weights that were used for this experiment were all equal to 1/3. This experiment fused the information from static features proposed in Chapter 4 with the ΔZCC regression features using score-level fusion. The results are shown in Table 6.2.

Table 6.2 Classification accuracy comparisons for the combination of ΔZCC Regression features and various static features combined through feature level fusion and score level fusion of Bayesian adapted systems GMM classifier.

<table>
<thead>
<tr>
<th>Feature Sets</th>
<th>Classification Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feature Level Fusion</td>
</tr>
<tr>
<td>LPCC</td>
<td>86.1%</td>
</tr>
<tr>
<td>Filterbank</td>
<td>91.9%</td>
</tr>
<tr>
<td>Centroid (SCA + SCF)</td>
<td>92.7%</td>
</tr>
<tr>
<td>Harmonic</td>
<td>93.2%</td>
</tr>
<tr>
<td>IMF</td>
<td>88.3%</td>
</tr>
</tbody>
</table>
6. 5. Summary

This chapter has discussed two methods for improving the performance of the basic GMM system used in the last chapter. Bayesian adaptation was proposed to overcome the challenges of the cumbersome process of collecting huge amounts of data from one subject and also it refines the tuning of the GMM parameters to the intended observed subject. The results of the Bayesian adapted GMM systems have shown that the adaptation process improves the overall classification of the system by an average of 5% which is desirable in a classification process.

The second optimization was to integrate the dynamic features into the static features that were proposed in Chapter 4. It is not possible to integrate dynamic features into the classification system using concatenation and hence score level fusion is proposed as an alternative solution to the problem. The results show that by integrating the dynamic features, the overall classification system was improved for all the static features set tested. An overall average 7% classification accuracy improvement was achieved through the integration of the dynamic ΔZCC regression with static features. The summary of classification results improvements of the system is shown below.

Figure 6.3 Accuracies comparisons of non-adapted system, Bayesian adapted system, and score level fusion
Chapter 7

Conclusions and Future Work

7.1. Conclusions

This thesis investigates the use of accelerometry for gait classification. It focused on detecting gait patterns of walking on flat surfaces, walking down slope, walking up slope, walking downstairs, and walking upstairs. All these gait patterns are important as they are commonly encountered during daily living activities. Gait models proposed are the harmonic model and the LP model and they have been demonstrated to be able to model the various gait patterns. Compared to the inverted pendulum model, these models are superior as these models are able to model the five gait patterns compared to the pendulum which is only able to model flat walking. Furthermore, these models have shown to be more feasible in terms of implementation in daily living monitoring as they only require data from a single sensor (triaxial accelerometer). Hence this is indeed simpler compared to the complex model which uses multiple sensors at various locations on the body (as this is not feasible to be used in a daily living monitoring environment).

The classification system proposal consisted of front end features extraction and a backend, this is a little bit different when compared to the existing hierarchical classification system. The primary drawback of such a system, however, is that finding such a set of rules is an incredibly time-consuming process involving what is largely a manual search through the data for similarities and differences between the signal classifications. The addition of other gait patterns or postures to the system also presents significant problems. At best, it may be a simple case of adding an extra leaf node to one of the branches. At worst, it may require a complete restructuring of the tree in order to arrive at the best classification results. Consequently, more automated methodologies such as the GMM are desirable.

A number of feature extraction algorithms were proposed and developed based on the parameters of the gait models described in this thesis. The linear predictive cepstral coefficient features were derived from the LP model. It was found that the
LPCCs were a more robust feature set compared to the LP coefficients. The filterbank features were derived based on the assumption that the triaxial acceleration signals were composed of gravitational, body and artefact accelerations. The thesis then describes the harmonic features which were derived from the proposed harmonic model in order to compensate for variability in walking rates. Lastly, the IMF features were investigated for differentiating between the gait patterns. The proposed features were found to be better suited for gait pattern classification when compared to the existing features such as statistical time domain, spectral and wavelets features.

Furthermore, all of the existing features were static features and carry little information about how they change over a span of several frames. Therefore, a novel linear regression $\Delta ZCC$ regression features were proposed as temporal features to model the variations of signal in the artefact band. It was found that by using these set of features alone the overall classification accuracy of the system was not as good when compared to the static features that were proposed but the $\Delta ZCC$ regression features were found to be complimentary when they are combined with the static features.

