An Investigation into the Relationship between Static and Dynamic Gait Features

A Biometrics Perspective

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Abstract

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Keywords: gait recognition, biometrics, motion capture, 3d laser scan, static, dynamic , database, forensics, prediction, walk.

Biometrics is a unique physical or behavioral characteristic of a person. This unique attribute, such as fingerprints or gait, can be used for identification or verification purposes. Gait is an emerging biometrics with great potential. Gait recognition is based on recognizing a person by the manner in which they walk. Its potential lays in that it can be captured at a distance and does not require the cooperation of the subject. This advantage makes it a very attractive tool for forensic cases and applications, where it can assist in identifying a suspect when other evidence such as DNA, fingerprints, or a face were not attainable. Gait can be used for recognition in a direct manner when the two samples are shot from similar camera resolution, position, and conditions. Yet in some cases, the only sample available is of an incomplete gait cycle, low resolution, low frame rate, a partially visible subject, or a single static image. Most of these conditions have one thing in common: static measurements. A gait signature is usually formed from a number of dynamic and static features. Static features are physical measurements of height, length, or build; while dynamic features are representations of joint rotations or trajectories.

The aim of this thesis is to study the potential of predicting dynamic features from static features. In this thesis, we have created a database that utilizes a 3D laser scanner for capturing accurate shape and volumes of a person, and a motion capture system to accurately record motion data. The first analysis focused on analyzing the correlation between twenty-one 2D static features and eight dynamic features. Eleven pairs of features were regarded as significant with the criterion of a P-value less than 0.05. Other features also showed a strong correlation that indicated the potential of their predictive power. The second analysis focused on 3D static and dynamic features. Through the correlation analysis, 1196 pairs of features were found to be significantly correlated. Based on these results, a linear regression analysis was used to predict a dynamic gait signature. The predictors chosen were based on two adaptive methods that were developed in this thesis: "the top-x" method and the "mixed method". The predictions were assessed for both for their accuracy and their classification potential that would be used for gait recognition. The top results produced a 59.21% mean matching percentile. This result will act as baseline for future research in predicting a dynamic gait signature from static features. The results of this thesis bare potential for applications in biomechanics, biometrics, forensics, and 3D animation.

Dedication

This Ph.D. thesis is dedicated to my mother, Mona Al Mutawa, and my father, Mansoor Alawar. Growing up in a home filled with love and ambition is what made me the man I am today.

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Even though some would regard the PhD journey as a very lonely process, yet it involves the input and support from many people. Without them, I would not have been able to reach where I am today.

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Terminologies Glossary

3D Convex hull

A 3D convex hull is the efficient 3D representation of convex shape constructed through the usage of an algorithm. In gait recognition, certain techniques use multiple cameras to reconstruct a 3D shape of the subject.

3D mesh

A 3D mesh is a 3D representation of polygon based surface or object. In this thesis, 3D mesh is referred to the surface and 3D object created from reverse engineering the original points from the scanned point clouds.

Angle variance

Angle variance is a term used in gait recognition to identify that the angle of a subject's walk in regards to the camera changes from one sample to the other.

Appearance based gait recognition

Appearance based gait recognition creates a gait signature from the pixel information extracted from a moving subject. This approach does not attempt to extract information of pose or joint rotation, but rather treats the extracted silhouette as pixel information. One of the most common features extracted using this technique is the Gait Energy Image (GEI).

Biometrics

The statistical explicit representation of a biological or behavioral phenomenon. This representation is often used to recognize or identify a person.

Centroid

Centroid is the term used to define the centre of an object or region in an image.

Closed circuit television (CCTV)

CCTV is a term used to describe video cameras and footage that is not meant to be used for broadcasting purposes. This term is commonly used for surveillance cameras.

Database covariants

This is a term used in gait recognition based database which defines the variations to a gait sample. These variations might include change of : shoes, clothing, gait speed, or lighting conditions of the same subjects in the database.

Dynamic features

These are the dynamic features that are extracted from a subject's gait to form a gait signature. Dynamic features relate to the motion extracted from the manner in which various joints move in a human. Dynamic features usually involve the element of time. Speed, rotation of knees, and stride length are examples of dynamic features.

Electromyography (EMG)

Electromyography is the process of measuring electrical activity in muscles using an electromyogram.

Fourier descriptors

This technique is a method used to describe the outline of an object in image processing, using the computed Fourier Transform of the boundary.

Gait

The cyclic motion of the joints that produces locomotion

Gait kinematics

These are the description of gait movement, which are usually represented as angles of joint rotations and distance displacement of motion. Most model based dynamic features are considered to be gait kinematics.

Gait kinetics

These are the forces in involved that lead to locomotion or gait. These forces include forces from muscles or ground reaction forces.

Histogram similarity

Histograms are normalized by the number of recorded samples. The similarity is calculated by measuring the absolute difference between two histogram representations.

Inertial sensors

Inertial sensors are sensors that measure inertia. These sensors are used in gait recognition to extract dynamic features without resorting to video cameras.

Krawtchouk moments

Krawtchouk moments are a discrete orthogonal moment that are based on the Krawtchouk polynomials

Mahalanobis distance

This measurement equals to the distance between a point X from the mean Y, using standard deviation as a unit of measure.

Model based gait recognition

Model based gait recognition techniques create a human model that would fit in the extracted silhouette of walking subject. This model includes information that can be extracted such as knee rotations, stride length, and hip rotations.

Motion capture

This is the process of recording the motion from a subject only using different types of sensors that include: cameras, accelerometers, and infrared cameras. Motion capture systems have the subject perform an action, and the information is saved as the positional and rotational information of each joint. The motion capture used in this thesis is an optical based one, in which reflective markers are placed on a subject. Several cameras around the subject record the markers over time, and reconstruct their positions in 3D on the native software.

OBJ format

OBJ is a 3D geometry file format commonly used in 3D graphics and animation software. In this thesis, the OBJ format is used in the 3D mesh files.

Point cloud

Point cloud is a term used to describe a set of points in 3D space defined by an X,Y, and Z coordinates. The coordinates represent the distance from the point to the centre of origin along the designated axes. In this thesis, a point cloud refers to the 3D points captured using the 3D laser scanner.

Point of Light Display

It is a video that displays motion of a human without showing the person's appearance. This is achieved through the placement of small white spheres on a subject wearing a totally black suit shot in a studio with a black background. The end result is a video with floating white spheres.

Principle Component Analysis(PCA)

PCA is an analysis method that is commonly in gait recognition for dimension reduction of a gait signature.

Procrustes shape analysis

This analysis is statistical based and is used to compare shapes of an object.

Radon transform

This technique is often used in image processing, which computes an image along specified directions.

Static features

These are the static features that are extracted from a subject's gait to form a gait signature. Static features are usually single measurements that do not involve the element time. They commonly represent measurements of height and build. Thigh length, torso width, and head length are example of static features.

Stride cadence

Is the number of strides per minute, and usually reflect speed of a gait.

Stride length

Stride length is the length of a single step in a subject. In gait recognition, stride length usually refers to the average length of steps in a subject's gait.

Chapter 1: Thesis Introduction

1.1. Introduction

People identification and verification is a very important process that involves many aspects of people's lives; from border control to email access., There are currently three methods of human identification or verification(Boyd and Little, 2005, Sebastian, 2013), which are:

1- Object based,

2- Knowledge based,

3- And biometric based.

An object-based method would involve a unique object, or token, that would be only in the possession of that person, which would act as a verification or identification of his/her identity(Boyd and Little, 2005). Keys are a main example of an object-based method. A Knowledge based method involves identification and verification through a piece of information. An example of such a method is an email password. A fusion of the methods is more common, such as a bank card, in which the card (object based) and a pin number (knowledge based) are required.

Biometrics can be described as a statistical explicit representation of a biological phenomenon (Prabhakar et al., 2011), or alternatively are also defined in other literature as a method to identify humans through one or more explicit features, both physical and behavioral (Goudelis et al., 2010, Prabhakar et al., 2011, Jain et al., 2004).

Although all these methods are used in various applications in our daily lives, the use of biometrics has several advantages over token or knowledge based identification or verification. First, the token in an object based method might be stolen, while in a knowledge based method, a password or pin can be electronically stolen or obtained (Prabhakar et al., 2011, Gafurov, 2007). Second, there are certain practicality issues with knowledge and object based methods. Remembering many different passwords for many accounts and online emails can be very hard to keep up with. Carrying many objects (passport, bank cards, and license) can be also overwhelming (Gafurov, 2007). Therefore it is more pragmatic to link the identity of a person to a personal distinct physical trait(Prabhakar et al., 2011). This is where biometrics excels, as it does not exhibit the disadvantages mentioned of the other two methods (Gafurov, 2007).

Although the origins are in law enforcement, applications of biometrics are now commonly seen in civilian situations such as access control(Jain et al., 2004).Fingerprints are one of the oldest biometrics to have been studied and used (Prabhakar et al., 2011). Although using the iris, as a biometric is not as old as use of fingerprints, yet it is considered as one of the most used biometrics in practical situations. Facial recognition has been a very active developing form of biometrics. Other emerging biometrics modalities have been developed and studied such as gait, palm print (Kong et al., 2009), skin(Goudelis et al., 2010), signature, odor(Delac and Grgic, 2004) , keystroke and gait(Prabhakar et al., 2011).

1.2. Gait

Gait can be described as a cyclic motion of the joints that produces locomotion or movement, such as a walk or run. An illustration of a human gait cycle can be seen in figure 1-1. Using gait, as a method to recognize and identify a person has been an attractive approach for two main reasons: its ability to be captured at a distance, and its noninvasive capturing method.

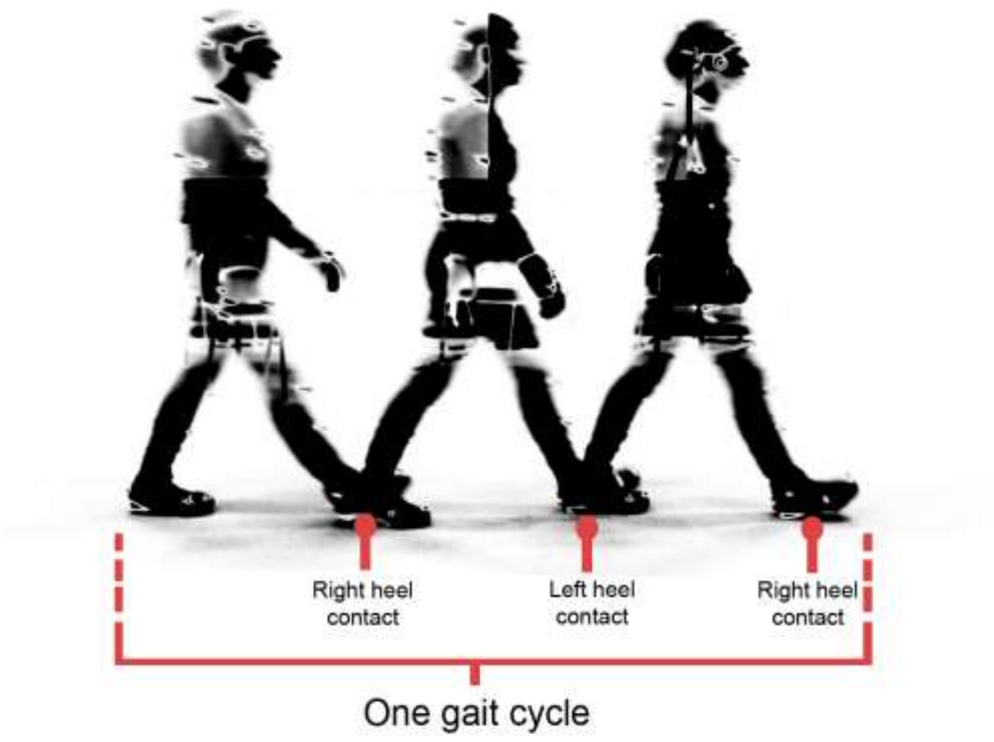

Figure 1: An illustration of a human gait cycle

The study of the biomechanics of gait is not limited to biometrics. On the contrary, it was involved in the clinical study of gait and its disorders far before gait emerged as a biometric. Gait analysis can be tracked back to a pre-computer age, when Aristotle produced theories around the manner in which humans and animals move (Baker, 2007). The Renaissance period witnessed great interest in the human body and its biomechanics, which was advanced through human dissection(Whittle, 1996). Gait analysis using computers was first introduced during the late 1970's when suitable computer systems were available for use at an affordable budget.

Gait analysis looks at several aspects, which include: gait kinematics and gait kinetics. Gait kinematics is the description of gait movement, which is usually represented as angles of joint rotations and distance displacement of motion. Such measurements can be captured using a video camera or a motion capture system. On the other hand, kinetics are the forces in action during gait, such as the forces between the feet and the ground. These measurements can be calculated through the use of floor sensors (Whittle, 1996).

Gait was not introduced as a means to recognize people until Cutting and Kozlowski proved that people could identify their friends through a Point of Light Display, which is video of moving light spheres, which are placed on a subject wearing black clothes(Cutting and Kozlowski, 1977). Later in 1993, Sourabh and Edward applied pattern recognition techniques to the kinematic data of a subject, and concluded that computer-based gait recognition is possible (Goddard, 1992). Gait recognition, which will be explained in further details in chapter 2, has since evolved in many different respects, from gait capture, to motion modeling and gait signature (feature) extraction. Until now gait recognition has been tested using a range of mediums that include standard video cameras, infrared cameras, and motion capture systems. In gait recognition human motion modeling can be performed in two or three dimensions depending on the application and medium used. Features extracted from a subject include many types of information that range from pixel information to motion and trajectories.

1.2.1. Gait and Latent Information

Most of the early gait recognition studies present conditions that are favorable for access control applications(Bouchrika et al., 2011), although biometrics' origins can be traced back to police work in criminal identification (Jain et al., 2004).Gait recognition has a great potential to be an effective means of identification in criminal investigation and forensic cases for several reasons. First, the prevalence of closed-circuit television (CCTV) cameras in most places provides a great source of information, especially considering that gait can be captured at a distance(Bouchrika et al., 2011). Second, the non-invasive method in which a gait signature can be captured is very favorable in criminal investigations, which usually involve uncooperative subjects. Third, in cases where criminals are masked and wearing gloves, gait captured via CCTV cameras can be crucial to an investigation, because gait is hard to hide or disguise.

A number of recent studies have emerged to discuss the use of gait in forensic cases (Bouchrika et al., 2011, Yang et al., 2014, Guan et al., 2013) It is clear that there are specific challenges facing the application of gait recognition in forensic cases, the main one being latent (or partial) information. Partial information describes the situation where information about the subject's gait is incomplete, e.g. where only a single frame of CCTV footage contains the subject, or parts of their body are occluded. This is similar to fingerprints in a crime scene, which are usually skewed, partial, or smeared. Crime scenes CCTV cameras came in different resolutions, angles, lens, and frame rate. With no constraints, performing comparison for identification becomes more difficult. Therefore, the goal in forensic or criminal cases would be to make the most out of limited data.

One approach to solving such a problem is making the optimum use of the partial evidence found. This approach has been adapted in cases of low frame rate video (Guan et al., 2013). The same approach is used by Yang et al, in cases of occlusion, in which part of the body is covered by a foreground element between the subject and camera(Yang et al., 2014).

Although such approaches provide potential solutions for specific challenges facing gait recognition's use in forensics, yet they do not perform a reconstruction or prediction of the whole gait dynamics and motion. Being able to predict the dynamics of a walk, regardless of whether the gait sample is partial or of a low frame rate can be crucial to the application of gait as an emerging biometric in forensic cases. This is one of the main challenges that this thesis aims to address. Various factors influence the manner in which a human walks. Factors such as age, gender, height, weight, body fat, muscle composition and strength(Yun et al., 2014) can influence a gait.

1.3. Research Aims

This thesis aims to study the relationship between 2d and 3d dynamic and static features through a correlation analysis. To conduct this analysis a database was created using motion capture and 3d laser scanning systems to provide optimum accuracy. Based on the correlation analysis, the study will conclude with the quality and accuracy assessment of the predictability of dynamic gait features that are specifically used for gait recognition applications.

The benefits of understanding the nature of this relationship is not limited to biometric and forensic based applications, but also transcends to biomechanics, clinical gait analysis, and 3D animation. The relationship between static and dynamic measurements from a computer vision point of view can provide an alternative insight into biomechanical human motion modeling. Being able to predict the dynamics of a gait from static measurements can potentially reduce the cost of gait analysis by taking away the need of using expensive gait motion capturing systems. Finally, predicting the motion component of gait through static measurement can provide an automatic method of animating walk cycles for 3d characters in animations and games, instead of the laborious manual process of hand key frame animations.

The following chapter will survey the background of gait research, and chapter 3 will describe the process of creating the database and its content and data. Chapter 4 will analyze the relationship between 2d static and dynamic features, while chapter 5 will discuss the relationship between the 3d static and dynamic features. Chapter 6 will discuss the creation of a prediction methodology as well as evaluate the accuracy and quality of the predictions. Finally, chapter 7 will discuss the main conclusions, contributions, and future research.

Chapter 2: Gait Recognition

2.1. Introduction

This chapter will build an understanding of what gait recognition is, how it has evolved, and the overall process of most gait recognition techniques. The chapter will specifically look into the various features that relate to gait, both static and dynamic. The chapter will conclude with the main challenges currently facing gait recognition progress, as well as defining the gap in previous work and the research questions in this thesis.

According to JE Boyd and J.J. Little, the definition of gait is the “coordinated, cyclic combination of movements that result in human locomotion”(Boyd and Little, 2005). Only cyclic motion is regarded as gait such as: walking, running, and jogging. Movements such as sitting down, carrying an object from the ground are not cyclic, and do not lead to motion, and are therefore not regarded as gait. Figure 2 shows multiple gait cycles, with one gait cycle specifically highlighted.

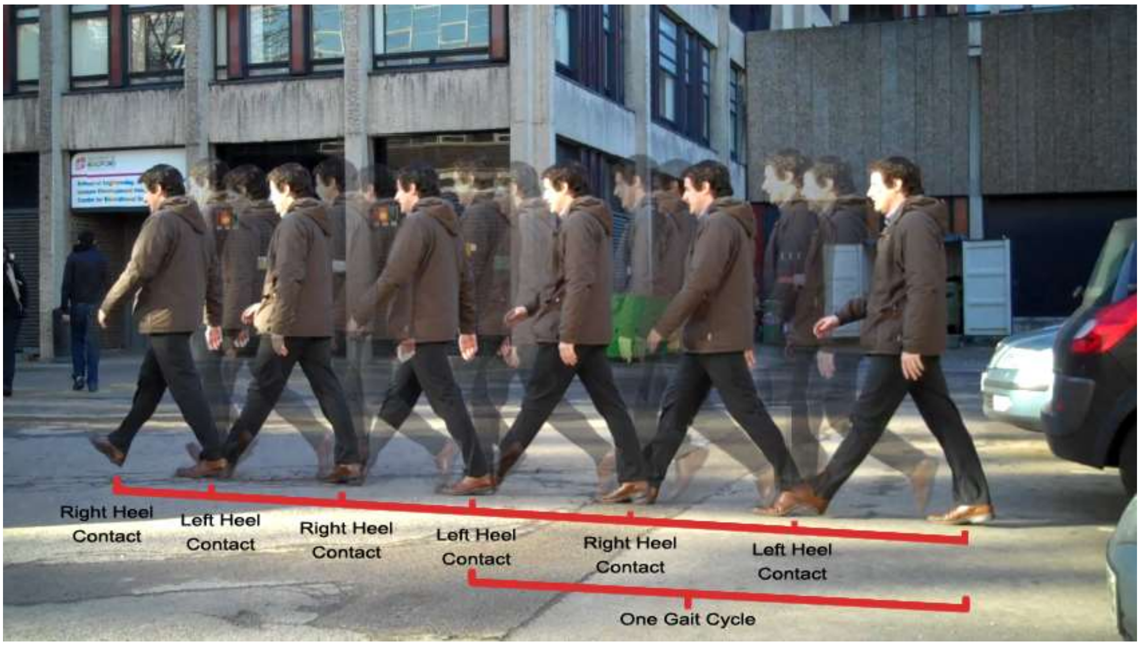

Figure 2: An example one complete gait cycle within cyclic walking motion.

2.2. History of gait recognition

Johansson was able to prove in an objective manner that human observers can discriminate people from animals when using point light displays (Johansson, 1973). Point light displays, are a video recording where white lights spheres are placed on a subject who is wearing black and are shot against a black background. The result is a video featuring floating white spheres, where the outline of the subject is not visible. Using the same Point of Light Displays, Cutting and Kozlowski managed to show that people can recognize their friends through their gaits, which went against the common convention that people recognize other people via physical appearance only (Cutting and Kozlowski, 1977). In addition to perception based studies, Nigel H Goddard showed in 1992, that computer based recognition was achievable from motion features in point light displays (Goddard, 1992).The study presented a method for differentiating between random moving points or those of a lights placed on a walking subject, and therefore demonstrated that human motion recognition was achievable in computer vision, without having to resort to using shape or colour information. It was not until 1994 in a study conducted by Niyogi and Adelson that pattern recognition techniques were used to recognize a person from the extracted subject's joint angle rotation signal, which in this case were extracted directly from ordinary video sequences without point of light displays (Niyogi and Adelson, 1994).

Following those initial findings, gait recognition grew to become an appearance (pixel based) technique. The introduction of the Gait Energy Images (GEI) allowed that technique to flourish. While in model based approaches, the introduction of phase-weighted magnitude as part of a gait signature was regarded as a major milestone in increasing the discriminating characteristics of a human's gait.

Many advancements in the field of biometrics overall, and gait recognition in particular, were assisted by the Human at a distance ID challenge (Sarkar et al., 2005). Sarkar et al.'s study provided the research community with a database for analyzing gait, as well as presenting main challenges, and outlining a baseline algorithm for testing and comparison. This was followed by growing interest in the field from several researchers and institutes such as MIT, Southampton University (Seely et al., 2008), University of Central Florida (Sarkar et al., 2005), and Osaka University (Makihara et al., 2012).

Gait has always been studied as an emerging biometric, yet in 2013 witnessed an increase in the studies around using gait recognition as a forensic and investigation tool, which will be discussed in a later section.

2.3. The Gait Recognition Process

Although gait recognition has evolved from its primitive beginnings, yet the general structure has remained consistent (Sebastian, 2013). Most gait recognition techniques follow a unified path. It first starts with the method of capturing; which can vary from standard video cameras to wearable sensors. The second step is silhouette extraction. This step involves motion detection and classification, which defines the regions in which the data belongs to a human's gait motion rather than an object's motion, such as a car or tree movement, or movement of the camera. Thirdly, a certain motion description or model is derived from the silhouette. In the fourth step, features are extracted from the model and are used to form a gait signature. Following this some techniques perform a fifth step of a feature selection or dimension reduction of the gait signature. Finally, a classifier method is used to find the closest match between the gait signatures captured and the gait signatures in a database. Figure 3 summarizes the gait recognition process.

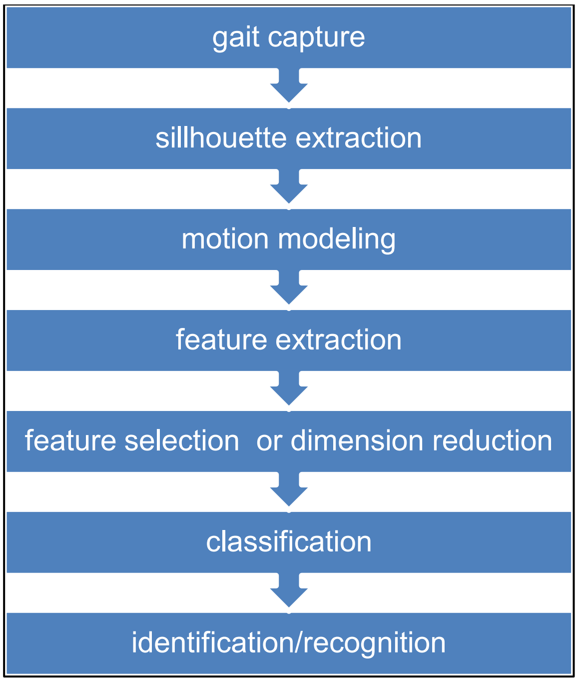

Figure 3: A diagram of the gait recognition process.

2.3.1. Gait capture

Just as facial recognition was tested using different capturing techniques and technology, gait capture has been tested using several different technologies as well. Although most are video based, there are a few exceptions in which other technologies were used for gait capture. Gait can be captured using any of the following mediums and methods: standard video (Sarkar et al., 2005), floor sensors (Middleton et al., 2005), wearable sensors (Rong et al., 2007), infrared cameras (Tan et al., 2006), motion capture (Razali and Manaf, 2012), laser scanning (Alawar et al., 2013), 3D stereo cameras (Ioannidis et al., 2007a), and time-of-flight cameras (Sivapalan et al., 2011). A summarized explanation of each of the capturing devices' usage and description can be found below.

Video

Video recorded using standard RGB cameras, is the most commonly used medium in the field of gait recognition research. Different cameras of different resolutions have been used in different techniques and databases. There have also been studies based on cameras with different frame rates and different levels of noise (Hayfron-Acquah et al., 2003), in order to simulate real world data that would usually be recorded by a low resolution and low frame rate surveillance system. Single camera systems are very common as they represent a similar setup to CCTV cameras in public spaces. Yet the nature of single cameras leads to several additional challenges, most importantly, occlusion; whether that is the self-occlusion of an individual's by their torso (for example) or occlusion by other objects within the scene.

Multiple cameras

Although a multiple camera setup can be regarded as standard video setup, it is important to distinguish this medium by itself, because of the nature in which such data is analysed and processed. In such setups, the problem of self-occlusion can clearly be reduced relative to single cameras. In addition to reducing occlusion the set-ups allow researchers to study the influencing factor of the camera angle variance, which is the angle variance at which the camera faces the subject, geometry in capturing different aspects of the gait cycles. These setups sometimes include a camera at 45 degrees from the subject to imitate a standard surveillance cameras. The CASIA database, for example, included numerous cameras at equal angle intervals, forming a 360 degrees video capture around the subject (Yu et al., 2006).

In 2006, a 3D Gait chamber was developed at the University of Southampton. The 3D gait chamber was created using 8 calibrated cameras to capture three dimensional gait data (Seely et al., 2008). In that study the data from the individual cameras went through the process of silhouette extraction, which is followed by the creation of 2.3.1. of the walking subject that is reconstructed from the individual silhouettes.. Although such systems provide a better alternative to single cameras, yet it is very uncommon for such a setup to be found in public areas with CCTV cameras due to cost effective measures in place. .