Two classification system optimization methods were investigated and proposed to improve the overall performance. The Bayesian adaptation algorithm was used to overcome the challenges of collecting large amounts of data from the target subject. The results of the Bayesian adapted GMM systems indicates that the adaptation process improves classification accuracy. Score level fusion was proposed to combine static and dynamic features. The results show that by integrating the dynamic features, the overall classification system was improved.

In conclusion, the research indicates that a single hip mounted triaxial accelerometer is an appropriate device for gait pattern monitoring. The LP model and the harmonic models parameters have been found to be effective and efficient in modeling the gait. The model’s parameters are derived and processed using signal processing algorithms which have shown to produce excellent features to be used for gait classification. The classification system performance is improved by incorporating the Bayesian adaptation and integrating dynamic features through score level fusion.
7.2. Future Work

Various other sources of gait variability were not investigated in this thesis, these include the effect of different surfaces and different foot wears on gait patterns. Further investigation of each specific gait patterns still need to be done. These include the effects of how different stairs’ width and the effect of different slope inclinations on the characteristics of the TA signal.

Another area of interest is the investigation of how gait classification would improve the accuracy of energy expenditure calculations. The problem of using the TA signal’s energy expenditure calculations is that the movement along the gravity axis such as downhill walking, or stairs down walking consumes higher energy due to impact of the TA sensor capturing the impact forces of the foot trying to avoid moving faster with gravity where the reality is that the body needs higher energy to produce movements that opposed the gravity. For instance, a person would get tired easily when walking uphill compared to walking downhill. Furthermore, precise energy expenditure approximations can be developed as the gait patterns have precisely been classified.

Further investigations of other factors such as height, weight, age and how these factors may affect the gait model and features can still be developed. Also the fatigue factor can also be investigated as the gait pattern of a tired person would be different when compared to a fresh person. In addition, the health status of a person would also affect their gait patterns (when they are feeling unwell, their gait patterns would be different when compared they are healthy and needs to be incorporated in the data collection process).
### Appendix A