Floor sensors and Wearable sensors

There are a few gait recognition techniques that use data from non-imaging devices, such as floor sensors or wearable sensors. These studies were motivated for specific applications. Floor sensors are sensors that are pressure or force sensitive and are mounted in a fixed position on the floor (Middleton et al., 2005). Floor sensor based gait recognition can be used in different applications, including building access application, and passport control. Depending on the algorithm and technique used, features such as stride length, stride cadence, and time on toe to time on heel ratio can be extracted from the floor sensors, and are used in the study by Middleton et al. In their study an 80% recognition rate was achieved in a database of 15 subjects.

Wearable sensors, can include many different types of sensor, in gait the most important are accelerometers (e.g. those present in typical mobile phones), which can potentially be used for identity authentication in mobile devices. In a study by Gafurov et al., wearable sensors were used to measure the acceleration of the body part they were attached to (Gafurov et al., 2010). The signal extracted from the sensor was then compared to other signals using a histogram similarity method. In this method, using the number of recorded samples; the histograms are normalized. The similarity is calculated through the matching score between the two gait signal's absolute distances. Although in the past these sensors were placed on the waist, Gafurov et al. have placed the sensor on the ankle, because it undergoes greater accelerations than other body parts while walking.

More recent studies have looked at the usage practicality of gait recognition in mobile phones. In a study by Hoang et al., the use of gait data from different accelerometers on different mobiles was tackled (Hoang et al., 2013). An adaptive mechanism was proposed by studying the effect of various preprocessing steps including: data segmentation, noise reduction and feature extraction.

The use of wearable sensor technology in gait recognition has the potential of being applied to identity authentication, as well as providing information about the identity of a mobile user in criminal investigations if such data has been recorded in similar manner to how GPS location is stored on a mobile.

Infrared

Infrared imaging was introduced as a solution for some of the problems faced in facial recognition applications (Goudelis et al., 2010). In facial recognition, infrared imaging has been able to extract features that are not present in standard cameras; in particular it is able to make certain features more visible in faces such as: veins or tissue maps. However, in gait recognition the major benefit is its effectiveness in night time surveillance where visible light is usually scarce. In some studies, the use of infrared was reported to help in providing a better silhouette (Ming et al., 2009). Later studies by DeCann et al looked further into the use of the infrared spectrum in gait recognition (DeCann et al., 2013). They created a database of gait samples captured using a short-wave infrared sensor. The aim was to test the state of the art gait recognition techniques at that period of time, and understand the challenges that are faced when using such a medium. Although using they suggest that the infrared spectrum is ideal for covert missions or nighttime applications. Although silhouette extraction using infrared involves less complex processing than standard video, yet challenges such as low contrast can create problems with silhouette extractions (DeCann et al., 2013).

Motion capture

Motion capture can provide more accurate motion data than most modalities mentioned in this section. In a study by Razali and Manaf, gait recognition was conducted using motion capture data. Principle component analysis (PCA) was used to reduce the dimensionality of the gait motion data, as well as represent the subject's gait in a PCA feature vector (Razali and Manaf, 2012). Euclidean distance was used to measure the match rate between the test subject's principal components to the principal components of subjects in the database. Although using motion capture provides optimum accuracy, yet because it involves extensive subject cooperation, the primary usage of it is to provide ground truth data rather than identify people in real-life situations. A subject wearing a motion capture suit with the motion capture cameras in the background on tripods can be seen in figure 1-3.

Figure 4: A subject wearing a motion capture suit with motion capture cameras on tripods in the background

3D and Laser scanners

3D scanning methods can differ in their technology or method of implementation. Most of these devices produce 3D coordinates that can be represented by point positions forming a point cloud (Böhler and Marbs, 2002). Few studies have made use of such technology. In 2008, Posada et al. developed a system that used a low cost 3D surface scanner that was used for clinical gait analysis application (Posada-Gomez et al., 2008). The aim was not to capture a full 3D surface of a subject, but rather specific parts of a leg pre-defined by physical markers placed on the subject. This analysis was conducted pre-treatment and post-treatment.

It was also proposed by Barnich et al. to use a biometric curtain in gait recognition (Barnich et al., 2010). In this system, two laser scanners would be placed on two adjacent corners in a path. These two scanners would form a virtual curtain. When a subject passes through the virtual curtain, a 3D slice of the subject's profile that intersects with the curtain is extracted. As the subject passes through this curtain, a series of slices are captured; forming temporal 3D features that are used to create a gait signature. Although this technique produces a novel and alternative approach to gait recognition, yet the setup and equipment needed are more complex and unpractical when compared to video based gait recognition.

In a study by Yamauchi et al., laser range sensors were also used (Yamauchi et al., 2009). In this process, the human motion was extracted using a 3D model that was fitted to the captured 3D data. Kinematic (dynamic features) and static features were extracted from the 3D model, which were then used for gait recognition. Although such technologies provide an alternative approach to the other sensors mentioned above, yet their high cost and lack of significant increase in performance or recognition rate does not make them an ideal approach in practical situations. However, in a similar manner to motion capture, laser scanners can provide the most accurate 3D measurements of a subject, and are therefore useful for providing ground truth data.

3d stereo and depth cameras

3D stereo cameras have been recently used in multiple disciplines including gait recognition. In (Ioannidis et al., 2007a), a 3D stereo camera was used to study the possibilities of utilizing the additional depth information in gait recognition. The depth data and the binary silhouette were grouped together using two methods of transform: 3D Radial silhouette distribution transform and 3D geodesic silhouette distribution transform. Their results show that the approach is viable, and achieves improved performance over the baseline of Sarkar et al. (2005)

Time-of-flight (ToF) and structured light cameras have also received attention in gait recognition studies, especially after the introduction of the Microsoft Kinect. ToF cameras use knowledge of the speed of light to determine the distance between a point and the camera, therefore reconstructing a three-dimensional representation of what the sensor is viewing. Several gait recognition studies have reported their results and attempts at using such technology. Milovanovic et al. used the Kinect camera to perform gait recognition on frontal facing subjects (Milovanovic et al., 2013). In (Lu et al., 2013), test subjects were recording walking arbitrarily using a Microsoft Kinect camera. Although the Kinect camera provides the beneficial addition of depth, yet its limited distance coverage proves currently inefficient for gait recognition at a distance.

As new imaging technology is developed, the number of ways of capturing gait increases. There is no one technology that provides the ideal tool, but the choice is rather based on the scope of its application, by understanding its limitations and utilizing its strengths.

2.3.2. Motion detection and extraction

Different gait recognition techniques use different methods to extract features from subjects, but the majority requires a silhouette. The silhouette is defined as the range of pixels that contain a subject in a video (Sarkar et al., 2005). This process can generally be processed in the following steps: Background estimation (environmental modeling), silhouette or motion detection, motion classification and tracking. Each of the steps will be described in the following subsections.

2.3.3. Background subtraction

It is important for any gait recognition technique to acquire a background image in order to define the foreground from the background. In ideal lab conditions, light, background, and foreground elements can be controlled kept consistent, making background subtraction relatively straightforward. But in real world environments the distinction between foreground and background is often not clear, and the challenge lies in identifying the dynamics of an environment, from illumination variance to background movement (trees, leaves, flags, etc.) (Wang et al., 2004).

The most commonly used method to extract a background would be to compute temporal average, or some related quantity (Sarkar et al., 2005, Hu et al., 2004, Ioannidis et al., 2007a). In (Sarkar et al., 2005), the background plate extraction is calculated by computing the mean and the covariance of the color channel in each pixel. The decision on whether a pixel is classified as background or foreground is based on the Mahalanobis distance between the pixel value and the mean value, where large values indicate the presence of motion. In (Hu et al., 2004), the Least Median of Squares method was used to compute a continuously updated background.

There are several methods to extract the silhouette, but the three main methods are: background subtraction, temporal differencing, and optical flow (Wang et al., 2004).

Optical flow techniques involve the use of flow vectors of moving regions (surfaces or edges) which are calculated in each frame, at each pixel, of a video to categorize local motion. Because of the heavy computational costs, techniques that use this method require special hardware for real-time application (Wang et al., 2004). Therefore a more computationally efficient method is required for background subtraction.

Background subtraction is a common method and is very effective in lab scenarios. This method involves the pixel by pixel subtraction of a current frame to a background reference. It is very dependent on a good background estimation, therefore any changes in background lighting or slight movement in any background elements can induce challenges (Wang et al., 2004). An example of background subtraction is shown in figure 5. To overcome such difficulties, temporal difference methods can be used. This method involves detecting the difference (at a pixel level) between two or more consecutive frames. It is robust to changes in background, but can result in holes present in an extracted silhouette as shown in figure 6 (Wang et al., 2004). Therefore, fusing the strengths of different methods, as has been demonstrated in the study by Wang et al, who used a combination of background subtraction and temporal differencing to create a computationally cheap and effective solution (Wang et al., 2004).

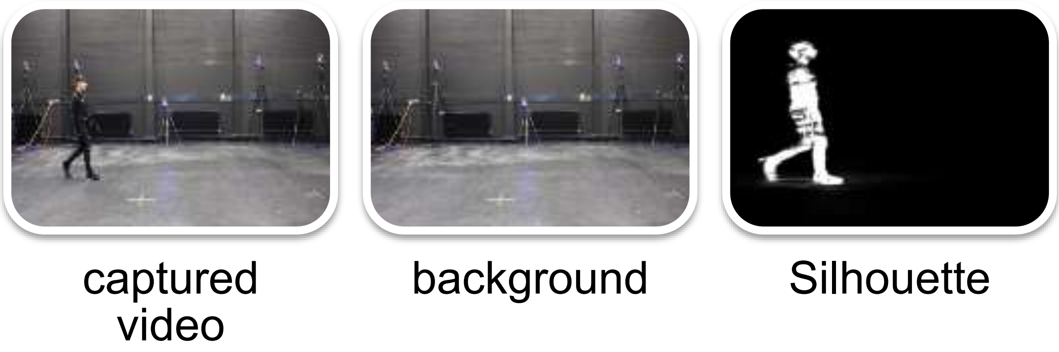

Figure 5: A silhouette is extracted when the captured video is subtracted from a background plate

Figure 6: Silhouette extracted using temporal differencing

Other segmentation methods have also been used. In a study by Sarkar et al.,the background is estimated by calculating the mean of every pixel over the entire sequence(Sarkar et al., 2005). To extract a silhouette, the Mahalanobis distance between the current pixel value and the mean value of the pixel over the whole sequence. Based on a manually defined threshold, the pixel is labeled as a background or foreground element. This technique produced a silhouette that is adaptive to a changing background, yet there are four major issues that interfere the creation of a perfect silhouette that include: shadows, setting the appropriate threshold, and moving objects in the background, as well as compression artifacts.

Segmentation will detect moving objects regardless of what the moving object is. The object can be a human, animal, car, or a plastic bag being blown away by the wind. Therefore, in gait recognition, it is important to separate human motion from other types of motion. This can be achieved using pattern recognition techniques, which might include shape based classification, or motion-based classification (Wang et al., 2004). It is also possible to merge both methods to increase accuracy. These methods involve the analysis of points, outlines, or even the bounding box surrounding the captured motion to classify the region as human, group of humans, or an object (Wang et al., 2004). Aspect ratio, area, and dispersedness are all features that have been measured in order to perform the classification.

Given that gait is a periodic and cyclic motion (Wang et al., 2003); this characteristic can be used to identify a walking human from a moving object, such as a car. Some techniques use self-similarity computations over a specified time of the same object to study the characteristic of the periodic motion (Wang et al., 2004).

One of the most shared challenges in any silhouette extraction is the change in lighting conditions, casting of shadows, and occlusion. In 2002, the HumanID gait challenge put forward one of the first gait recognition databases shot outdoors, in order to create an obstacle for the research and professional community to tackle (Sarkar et al., 2005).

Dealing with occlusion is unavoidable, whether it is self-occlusion or an object or foreground element occlusion, as in figure 7 (Wang et al., 2004). One of the recommended solutions is using a multiple camera setup in a way where it is possible to view the subject from most angles. Another solution is the use of 3D capture techniques similar to SOTON 3D Gait Database (Ariyanto and Nixon, 2011, Liu and Tan, 2010, Seely et al., 2008, Middleton et al., 2006).

Figure 7: The subject's leg is occluded by a foreground element(a car).

Shadows cast by moving subjects can be problematic in silhouette extraction as shown in figure 8, since shadows also have cyclic motion that is different from the background. There are several methods to solve this in which the proposed algorithm makes use of color information in order to lower the effect of shadows. Many of those are dealt with in (Wang et al., 2004), while a similar method is used in (Ioannidis et al., 2007a), in which an analysis of image in the HSV color space over a sequence of frames helps to remove shadows.

Figure 8: Shadows present a challenge in silhouette extraction.

The method of choosing the right silhouette extraction method is crucial and heavily depends on the specific challenges facing the application, and the method of gait recognition used. Lighting conditions, unstable backgrounds, non-human moving objects, and occlusion are all challenges faced in silhouette extraction. There are studies mentioned earlier that tackle each of the challenges except for occlusion. Occlusion is one of the challenges that will be later discussed in the Forensic approach challenges, and will be referred to as partial spatial information.

2.3.4. Human motion representation

After a silhouette is extracted, gait recognition systems must make sense of the changing pixel values that are associated with the walking person. Ideally minimalistic or feature based representation of human motion needs to be extracted to provide concise and a complete description of motion. The first step in representing human motion in gait recognition applications is defining a gait period. A gait period is considered one complete walk cycle. The main characteristic of a walk that is most commonly used is the distance between each foot. When the feet are furthest apart (full stride stance, or double foot support), the silhouette would be the widest. When the two feet overlap, the pixel width of the silhouette would be at its lowest (Sarkar et al., 2005). Therefore the time elapsed between the minimum and maximum width of the silhouette can be used to define the gait period. This technique is only effective in the case when the walk is parallel to the camera lens (fronto-parallel). In (Huang and Boulgouris, 2010), instead of measuring the whole binary silhouette, only the lower part was measured to find the start of a gait cycle. Another method is to use the number of pixels of the extracted human gait, where the time point at which the number of white pixels in a binary silhouette image are at their lowest is used as a point of reference (Hosseini and Nordin, 2013).

After defining a gait period, most gait recognition techniques represent human motion by two different approaches. They can either be: an appearance based method; or a model based method(Hu et al., 2004).

Appearance based methods

Appearance based methods can be described as features that are extracted based on pixel information or silhouette without consideration of the kinematic or kinetics of a gait (Hu et al., 2004, Wang et al., 2003). Appearance based methods in their simplest form can represent the temporal aspect of a gait in a single representation by averaging the sequence of frames of a gait cycle (Hosseini and Nordin, 2013). An example of an averaged walk sequence is illustrated in figure 9. Such techniques had great appeal in early studies of gait recognition, and are also used in current real time applications, because of their low computational cost and complexity (Hu et al., 2004).

Although appearance based methods might be thought of as being restricted to two dimensions, in (Shakhnarovich et al., 2001, Liu and Tan, 2010, Seely et al., 2008) a 3D hull can be treated and processed in the same manner as a single 2D binary silhouette would be processed. From a single 3D hull, an unlimited number of 2D silhouettes can be created.

Figure 9: An averaged sequence of extracted silhouette of a walking subject

Model based methods

Although appearance based methods are computationally cost effective, yet changes such as wearing a trench coat, carrying a bag or backpack, or wearing a skirt can effectively change the extracted silhouette, hence affecting the extracted appearance (pixel based) features. Several studies suggested that an accurate model-based feature extraction in which joint location and movement is measured, can overcome challenges faced in appearance based methods. Although model based approaches have a great potential, their high computational cost remains an issue when compared to the less intensive appearance based methods (Hu et al., 2004).

Model based methods can be described as techniques in which features are extracted from the modeling of human motion's kinetic and kinematic features (Hu et al., 2004). Kinetics of a gait are the forces acting upon a gait, from muscle and joint induced forces, to ground reaction forces. The kinematics of gait are the range of motion, trajectories, and angles of various joints' motion. Model based techniques' dynamic features are usually constituted of kinematic measurements rather than kinetics because, kinetics are not measurable using vision based sensors. The dynamic features are also divided into two categories: 2D and 3D modeling techniques.

Human motion can be modeled and predicted because the range of motion is restricted and can be estimated through rules defined by biomechanical gait models. Motion modeling usually involves prior knowledge to predict the present and the following pose. This knowledge and model is represented in many forms, ranging from a simple stick figure, to a detailed 2-D or 3-D contour (Wang et al., 2004). In 1994, one of the first model based techniques used a simple stick-figure which was fitted to a silhouette to describe the motion of the upper and lower legs (Niyogi and Adelson, 1994).

Ziheng Zou et al's study made use of as many 2D model based features as possible (Zhou et al., 2006). In their study, a simplistic 2D articulated model of a walker consisted of boxes to represent: torso, upper leg, lower leg, and feet. The parameters used in this model are divided into static and dynamic. The parameters that described the model were: head radius, torso width, torso length, leg width, thigh length, and calf length. A circle is used to represent the head. The model had no recognition of whether the leg was right or left because it was difficult to differentiate feet angles and orientation, as they are hard to recognize in outdoor conditions with changing lighting and other complexities.

In a study by Lee and Grimson, ellipses were used instead of boxes(Lee and Grimson, 2002). These ellipses roughly represented: upper and lower leg parts, torso, arms, and head. The ellipses were applied to the binary silhouette after it was divided into 7 regions. This method attempts to define the size and orientation of the different parts.

Zhou et al. attempted at modeling gait using a Bayesian framework (Zhou et al., 2006). It was based on strong prior knowledge which was formed from knowledge of the basic composition of joints, which was implemented as a specific model, alongside data that was built upon a hidden Markov model (HMM). The model consists of 12 parameters (both static and dynamic). The dynamic features were only of the lower limbs (thigh, shin, and feet),while the static features included: head radius, torso width, torso length, leg width, thigh length, calf length, the right and left thighs' angle, the right and left calves' angle, and the right and left foot angle.

The previously mentioned model based techniques lacked any use of biomechanical or physics based techniques. These were introduced in

Johansson's study, which described human motion as several pendulum motions that are linked at various joints (Johansson, 1973). These pendulums have start and end points that are constant in length. Similarly, modeling techniques using the core idea that leg motion is based upon pendulum-like mechanics are deployed (Yam et al., 2002). These same techniques are later used in a study at the University of Southampton. For example, Ariyanto and Nixon try to create 3D motion models of humans using the SOTON 3D Gait database (Ariyanto and Nixon, 2011). In this work, 3D cylinders were best fitted to the gait samples, and were limited only to the thigh and shin. This provided a model with an accurate estimation of three dimensional degrees of freedom compared to other limiting two dimensional techniques. This technique, however, was only successful when multiple cameras are present. Therefore in a study by Zhao et al, the authors deployed a technique that would work with a single camera. In the study by Zhao et al, a more complicated model for three-dimensional human form was used to extract gait features (Zhao et al., 2006). In addition to extraction of lower limb 3D dynamics, other features were used, such as upper arm, lower arm, shoulders, and head (Ariyanto and Nixon, 2011). In the study by Yamauchi et al., a 3D model was used to sample gait, through the accurate estimation of the key 3D poses, and then performing an interpolation for the angles in between (Yamauchi et al., 2009).

Krzeszowski et al. deployed a more detailed 3D model by using 11 segments: pelvis, spine, head, right and left upper arm, right and left forearm, right and left upper leg, and right and left lower leg. Each segment was specified a degree of freedom (Krzeszowski et al., 2013).

2.3.5. Feature extraction

Depending on the method of motion representation (appearance or model based), features are extracted to create a vector or variable that contains the distinct characteristic of an individual gait cycle. Before such a process is performed, most gait recognition techniques crop a gait sequence to one gait cycle. One gait cycle, as mentioned earlier, can be described as the period between two heel strikes of the same feet. Therefore; as an example, the gait cycle would start from when the left heel touches the ground. It would include the data of when the foot is planted on the ground as the right foot moves forward and is then planted, while the left foot will be raised once more and moved forward. The gait cycle will end once the left foot's heel strikes the ground again. Using appearance based methods, this is most commonly achieved by defining the point where the bounding box surrounding the person in motion is at its maximum width, which corresponds to when a heel strike occurs. This technique is also used in 3D gait data, where the 3D bounding box formed by the 3D volume representation surrounding all silhouettes is used to define one gait cycle, starting when the width of bounding box is at its maximum, and ending at the following maximum (Ariyanto and Nixon, 2011).

Other techniques calculate a gait sample by initializing it when the number of pixels in a silhouette is at its minimum (Ioannidis et al., 2007a, Boulgouris et al., 2004). This does not represent a heel strike, but rather a mid-stance in which one foot is on the ground, while the alternate foot is raised and has travelled approximately half the distance. Similar to the previously mentioned techniques, every other consequent minimum equates to one gait cycle. Whether using appearance or model based methods, defining a unified start and end of a gait cycle is essential in biometric application for the validity of the comparison between an unknown subject and the subjects in a database.

Appearance and pixel related features

Appearance based feature extraction depends directly on the binary silhouette extracted. It is usually followed by an extraction technique that would describe the silhouette in an efficient manner. Some methods use techniques to define the outline, while others take into consideration the whole binary shape, while some use the output of optical flow functions.

Binary shape images are a common gait signature representation. . Han et al. introduced the use of the Gait Energy Image as a gait feature. In essence, it describes the whole gait cycle using a single image that is equivalent to the average image of all frames in a single gait cycle(Han and Bhanu, 2006). In the study by Huang and Boulgouris, based on the Gait Energy Image, a weight shifted energy image is used as a feature (Huang and Boulgouris, 2010). This technique takes into consideration the discriminatory value of each three sectors of the silhouette separately: legs, torso, and head. In other studies, three views of the silhouette were extracted: frontal, side, and top. Each set was then averaged to form a single 2D image of the silhouettes (Liu and Tan, 2010, Seely et al., 2008).

The main challenge in using GEI is angle variance. Depending on the angle between the subject and the camera, the GEI can considerably change; therefore reducing recognition rates. To overcome this challenge, Liu et al.

created a new gait feature descriptor using two methods fused into one. They fused the Radon Transform technique and the Gait Energy image, and created the REI (Radon transform based energy image). Using this feature it was found that different individuals could be discriminated with similar recognition rates to standard camera geometries, suggesting that the method makes gait recognition robust to changes in camera geometry (Liu and Tan, 2010). Most of the appearance based techniques assume that the subject will walk in one direction. Yet in many real life scenarios, a subject would arbitrarily move in changing directions. Therefore in a recent study by Lu et al. the gait sequence was clustered depending on the direction of the subject's walk. Since the subjects were walking arbitrarily, it was not possible to automatically detect a gait period. Therefore, frames of a similar view were clustered together. Each cluster was then averaged using the GEI technique(Lu et al., 2013). The results of using this technique achieved similar results to most state of the arts techniques.

Another form of using GEI was proposed by Wang et al. In an averaged image, timing information is lost. Therefore in their study they combined the GEI feature with a colour map which preserved temporal information to create a chrono-gait image (CGI) (Gu et al., 2010). While in the study by Xu et al, local augmented features were used to extract features from the GEI(Xu et al., 2012).

Although the use of GEI and its varieties is common, yet other feature spaces such as the EigenGait have displayed similar accuracy rates. BenAbdelkader et al. created a feature called the EigenGait. It is similar to EigenFace which was developed by Sirovich and Kirby in 1987, and later used by Mathhew Turk and

Alex Pentland in face classification. In the EigenGait method, self-similarity feature is extracted from each pair of frames in a gait sequence. This output is then processed using dimensionality reduction, producing a feature that can be used for recognition using common pattern recognition algorithms. Using the EigenGait, classification rate of 77% has been achieved(BenAbdelkader et al., 2001).. In another study, Eigenspace is also used but in a different manner (Hosseini and Nordin, 2013). The average silhouette undergoes an Eigenspace transformation that is based on Principal Component Analysis (PCA), which is then used as a gait feature.

To reduce computation and dimensions of a signature matrix or vector, some techniques use the outline of a silhouette instead of the whole shape. In one study, general Radon based transforms are used to describe the shape . This method proves to be able to save detailed data regarding the binary image, especially the leg and arm area (Ioannidis et al., 2007a). Wang et al. used an Eigen-shape as a gait signature which was driven from the binary silhouette using Procrustes shape analysis(Wang et al., 2003). PCA was used in another study to reduce the dimensionality of the averaged silhouette (Hosseini and Nordin, 2013). Other techniques use Fourier descriptors to describe the boundaries or outline of a gait's silhouette's shape. In a study by Mowbray et al., the outline of the silhouette was expressed using the Fourier series' coefficients as descriptors (Mowbray and Nixon, 2003). In another study, Fourier descriptors were used to define local and global features(Guang-Jian et al., 2004). While Xiaoqi et al target the use of Fourier descriptors on four frames only, which represented key poses in a gait cycle (Xiaoqi et al., 2008).

Static features and dynamic features

Appearance based techniques extract features directly from images, whereas model based techniques use the image information to fit the parameters of a pre-defined model, and underlying motion parameters are then extracted from the model. Model based approaches extract two distinctive types of features: static and dynamic. Static features can be described as features that do not have a temporal component, and can be extracted from one frame within a sequence. They are also described as measurements of body build and height (Hu et al., 2004).

One of the early attempts at extracting dynamic features from a gait sample was conducted by Lee and Grimson. In this technique ellipses were fitted to 7 regions in the silhouette: head, front of torso, back of torso, right thigh, right calf, left thigh, left calf. Although the technique's main aim was to extract dynamic features, static features such as: the centroid, aspect ratio of width to length, and the orientation of the ellipses were also used (Lee and Grimson, 2002).

Static features are also extracted in 3D based models and gait recognition techniques. In a study by Ariyanto and Nixon, certain features such as height and stride length are extracted (Ariyanto and Nixon, 2011). A unique feature in this technique was the use of a footprint pose as a static feature. The footprint features consist of width, length, and orientation. Zhao et al., extracted other 3D static features such as length of upper arm, lower arm, head, shoulders, upper leg, lower leg, upper body, and hips which were used for gait recognition (Zhao et al., 2006).

Dynamic features

On the contrary to static features, dynamic features differ in that they involve the extra dimension of time, and usually involve joint angles and trajectories (Hu et al., 2004). The most common feature representation is the phase-weighted magnitude based on the Fourier Transform of a cyclical gait signal, which is in turn is created from the registered rotation of the thigh and knee joints. It was first introduced in a study by Cunado et al. at the University of Southampton (Cunado et al., 1997).