The list of subjects of which gait’s data were collected

<table>
<thead>
<tr>
<th>Number</th>
<th>Subject</th>
<th>Type of Shoes</th>
<th>Age</th>
<th>Height</th>
<th>Weight</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Subject1</td>
<td>Formal Shoes</td>
<td>27</td>
<td>164</td>
<td>63</td>
<td>M</td>
</tr>
<tr>
<td>2</td>
<td>Subject2</td>
<td>Sandals</td>
<td>28</td>
<td>171</td>
<td>61</td>
<td>M</td>
</tr>
<tr>
<td>3</td>
<td>Subject3</td>
<td>Soft Shoes</td>
<td>35</td>
<td>153</td>
<td>64</td>
<td>F</td>
</tr>
<tr>
<td>4</td>
<td>Subject4</td>
<td>Sport Shoes</td>
<td>27</td>
<td>176</td>
<td>65</td>
<td>M</td>
</tr>
<tr>
<td>5</td>
<td>Subject5</td>
<td>Sport Shoes</td>
<td>31</td>
<td>163</td>
<td>80</td>
<td>F</td>
</tr>
<tr>
<td>6</td>
<td>Subject6</td>
<td>Sport Shoes</td>
<td>25</td>
<td>173</td>
<td>55</td>
<td>M</td>
</tr>
<tr>
<td>7</td>
<td>Subject7</td>
<td>Sandals</td>
<td>24</td>
<td>156</td>
<td>42</td>
<td>F</td>
</tr>
<tr>
<td>8</td>
<td>Subject8</td>
<td>Sandals</td>
<td>24</td>
<td>187</td>
<td>85</td>
<td>M</td>
</tr>
<tr>
<td>9</td>
<td>Subject9</td>
<td>Sport Shoes</td>
<td>23</td>
<td>188</td>
<td>74</td>
<td>M</td>
</tr>
<tr>
<td>10</td>
<td>Subject10</td>
<td>Sport Shoes</td>
<td>27</td>
<td>172</td>
<td>63</td>
<td>M</td>
</tr>
<tr>
<td>11</td>
<td>Subject11</td>
<td>Sport Shoes</td>
<td>22</td>
<td>181</td>
<td>80</td>
<td>M</td>
</tr>
<tr>
<td>12</td>
<td>Subject12</td>
<td>Soft Shoes</td>
<td>22</td>
<td>176</td>
<td>62</td>
<td>M</td>
</tr>
<tr>
<td>13</td>
<td>Subject13</td>
<td>Sport Shoes</td>
<td>44</td>
<td>181</td>
<td>85</td>
<td>M</td>
</tr>
<tr>
<td>14</td>
<td>Subject14</td>
<td>Soft Shoes</td>
<td>27</td>
<td>178</td>
<td>55</td>
<td>M</td>
</tr>
<tr>
<td>15</td>
<td>Subject15</td>
<td>Sport Shoes</td>
<td>32</td>
<td>162</td>
<td>53</td>
<td>F</td>
</tr>
<tr>
<td>16</td>
<td>Subject16</td>
<td>Formal Shoes</td>
<td>45</td>
<td>160</td>
<td>52</td>
<td>M</td>
</tr>
<tr>
<td>17</td>
<td>Subject17</td>
<td>Sport Shoes</td>
<td>27</td>
<td>175</td>
<td>53</td>
<td>M</td>
</tr>
<tr>
<td>18</td>
<td>Subject18</td>
<td>Sport Shoes</td>
<td>28</td>
<td>155</td>
<td>50</td>
<td>F</td>
</tr>
<tr>
<td>19</td>
<td>Subject19</td>
<td>Formal Shoes</td>
<td>28</td>
<td>178</td>
<td>68</td>
<td>M</td>
</tr>
<tr>
<td>20</td>
<td>Subject20</td>
<td>Sport Shoes</td>
<td>21</td>
<td>174</td>
<td>52</td>
<td>M</td>
</tr>
<tr>
<td>21</td>
<td>Subject21</td>
<td>Sport Shoes</td>
<td>57</td>
<td>173</td>
<td>80</td>
<td>M</td>
</tr>
<tr>
<td>22</td>
<td>Subject22</td>
<td>Soft Shoes</td>
<td>25</td>
<td>165</td>
<td>55</td>
<td>M</td>
</tr>
<tr>
<td>23</td>
<td>Subject23</td>
<td>Sandals</td>
<td>29</td>
<td>160</td>
<td>68</td>
<td>F</td>
</tr>
<tr>
<td>24</td>
<td>Subject24</td>
<td>Sandals</td>
<td>25</td>
<td>177</td>
<td>80</td>
<td>M</td>
</tr>
<tr>
<td>Subject</td>
<td>Type</td>
<td>Age</td>
<td>Weight</td>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------</td>
<td>------------</td>
<td>-----</td>
<td>--------</td>
<td>--------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>Formal Shoes</td>
<td>30</td>
<td>168</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>Sport Shoes</td>
<td>27</td>
<td>178</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>Sandals</td>
<td>28</td>
<td>154</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>28</td>
<td>Sandals</td>
<td>21</td>
<td>163</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>29</td>
<td>Sport Shoes</td>
<td>21</td>
<td>152</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>Formal Shoes</td>
<td>32</td>
<td>178</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>Formal Shoes</td>
<td>27</td>
<td>162</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>32</td>
<td>Sport Shoes</td>
<td>22</td>
<td>160</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>33</td>
<td>Sport Shoes</td>
<td>27</td>
<td>177</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>34</td>
<td>Sport Shoes</td>
<td>27</td>
<td>170</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>35</td>
<td>Sport Shoes</td>
<td>23</td>
<td>174</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>Formal Shoes</td>
<td>64</td>
<td>183</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>37</td>
<td>Soft Shoes</td>
<td>25</td>
<td>176</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>38</td>
<td>Sandals</td>
<td>27</td>
<td>169</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>39</td>
<td>Formal Shoes</td>
<td>26</td>
<td>175</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>Sandals</td>
<td>26</td>
<td>184</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>41</td>
<td>Sport Shoes</td>
<td>24</td>
<td>178</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>42</td>
<td>Sport Shoes</td>
<td>53</td>
<td>160</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>Formal Shoes</td>
<td>45</td>
<td>164</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>44</td>
<td>Soft Shoes</td>
<td>30</td>
<td>160</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>45</td>
<td>Sport Shoes</td>
<td>36</td>
<td>168</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>46</td>
<td>Sport Shoes</td>
<td>21</td>
<td>181</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>47</td>
<td>Sport Shoes</td>
<td>29</td>
<td>174</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>48</td>
<td>Formal Shoes</td>
<td>59</td>
<td>167</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>49</td>
<td>Sport Shoes</td>
<td>24</td>
<td>173</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>Sport Shoes</td>
<td>27</td>
<td>162</td>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>51</td>
<td>Sport Shoes</td>
<td>29</td>
<td>168</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>52</td>
<td>Sport Shoes</td>
<td>26</td>
<td>171</td>
<td>M</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Bibliography