As mentioned earlier, Lee et al.'s study conducted one of the earliest attempts at extracting dynamic features from a gait sample. In this study ellipses were fitted to the 7 regions in the silhouette. The relationships between the ellipses were then analysed in a temporal manner to extract features to represent the dynamic component of the gait.. Both an averaged result and a magnitude and phase were computed for the features over time (Lee and Grimson, 2002).

Unlike two-dimensional models, three-dimensional models can provide extra information in trajectories and angle rotations. In Ariyanto and Nixon's study, dynamic features from the hip, thigh, and knee are used(Ariyanto and Nixon, 2011). Cylinders are fitted to the 3D gait data, and are used to extract both the lateral and frontal rotations of the thigh and knee joints. These angles are then used as gait features after applying a Discrete Fourier Transform to acquire information about the frequency component, which is similar to the phase-weighted magnitude features extracted by Yam et al. (Yam et al., 2002) and Cunado et al. (Cunado et al., 1997). While the hip's transformational data, 3D world position, was used as a dynamic feature. This early technique in 3D gait recognition technique managed to achieve a 79% recognition rate on an internal database of 48 subjects.

There are certain gait recognition techniques combine features from multiple approaches. Wang et al. used appearance based features, as well as dynamic features to recognize the identity of a subject in an internal database of 20 subjects (Wang et al., 2004). The fusion of both methods increased the recognition rate by 10%; from 87.5% to 97.5%.

There are other dynamic features that could potentially be considered in computer vision based gait recognition from other applications. There are features that were used by the Institute of Forensic Medicine in Copenhagen, that were not considered by most computer vision based gait recognition techniques such as: inversion/eversion in ankle, and the lateral flexion of the dorsal column in the spine (Larsen et al., 2008). These Lateral flexion and inversion and eversion of the ankle usually require 3D measurement of the rotation of the joints. Although mentioned By Larsen et al as not being used in computer vision based gait recognition, in a 3D based gait recognition technique developed at the University of Southampton, the knee angle from a frontal view was also used as a dynamic feature (Larsen et al., 2008), which proves that consideration of features used from other disciplines can improve efficiency and accuracy of gait recognition techniques.

Table 1 lists features of different types used in gait recognition.

Table 1: A list of various appearance, static, and dynamic features used in gait recognition techniques

Feature	Feature type	Gait recognition technique method	Extraction method
Height	static	(Johnson and Bobick, 2001)	model based
Length of legs	static	(Johnson and Bobick, 2001)	model based
Length of torso	static	(Johnson and Bobick, 2001)	model based
Length of stride	static	(Johnson and Bobick, 2001)	model based
Phase weighted magnitude Knee angle	dynamic	(Zhou et al., 2006)	model based
Phase weighted magnitude thigh angle	dynamic	(Zhou et al., 2006)	model based
Binary silhouette similarity	DYNAMIC/STATIC	(Gafurov, 2007)	appearance
Phase based features extracted from dense flow distribution	Dynamic	(Little and Boyd, 1998)	appearance
Eigen shape from Binary silhouette outline from Procrustes Shape analysis	Dynamic	(Wang et al., 2003)	appearance
Weight Shifted Energy Image	Dynamic	(Wang et al., 2003)	appearance
Height amplitude oscillation	Dynamic	(Boyd and Little, 2005)	appearance
Length of upper arm	Static	(Zhao et al., 2006)	model
Length of lower arm	Static	(Zhao et al., 2006)	model
Length of shoulder	Static	(Zhao et al., 2006)	model
Length of upper body	Static	(Zhao et al., 2006)	model
Length of hips	Static	(Zhao et al., 2006)	model
Length of upper leg	Static	(Zhao et al., 2006)	model
Length of lower leg	Static	(Zhao et al., 2006)	model
Length of head	Static	(Zhao et al., 2006)	model
Distance from knee to root	Dynamic	(Zhao et al., 2006)	model
Distance from ankle to root	Dynamic	(Zhao et al., 2006)	model

Distance between right and left knee	Dynamic	(Zhao et al., 2006)	model
Distance between right and left ankle	Dynamic	(Zhao et al., 2006)	model
Gait frequency	Dynamic	(Guo and Nixon, 2009)	model
Gait phase	Dynamic	(Guo and Nixon, 2009)	model
Ankle rotation	Dynamic	(Guo and Nixon, 2009)	model
Hip rotation	Dynamic	(Guo and Nixon, 2009)	model
Head width	Static	(Guo and Nixon, 2009)	model
Head length	Static	(Guo and Nixon, 2009)	model
Width of torso	Static	(Guo and Nixon, 2009)	model
Head x offset	Static	(Guo and Nixon, 2009)	model
Head y offset	Static	(Guo and Nixon, 2009)	model
Leg width at hip	Static	(Guo and Nixon, 2009)	model
Leg width at knee	Static	(Guo and Nixon, 2009)	model
Leg width at ankle	Static	(Guo and Nixon, 2009)	model
Hip y offset	Static	(Guo and Nixon, 2009)	model
Foot width	Static	(Guo and Nixon, 2009)	model
Foot length	Static	(Guo and Nixon, 2009)	model
Centre of torso	Dynamic	(Guo and Nixon, 2009)	model
Pelvis width	Static	(Guo and Nixon, 2009)	model
Gait symmetry map	Dynamic	(Guo and Nixon, 2009)	appearance
Gait Energy image	Dynamic	(Han and Bhanu, 2006)	appearance

Radon Transform based Energy Image	Dynamic	(Liu and Tan, 2010)	appearance
EigenGait	Dynamic	(BenAbdelkader et al., 2001)[	appearance
HTI(Head-Torso-Thigh)	Dynamic	(Tan et al., 2006)	appearance
Height	Static	(Johnson and Bobick, 2001)	model based
Length of legs	Static	(Johnson and Bobick, 2001)	model based
Length of torso	**Static**	**(Johnson and Bobick, 2001)**	**model based**

The features listed in the table above contain 47 gait features. They are based on appearance and model based gait recognition techniques. Out of the 47, 26 are static features, while 21 are regarded as dynamic. The features do cover many different feature spaces and approaches of representing a human's gait, yet they are all two dimensional in their representation. Even in previous studies in which claimed to have approached gait in a 3D manner, end up using two dimensional features in classification. Such as the 3d hull in which a 2D GEI is extracted depending on the angle needed (Seely et al., 2008).

2.3.6. Dimension reduction and feature selection

Various techniques use different numbers and vector sizes to represent a gait signature. In some cases dimension reduction or feature selection is important. There are three main reasons such a step is required and can be summarized as (Guo and Nixon, 2009):

1- Avoid low performance in classification,

2- Avoid use of redundant features,

3- Reduce storage, computation load, and bandwidth requirements in gait recognition systems.

In the study by Han and Bhanu, Principal Component Analysis (PCA) and Multiple Discriminant Analysis (MDA) are used for dimension reduction of the Gait Energy image(Han and Bhanu, 2006). PCA is also used to reduce the dimensions of a similarity plot to produce the EigenGait(BenAbdelkader et al., 2001).

It has also been shown that not all features initially extracted are important in recognition. In one study, 32 features out of the original 56 were selected based on ANOVA, and the recognition rate was very similar to when using all features(Lee and Grimson, 2002). In the study by Little and Boyd, ANOVA was used to measure the discriminatory characteristic of a feature(Little and Boyd, 1998). Although no features were excluded in this study, the effect of each individual feature was studied. In another study, Mutual Information is used to evaluate and select the highly discriminatory features (Guo and Nixon, 2009). Mutual information was compared to ANOVA and the use of the correlation coefficient for feature selection and reduction. Mutual information was found to be a stronger feature selector. Mutual information achieved a 90% correct recognition rate using only 25 features, while ANOVA required 29 features and the correlation-based method required 35 features to reach to the same correct recognition rate.

2.3.7. Classification and Recognition

The final step in most gait recognition techniques is classification. In this step, the test subject is compared to the subjects in the database. Depending on the classification method used, the technique will suggest the closest gait in the database to the test subject. In some studies, three classifiers were used: Nearest Neighbour, Kth Nearest Neighbours, and Nearest Neighbour with class exemplars(Little and Boyd, 1998, Wang et al., 2003). The K^{th} Nearest Neighbor and leave-one-out cross validation classifier can be seen to be one of the most common techniques and used in several studies (Ariyanto and Nixon, 2011, Yam et al., 2002, BenAbdelkader et al., 2001).

A genetic algorithm was used in on study to fuse three different sets of features to find the best match(Ioannidis et al., 2007a). Johnson and Bobick suggested the use of an expected confusion matrix instead of a recognition rate, to report the results of the classification (Johnson and Bobick, 2001). It was suggested to use this method in order to predict how a feature will translate to a larger population than the tested sample databases, which usually contain between 20-200 subjects. Despite the range of different classifiers used, it is still not clear which will deliver the best classification, and different classifiers may need to be applied depending on the application and features of interest.

2.4. Challenges in gait recognition

Gait recognition techniques have evolved from their primitive methods in the mid 90’s to its current status. Different methods have been studied that include pixel appearance based methods and model based methods. The gait recognition process has been constant as explained in the previous sections. Perfecting each step and identifying the limitations and challenges faced will lead to better application of this emerging biometric. The Human Gait Challenge was one of the first published attempts at identifying the main challenges in gait. (Sarkar et al., 2005) The challenge offered a database and a baseline algorithm for other research and studies to compare with. In this Challenge only five covariates were taken into consideration: angle variance, carrying a briefcase, time, surfaces, and shoes. Other challenges also emerged later that relate more to the practical application of gait recognition, such as forensic usage of biometrics, unconstrained walk direction, occlusion, and comparisons between different camera sensors. Each of the previously mentioned challenges will be briefly described as well as mentioning proposed solutions and approaches to such challenges.

2.4.1. Angle variance

Since most early gait recognition techniques used subjects walking in a single direction perpendicular to the camera, it was clear that the first challenge was change of angle. Angle variance was an early issue recognized by various studies as a main challenge for actual implementation of gait recognition. Several studies suggested the use of features that were unaffected or minimally effected by the angle at which the video sequence was shot at. Huang and Boulgouris proposed the use of an algorithm, which would be a potential solution for angle variance. It builds upon the fact that people in real life situations would not walk in a straight line(Huang and Boulgouris, 2010). Therefore; the algorithm extracts features from the first gait cycle in which the subject is parallel to the camera plane. Such a solution will only work if the subject ever walks parallel to the camera plane. Therefore an alternative solution was proposed in a study by Johnson and Bobick. The features used in defining the gait signature were transformed using a depth compensation method(Johnson and Bobick, 2001). This compensation is driven by pre-calibrating a camera with a subject of known height and body parameters. This method achieved a recognition rate ranging between 91-100%. The test was conducted on a database of only 18 subjects, and the test was limited to using static features to build a gait signature for the subjects. Therefore, the depth compensation method was only tested for its effectiveness on measuring static features, and no tests were conducted using the dynamic features.

Ultimately, to solve such a challenge it would be necessary to record gait samples using three-dimensional techniques. Because of the nature of 3D data being invariant to camera angle, gait signatures captured from such systems can be used to overcome the angle variance challenge (Ariyanto and Nixon, 2011).

2.4.2. Clothing and carrying objects

Clothing is one of the main problems in most gait recognition techniques, especially ones that depend on appearance based methods. Wearing a skirt or long jacket can affect the silhouette; therefore; reducing recognition rate One approach is to use the Bayesian framework in extracting a gait model from a single frontal camera(Zhou et al., 2006). This was tested on subjects with different clothing, including trench coats and skirts. The results found were promising and have achieved a recognition rate of 68%. It is interesting to note that trench coats and long skirts had a similar effect on the accuracy of the gait model. These two variants proved to produce less accuracy compared to the effect of carrying a bag back.

Two other approaches are proposed by Lee and Grimson(Lee and Grimson, 2002). The two methods of dealing with the features proposed were: averaging, and spectral analysis (phase and magnitude of the Fourier transform). It was found that the Spectral component performed considerably better than the average component, and was less affected by change of clothing. Another solution was purposed by Guan et al. (Guan et al., 2012). The study takes into consideration that when applying machine learning algorithms for recognition purposes, overfitting of the database data can be a problem for appearance based methods. Instead of training on extraction of gait features, clothing appearance features will be picked up when one subject appears wearing a trench coat in one sequence, and without a trench coat in another. Therefore; the study proposes classifying using a random subspace method and combining multiple inductive biases to avoid overfitting. Using this approach provided a result similar to the state of the art, as well as being more robust to change in walking conditions, including change of clothing.

Clothing is a major influencing factor to gait recognition, especially if appearance pixel based methods are used. In the study by Yu et al, the aim was to quantify the effect of angle variance, clothing, and carrying an object on gait recognition(Yu et al., 2006). It came to the conclusion that clothing can have a greater affect on recognition than carrying an object. It is important to note here that an appearance based method was used (GEI-Gait Energy Image), which would be highly affected by appearance change. Therefore, using model based approaches would make feature extraction more robust to these variants than in pixel based methods. Yet the unanswered question would be, how much does clothing affect the kinematic or dynamic features, rather than the appearance based features.

2.4.3. Physical body changes

Physical body changes include weight gain, pregnancy or medical procedures. Studies conducted in the clinical gait analysis field have looked previously at such factors. In their study, Chang and Bekey created an experiment to predict changes in electrical activity of muscles around the ankle post ankle surgery (Chang and Bekey, 1978). Although the study was conducted in 1978, it is still an indicator that even a small alteration can cause possible changes in gait mechanics. There is yet to be a study in computer vision based gait recognition that studies these changes and their influence in gait recognition accuracy.

2.4.4. Shoes and surfaces

Although different shoes are considered a problem in gait recognition, it was found to be less significant than changes in surfaces, carrying a briefcase, or passage of time (Sarkar et al., 2005).

Surfaces have been reported to be one of the most influential factors on gait recognition. In the Human ID challenge gait database, change in surfaces on which the subjects were walking resulted in the lowest recognition rates when compared to other covariants using the baseline algorithm (Phillips et al., 2002). A justification for such an influence can be found in biomechanical studies. Based on biomechanical studies, any change in surfaces can cause changes in ground reaction forces causing a change in kinetics and kinematics of a gait dynamic (Feehery Jr, 1986). Although in a later study byTillman et al the authors found no significant change in ground reaction forces, yet in another study the electromyography(EMG) data, which describes muscle activity, was different when running on different surfaces(Tillman et al., 2002) (Wang et al., 2014). These changes can be due to personal judgement of humans in order to compensate for the difference in impact sensation between surfaces (Feehery Jr, 1986).

2.4.5. Time passage between two gait samples

Time has been reported by several pieces of research to be a significant influencing factor in gait recognition. In one study, it was found that passage of time between two gait captures lowers recognition rate more than the other covariates (shoes, surfaces, angle variance, carrying a briefcase) (Sarkar et al., 2005). The problem of time passage in gait recognition could be caused by several factors. The method of acquisition of the video might differ, as well as change of clothes and shoes (Sarkar et al., 2005). The same conclusion was also reached to in 2010 by Gafurov et al., in which wearable sensors were used(Gafurov et al., 2010).

The work of Matovski et al. suggests the opposite of the conclusions of similar studies. (Matovski et al., 2012) Their study was conducted in a manner in which time passage was tested independently and in a manner in which clothing, shoes, and setting were controlled. It was found that there was not a significant effect on a gait signature when time passage spanned from six to nine months. Therefore, the problem was not mainly passage of time, but rather other factors that included clothing, shoes, and angle variance.

2.4.6. Large databases for benchmarking

Gait recognition based database are considerably smaller in subject numbers than their counterparts in other major biometric modalities. Major biometric modalities, such as iris, fingerprint, or face, have databases with significantly more examples than most gait recognition databases. Such numbers provide a more accurate insight into the feasibility and actual individuality and discriminatory characteristic of a biometric trait. These unified databases also provide a unified platform on to which various algorithms and techniques can be benchmarked. Most research in gait recognition is tested on local databases usually containing an average of 20 subjects, which does not provide a clear manner in how different recognition techniques can be compared. A need for a unified database like the ones used in the field of fingerprint matching is required.

The Human Gait challenge in 2002 was one of the first attempts at offering a shared gait database for the research community, in which recognition techniques can be benchmarked (Sarkar et al., 2005). Up until 2011, most gait databases did not have more than 152 subjects. Since then the OU-ISIR gait database has been often used as a benchmarking platform and currently contains more than 4000 subjects (Makihara et al., 2012).

2.4.7 Practical and Forensic challenges

Although the majority of the previously mentioned challenges (Such as physical change, clothing, and time passage) can fall under forensic challenges, yet forensic criminal evidence has specific challenges. These challenges include: difference in video sensors, difference in camera lens, difference in frame rates, and Latent (or partial) information or samples.

2.5. Forensic challenges

Although several previously mentioned studies have proved that gait can be used as a biometric using computer vision based techniques, the majority were tested in favorable conditions. Yet in forensic based approaches several challenges arise and must be studied and overcome for a practical application of gait recognition techniques. Some of these challenges are being addressed by other studies such as different lighting conditions, angle variance, shoe type, time passage between gait capture, and flooring. But there are other challenges more specific to forensic applications of gait recognition that are less addressed. One of the main forensic challenges is latent information. The problem of latent information can further be broken down into: low temporal and spatial resolution, and partial temporal and spatial gait cycles. An illustration of these challenges can be seen in figures 10-13.

Figure 10: An example of a low spatial gait data (pixelated)

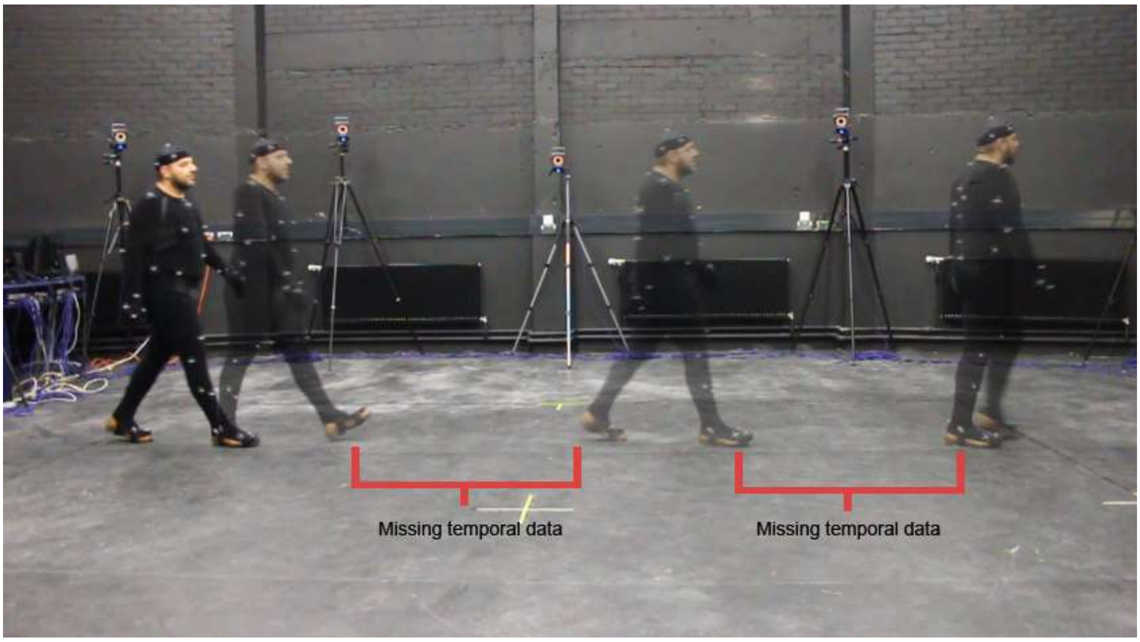

Figure 11: An example of a low temporal resolution of a gait data (Low frame rate)

Figure 12: An example of gait data with partial spatial data, where not the whole subject appears on camera.

Figure 13: An example of gait with partial temporal data, where the subject does not complete a full gait cycle on camera

For gait to be used in forensic applications, the source of the gait signature would usually be extracted from CCTV footage. CCTV footage's spatial and temporal resolution can greatly vary. Spatial resolution can be described as the number of pixels representing the person in focus in a single frame. Temporal resolution on the other hand is the number of frames representing a certain period of time, which is usually measured in frames per second (fps). Partial temporal gait cycle is an incomplete gait cycle, which can be caused by the subject leaving the field of view of the camera, or being totally occluded by an object in the foreground. Partial spatial gait cycle is the condition when only part of the body appears in a gait cycle because of an object hiding part of the body, as in when a subject walks behind a fence, and only the upper body appears on camera.

In certain situations, the CCTV camera footage is of a low frame rate or low resolution. Most model based gait recognition studies extract gait signatures using videos that are 60, 30, or 25 frames per second (fps). Some CCTV cameras record as low as 1 fps (Akae et al., 2012). Depending on how far the subject is from the camera, the amount of pixel data available to extract model based gait features can vary. Potential approaches to tackle low frame rate videos have been conducted in two studies (Mori et al., 2010, Akae et al., 2012). Akae et al. tackle the low frame rate challenge by using a super resolution approach. High frame rates gait sequences are used in the training stage. This techniques is currently performs better than other approaches, especially when the frame rate is lower than 5 frames per second. Although these approaches offer an initial solution to such a challenge, yet they would potentially not perform well if angle variance is introduced. The methods are only applicable in cases where angle variance is minimal, and using appearance based gait recognition techniques. There is no 3D or model based solutions for low frame rate footage in gait recognition.

<u>2.5.1. relationship and prediction (in biomechanics)</u>

As mentioned earlier, this thesis aims to predict dynamic features from static features. Although various gait recognition techniques take into consideration both static and dynamic features, there are no study in gait recognition research that attempts to describe a detailed relationship between both types of features.

For example, certain gait recognition techniques use dimension reduction in which the redundant and the least discriminative features are excluded. Guo and Nixon conducted a feature selection based on Mutual Information. Although a by-product of this study is the elimination of features that show a statistical dependency, yet the nature of the dependency and relationship was not explored (Guo and Nixon, 2009).

On the contrary to gait recognition related research, in biomechanics there is a particular interest in the relationship between static measurements and their ability to predict gait dynamics in order to diagnose abnormalities of a person's gait. In 1989, Hamill et al. conducted a test to study the relationship of static physical measurements of the lower extremity and dynamic features(Hamill et al., 1989). The measurements included: foot arch index, range of motion of the ankle, and other orientation and angular measurements. These were compared to data collected from a floor force platform, a 3D electrogoniometer, and angle measurements extracted from a high-speed camera. The outcome of the research proved that there is a limited canonical correlation between the data from angle measurements and measurements taken solely from the lower extremities.

Although in the study by Hamill et al. (Hamill et al., 1989) the static measurements were limited to the lower extremities; according to McPoil et al. not all measurements were included in the study(McPoil and Cornwall, 1996). They included more static measurements but reached a conclusion similar to Hamill et al. In a later study, measurements taken from a radiograph were compared to the same foot's regional plantar pressure distribution (Cavanagh et al., 1997). Using multiple regression analyses, only 35% of the variance in the dynamic features can be predicted by the measurements taken. Cavanagh came to the conclusion that factors other than lower feet measurements need to be considered. In more recent studies, other static measurements were used to predict either dynamic motion or disabilities(Hunt et al., 2000) (Cornwall and McPoil, 2011). They share similar conclusions that some measurements are a good predictor of motion, but not disabilities. Because medical gait analysis is concerned with predicting possible injuries or abnormalities, promising results concerning rotation of knees in the mentioned studies were disregarded (Hamill et al., 1989, McPoil and Cornwall, 1996). These correlations between the knee rotations and static measurements suggest a relationship that could be exploited in the area of gait recognition research.

A piece of research published in 1978 studies the transformational matrix between a gait feature vector pre and post operation (Chang and Bekey, 1978). To the contrary of most gait signatures discussed in this chapter, this research extracted its features from EMGs (electromyograms) which measure the activity of muscles. In the field of biomechanics, studies were conducted to study the relationship between diseases or disorders and gait kinematics and kinetics(Crowther et al., 2007). Such relationship studies help in the understanding of where rehabilitation programs can concentrate their efforts.

The study of the relationship between mass related static features and dynamic features, and the prediction potential of mass related measurements has also been looked at in previous studies. There are several studies that have looked at volume or mass related static measurements. In a study by Van Den Bogert et al., adding mass to the limb contributes directly to effort and stride length (van den Bogert et al., 2012b). This indirectly suggests that a change in mass can contribute to a change in kinematics; which would need to be taken into account to improve existing gait models. In another study, Wong et al looked at how static parameters or features of a human can affect body kinematics and improve tennis serves (Wong et al., 2014). The results showed that body-mass index was correlated to serve speed; therefore the mass of a person is correlated to certain dynamic and motion related features. The relationship between body fat composition and gait speed was the focus of a study that aimed to understand which body part contributes most to gait speed (Beavers et al., 2013).

2.6. Gap

As mentioned in section (about forensic challenge of latent information) , one of the main challenges in gait recognition is processing latent information, which includes low resolution temporal and spatial data, and partial temporal and spatial data. Here we observe that even in the absence of full temporal data, there is usually access to an image of the subject that includes some static information. Whether low resolution, slow frame rate, incomplete gait cycle, or body occlusion; certain measurements using photogrammetry can be extracted from these images. Therefore, if a relationship can be established between static and dynamic features, such measurements can potentially translate to a dynamic gait signature.

Based on the biomechanical studies that have explored the relationship between static and dynamic features mentioned earlier, there are two points that need to be taken into consideration. First, it is very clear that no study has evaluated a comprehensive set of static features that include measurements of the upper and lower body. Secondly, previous research indicates the existence of a correlation between certain static and dynamic features, but these results were disregarded because of their irrelevance to the objectives of those studies. Therefore in this thesis one of the main aims is to carry out a more complete investigation of the relationship between static and dynamic gait features, and to evaluate the potential application to gait recognition.

There is also a need in computer vision related gait recognition research to study the subject as a 3D form. Although the mentioned studies in section 2.6 use mass related measurements, yet they are not measurable by image or video based sensors. The use of volume, rather than mass, is a more pragmatic static feature to measure using vision-based systems. In a study by Hajný and Farkašová, the weight of body segments was predicted. The prediction was based on using three coefficients, and the measure of the height and weight of a subject. Each body segment had an assigned value for the three coefficients. The study mentions that a more accurate representation would be better, but not possible in their study. In this thesis 3D features will be explored in much greater depth, particularly considering the relationship to 3D dynamic gait features(Hajný and Farkašová, 2010),.

2.6.1. Research Questions.

From the above, it is clear that the prediction of dynamic features from static features, or latent information, is an important challenge in gait recognition, and yet has only been addressed in a very limited way. This thesis will do this by exploring four main research questions:

1- Is there a relationship between static and dynamic features?
2- How accurate and discriminative is the predicted dynamic features from static features?
3- Can dynamic features that have been predicted from static features be used for gait recognition?
4- Does using 3D rather than 2D increase the dependency between static and dynamic features?

This thesis will draw upon a similar methodology used in biomechanical studies in studying the relationship between dynamic and static features; yet the features used are based on static and dynamic features used in computer vision based gait recognition and the final goal will be to test the relationship in a gait recognition paradigm.

2.6.2. Assumptions and hypothesis

There are two main hypotheses in this thesis, which are:

1- There is a relationship between human's static features and the dynamics of a gait;
2- The predicted dynamic features from static features can be used for gait recognition.

In the study and analysis carried out, several assumptions are taken into consideration. First of all, it is assumed that all subjects have conducted a normal walk, and have not attempted to deliberate change the manner of their gait. It is also assumed that the subjects suffered no previous bone or muscle related injuries in the past.

It is also assumed that the data used from the motion capture and laser scanner are error free, and create a perfect representation of the dynamic and static features. In chapter 4 when 2D static features and correlated to 2D dynamic features, it is assumed that the measurements are taken from a frontal facing camera. While in chapter 5, it is assumed that the static measurements (volume and surface area) , are taken using multiple cameras or a camera with a depth component.

2.7. Conclusion

Gait has the potential to act as an emerging biometric for several reasons. It can both be recognized at a distance and can be tracked for use in surveillance. Depending on its application, several different technologies can be used to capture gait data such as; floor sensors, wearable sensors, and video cameras. Gait recognition is usually achieved using two main methods: appearance based (non-model), and model based. Non-model appearance based represents gait by its pixel value and changes of the silhouette’s outline or shape. Model based methods rely on building models to extract the kinematics of a gait. Appearance based methods are computationally cost effective, but are prone to lowered accuracy by several factors such as: changing of lighting conditions, change of clothes, or the carrying of a bag. Model based methods are resistant to such changes because of their approach, which relies on the underlying dynamics rather than appearance and shape.

Gait recognition faces several main challenges. The forensic application of gait recognition faces specific challenges such as coping with latent information. In this thesis, the possibility that dynamic features might be predicted from latent information, or even a single image, will be explored. This has not been attempted in previous studies. In biomechanical studies, the relationship between static and dynamic features has been studied, and this thesis will draw upon this research for its methods, yet adapt them to computer vision based gait recognition. This thesis therefore addresses the topic of defining if there is a relationship between dynamic and static features, as well exploring as the potential of predicting dynamic features from 2D and 3D static features.

Chapter 3: University of Bradford Multi-Modal Gait Database

3.1. Introduction

Gait databases are a very important factor in the evolution of gait as an emerging biometric. Creating databases and making them available to the research community has proven to be a main contributor to the development of various gait recognition techniques. One of the earliest was the USF HumanID gait challenge database (Sarkar et al., 2005). This database provided gait samples recorded using standard 2d cameras, of each subject with different covariants that were regarded as the main challenges in that period of time; such as: angle variance of camera, clothing, surface, and shoes. Other databases followed their lead. CASIA gait database (Yu et al., 2006) offered three different databases that were an alternative to the USF gait database. They both provide abundant 2D video data of walking subjects with different variants (Clothing, shoe, surface, and angle). A lot of gait recognition related databases emerged following DARPA's Human ID at a Distance program such as the University of Southampton's 3D Gait Database(Seely et al., 2008), the Carnegie Mellon University's MoBo database, the HUMABIO database. Other Databases concentrated on the subject sampling choices such as the MMUGait database that included male subjects wearing Malaysian national cloths that were long and covered most of the legs(Ng et al., 2014). The OU-ISIR Gait

Database(Iwama et al., 2012) contains a better distributed sample of gender and age, while other databases, have a strong bias towards young males. Before the assembly of the OU-ISIR database, none of the previous mentioned databases had more than 152 subjects. The OU-ISIR currently has over 4000 subjects.

Some databases specifically targeted certain sensors for their capture of gait. The West Virginia University's outdoor short-wave infrared dataset used infrared sensors that are relevant to surveillance and military applications of gait recognition(DeCann et al., 2013). Ngo et al. used in their study the largest database using inertial sensors to capture gait (Ngo et al., 2014). 744 subjects were asked to attach a smartphone around their waist to capture data from the accelerometer and gyroscope. Table 2 lists the various databases including information about its size, recording medium, and the variants used in the sample.

Table 2: A list of gait databases used for gait recognition testing and studies

Database name	Subjects	Samples	Method of recording	Data covariates	Year
HumanID Gait Challenge Problem(Sarkar et al., 2005)	122	1870	single Video camera	Five covariates: 1- Angle 2- shoe type 3- walking surface 4- carrying briefcase 5- elapse of time	2002
UCSD(Hayfron-Acquah et al., 2001)	6	42	single Video camera	1- walking surface 2- incline	1998

Georgia Tech(Johnson and Bobick, 2001)	20	Not available (N/A)	Video	1- angle variance 2- Location variance(in/outdoors)	2001
Carnegie Mellon University (MoBo)(Gross and Shi, 2001)	25	100	6 video cameras	1- Gait speed 2- incline walk 4- walking with a ball	2001
University of Maryland HID Database dataset 1(BenAbdelkader et al., 2002)	25	N/A	Video camera	1- Angle variance	2001
University of Maryland HID Database dataset 2(BenAbdelkader et al., 2002)	55	N/A	Video Camera	1- arbitrary walking	2001
Southampton gait 3d chamber(Seely et al., 2008)	N/A	N/A	Multiple cameras forming a 3d gait capture	1- 3d gait capture	2008
Southampton Soton Database(Nixon et al., 2002)	~100	N/A	Video camera	angle variance	2002
University of Bradford multi-modal gait database(Alawar et al., 2013)	38	1520	1- two video cameras 2- motion capture 3- laser scanner	1- Gait speed 2- Carrying a bag 3- gait transition from walk to run	2011
HUMABIO(Ioannidis et al., 2007b)	75 & 51 (48 shared)	N/A	1- single camera 2- stereo camera	1- shoe types 2- with a hat 3- with a briefcase 4- time passage between recording of subjects	2007
CASIA Dataset A (Yu et al., 2006)	20	240	single camera	1- Angle variance	2001

CASIA Dataset B (Yu et al., 2006)	124	372	11 cameras	1- Clothing(coat) 2- Carrying a bag 3- angle variance	2005
CASIA Dataset C (Yu et al., 2006)	152	610	1 infrared (Thermal) camera	1- Walk speed 2- carrying a backpack	2005
West Virginia University's Outdoor Short-wave infrared dataset (DeCann et al., 2013)	155	N/A	1- Short-wave infrared camera	1- unconstrained outdoor environment 2- spatial resolution	2013
Inertial sensor-based gait database (Ngo et al., 2014)	744	N/A	1- Accelerometer 2- gyroscope	1- inclination	2014
MMUGait Database (Ng et al., 2014)	82	1640	video camera	1- clothing(long male clothing)	2014
OU-ISIR Gait Database (Makihara et al., 2012)	4007	N/A	Video camera	1- angle variance 2- spatial resolution 3- gender	2011

Although there are many databases available for gait recognition, none of them could provide an accurate representation of joint movement and rotation; as well as an accurate representation of the 3D human body form. Therefore; the core of this database was the use of motion capture and 3D laser scanning technology. The motion capture data would provide the accurate dynamics of a walk, while the 3D laser scanner would provide the accurate 3D human body. This kind of accuracy would facilitate the study of the relationship between the body's physical composition (size, height, build) and the walking dynamics. Further research goals will be discussed in section 4 of this thesis.

The aim was to develop a multi-modal gait database to be used as a benchmark to apply various gait recognition experiments and techniques. The database used video, multiple view cameras, motion capture, and laser scanning.

3.2. The Set up

The main objective of the database was to provide one unified database that includes different modalities in regards to recording mediums used. In this database, every gait sequence is available in 3 formats:

1- video recording of a subject parallel to the camera's recording plane,
2- an alternative video recordings of the subject at an angle as shown in figure 14,
3- And motion capture data (3D motion data).

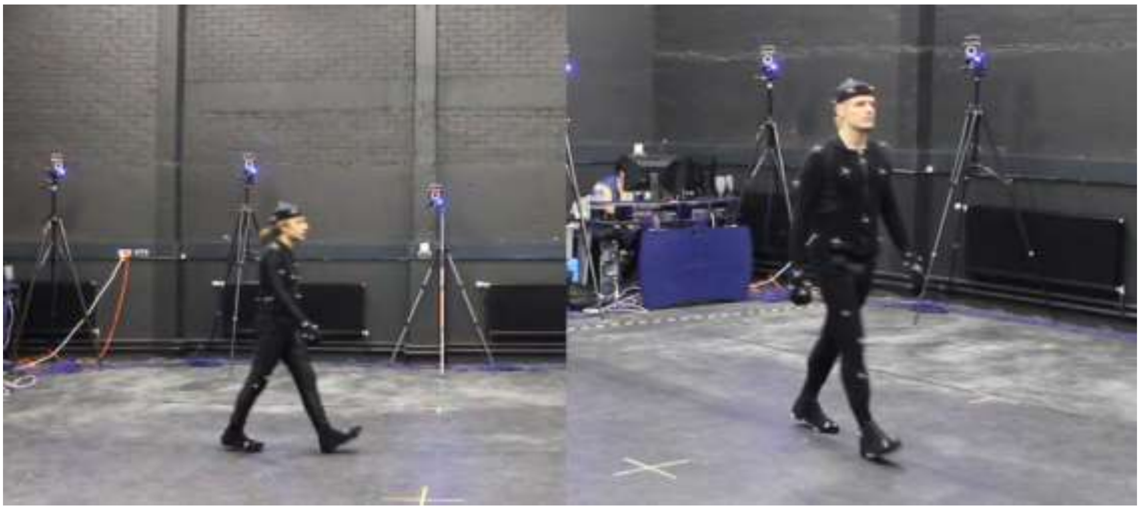

Figure 14: Sample from the video capture of subjects in the database. (left) A frontal paralel angle (right) an angled video camera.

Accompanying the motion data formats is two 3D point cloud (3D measurement data) datasets:

1- 3D scan of room

2- 3D scan of the participant

Since the use of treadmills is debatable (Shutler et al., 2004), it was decided to not use them in this database and rely on the length of motion capture studio. The database initially developed in 2011 and included 20 participants. 18 further participants were added in 2013, including repeats of 3 subjects to ensure the long-term repeatability of measurements. Currently the database includes 38 participants. Each participant was asked to wear the motion capture suit. First, a 3D laser scan was captured of the subject. The four scans taken of every subject were conducted separately. First, a front scan was taken, followed by the right side, the back, and the left side. To maintain the same pose between scans, placement points for the feet were used, as well as a defining the position of the arm through the use of two chairs (the subjects would rest the tip of their finger on the chair to maintain stability). Although there were minimal movements between scans, yet it provided a more accurate measure of volume than the use of volume estimating algorithms from single scan. The same procedure was followed to scan subjects from two sides only. and conduct the following actions in the chronological order within an estimated 1-hour duration:

1- conduct a walk 8 times across the room

2- conduct a run 8 times across the room

3- conduct a walk to run transition 8 times

4- conduct a walk carrying a bag using the left arm 8 times

5- conduct a walk carrying a bag using the right arm 8 times

Each walk and run was conducted over a distance of 13.5 metres. The subjects were asked to walk or run at their own comfortable pace. One walk or run consisted of walking/running from one end of the motion capture studio to the other end. This procedure would be repeated 8 times for each type of gait captured. Samples of the five actions are illustrated in figures 15-19.

Figure 15: Sequence image from a walk sample in the gait database

Figure 16: Sequence image from a run sample in the gait database

Figure 17: Sequence image from a walk to run transition sample in the gait database

Figure 18: A database Sequence image of a walk sample carrying a bag on the right side

Figure 19: A database Sequence image of a walk sample carrying a bag on the right side

3.2.1. Hardware and software used

The recording of the data took place at the Motion Capture Studio at the School of Computing, Informatics, and Media, University of Bradford. In the following section, a detail of the each aspect of the set up will be discussed in details

The database was used in this thesis as well as being used as a test bed for new Gait-based techniques. In this multi-modal database, gait was captured using three mediums: Motion capture, video camera, and 3D laser scans. Each medium is discussed in more details in the sub-sections to follow.

Motion Capture

The motion capture system used in this database consists of 16 Vicon T20 cameras. Figure 20 shows the motion capturing area encapsulating within the box lines, and part of the Vicon T20 cameras on tripods. These cameras offer a resolution of 2 megapixels and capture at 500 frames per second 10-bit grayscale images. The cameras and motion capture process are managed and controlled by software called Vicon Blade. Blade provides the control and management of actor (subject) setup, recording the motion capture data, and clean up. These steps will be explained in more details in the following sections.

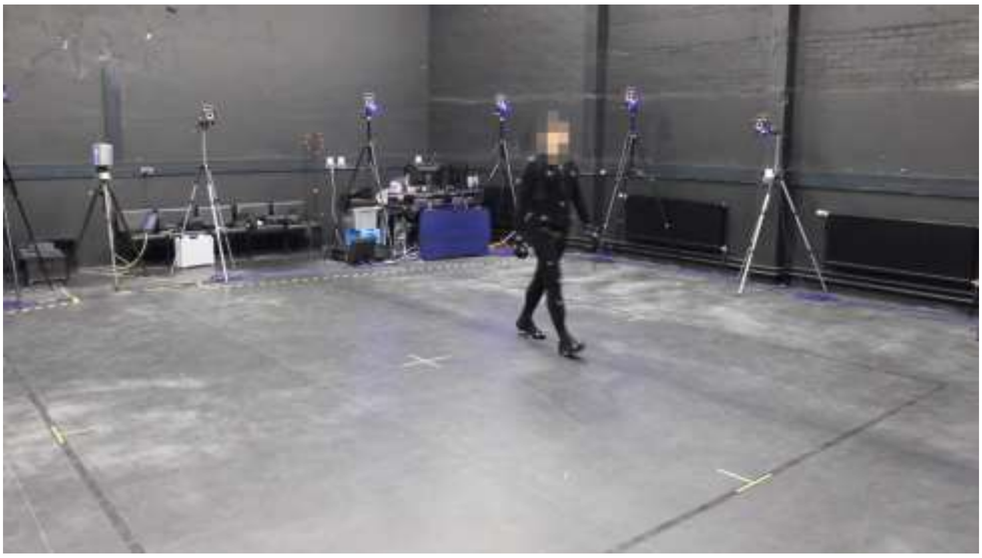

Figure 20: An image of a subject performing a walk in the University of Bradford Gait Database.

Marker setup is the manner in which the white reflective markers are placed on a subject. The marker setup, as shown in figure 21, used in this database is the standard used at the University of Bradford motion capture studio, which is usually intended for real-time 3D simulation for the fields of entertainment and video games. The marker setup is illustrated in figure 21.

Figure 21: illustrates the marker setup used in capturing the gait cycles in the database

Video camera setup

The subject's Gait was captured using two cameras. Both cameras were placed on a tripod. One camera was placed parallel to the walk direction of the walk in order to capture a side view of the walk. The second camera was placed in an angled position. Figure 22 illustrates the camera setup and positioning relatively to the subject walking.

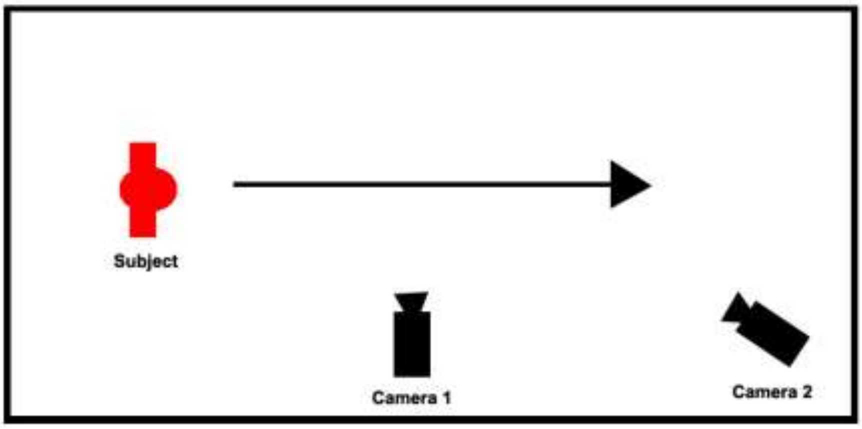

Figure 22: An illustration of the video camera setup used in the database

The cameras used in this database were the Canon EOS 5D Mark II. The video recorded was of a full HD resolution (1920 x 1080), at 25 frames per second.

3D Laser scanning

The 3D laser scanner used in this database is the Faro Laser Scanner Photon 120. This scanner scans a 360-degree horizontal field of view with a speed of 120,000 points per second. In this setup, the laser scanner was controlled, and the recording was managed through, the use of the software Faro Scene version 5.1. Faro scene provided an interface to control the quality, resolution, focus, and management of the point cloud captured using the laser scanner.

The first phase of data capture, as illustrated in figure 23, the scanner was used to take two scans of the subject: one from the front, and another from the back. During the collection of the second set of subjects, four scans were captured: front, back, right and left. The four sides scan is illustrated in figure 24. The scans were done before the motion capture recording started. Although there is a very minimal risk of using a laser, precautions were taken by the use of safety goggles.

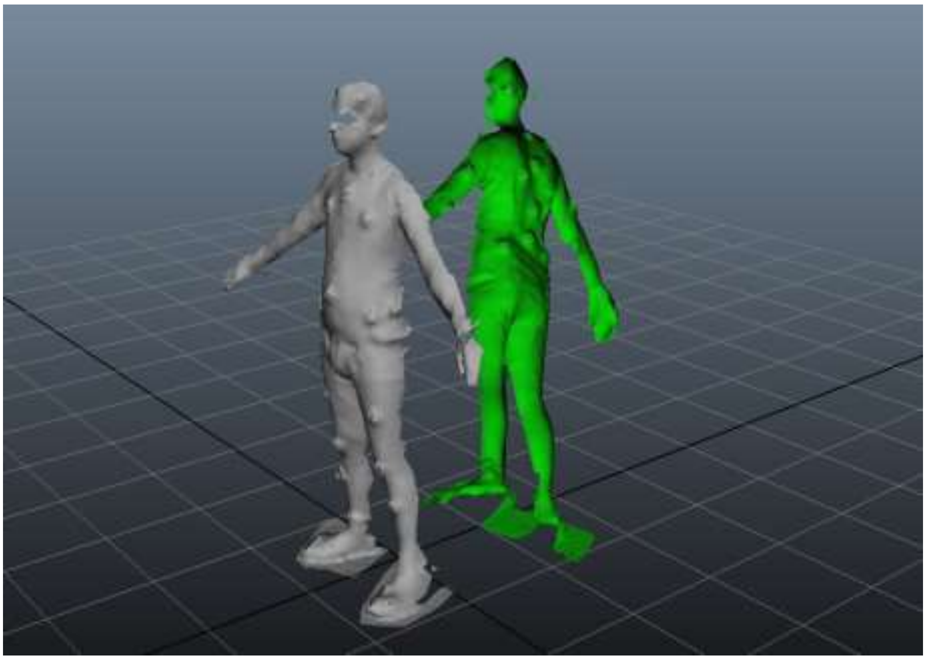

Figure 23: An example of the 2 laser scans conducted in the first phase of the database.

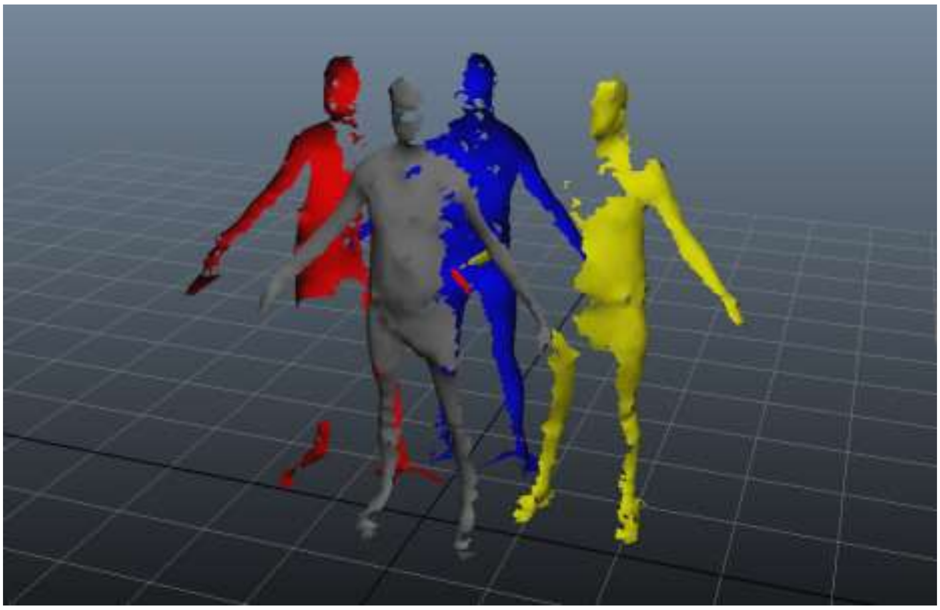

Figure 24: An example of the 4 laser scans captured in the second phase of the database.

3.3. Ethical Procedures

The process of capturing subjects as explained in previous sections has been ethically approved in March of 2011. An extension for the ethical approval was applied for in March 2012, to conduct the study until February of 2014. The extension was approved of on May 2012. The application consisted of project proposal, consent form, information sheet, and an application form which can be found in appendix 3.1 and appendix 3.2

Certain precautions had to be in place in regards to health and safety. The two main harm or distress would be caused by the laser used in the 3D laser scanning and possible running injuries involved in the motion capture. A safety goggle was used to avoid harm caused by the laser, and to reduce potential injury from running, subjects were asked to run at a comfortable pace that wouldn’t cause distress.

To ensure confidentiality and anonymity, no personal data related to identity were stored with information captured. Subjects are identified by their subject number (subject 01 , subject 02, subject 03…etc.). The video does reveal their faces, but this information is blurred to avoid any identification of the identity of the subject, unless the subject has signed an agreement and release form for pictures of his/her face to appear in the database or further publications.

3.4. Subjects

The initial subjects were contacted through the use of flyers within the Visual Computing Centre and the School of Engineering, Design, and Technology at the University of Bradford. Each volunteer was required to read an information sheet about the database and the process of recording. They were each requested to sign a consent form before any recording session took place. 20 subjects were recorded initially in 2011, and 18 more subjects were added in 2013.

The first set of subjects consisted of 3 females and 17 males. The average age was 30, and ranged from 22 to 45. The Average weight was 76.9 Kilograms, ranging from 50 to 130 kilograms. The average height was 172.3 centimetres, with a range of 158 to 190 centimetres. The ethnicity of the participants included: European white, Asian British, Middle Eastern, Chinese, Indian, and Persian. The database was later expanded to include 18 further subjects using identical protocols. The new subjects consisted of 14 males and 4 females.

3.5. Data collection and storage

After the recording session of the subject, the video, motion capture, and laser scan data was saved to an individualised folder following a naming system (Sub_####) that included primarily the Subject ID number, in order to maintain anonymity of subjects. For example all of subject #1's data is included under the folder Sub_0001. Under each subject's folder are another five folders: video (/vid) , motion capture data (/mcp), 3d scan point cloud data (/3dp), subject information (/inf), and processed data (/dat).

The /Vid folder contains the two video files: side and front; and are named by the following convention:

Sub_####_Vid_XX,

where #### is the subject id number, and XX is the camera angle (SD for side, and FT for front). For example, the frontal camera video of subject 1 would be named: Sub_0001_Vid_FT.

The /mcp folder contains all the motion capture data and is divided into five folders: walk (/wlk), run (/run), walk to run transition (/w2r), carrying a bag with right arm (/bgR), and carrying a bag with left arm (/bgL). Each folder respectively contains the motion capture data affiliated with its class. The files follow the following naming convention:

Sub_####_mcp_xxx_yy,

where #### is the subject id, xxx is action type (wlk, run, w2r, bgR, and bgL), and yy is the sample number. For example, subject #1’s second walk motion capture data would be named as: Sub_0001_mcp_wlk_02.

The /3dp folder contains the 3d point clouds recorded by the Faro laser scanner. Within this folder are the two scans of the subject and use the following naming convention

Sub_####_3dp_XX,

where #### is the subject’s id , and XX is the angle of the scan: FR for front, and BK for back. For example, subject #1’s front point cloud file will be named as Sub_0001_3dp_FR.

The /inf folder contains one txt file that holds various information about the subject which includes age, weight, gender, and other static measurements of the subject’s body. The contents of this file will be discussed in more details in section 3.5 and section 4.

The /dat folder contains a single txt file that holds the processed dynamic features of a subjects gait, and will be discussed in details in section 3.5 and section 4.

3.6. Data processing and analysis

Each data type followed a specified procedure to convert the raw data into useable data for further analysis and testing.

3.6.1. Video

The video data requires being:

1- Classified and cut;

2- And processed manually to track dynamic features.

The data recorded in the session was shot continuously, which means for each subject; all forms of gait are included in one continuous video file. Therefore there is a need to cut the video into sections according to their form (walk, run, walk to run transition, walking with a bag). Instead of using a video editor do perform the cuts and output several other files, it was rather divided within the same program that was used for video tracking. The video tracking software was used to track the different features of a subject's gait. Pixel Farm's PFTrack (version 5.0) was used to divide the videos. The videos were divided based on one gait sample per gait type. Pixel Farm PFTrack was also used to track the joints that are required to process the dynamic gait features.

Once the video divided according to its sequence number and form, tracking of key joints was done on the subject using PFtrack's automated tracking tool. When the automatic tracking tool failed to track properly, manual tracking from user input was used. The joints that were tracked include: mid-section of the hip, left and right knee, left and right ankle, left and right ball of the feet, left and right feet tip, left and right shoulders, left and right elbows, left and right wrist, and finally the top tip of the head.

Finally, the tracked data is exported as individual files that represent the vertical(X) and horizontal(Y) positions of the tracked point. The files are saved using the following naming convention:

Sub_####_dat_xxx_yy_o_Joint_A

Where #### is the subject ID, xxx is the gait form, yy is sequence number, o is the left(L) or right(R) side of the body, joint is the name of the joint being tracked, and A is the axis(X or Y). Therefore, subject #1's X-axis tracking of the right knee when the subject conducts his/her first walk sample is named as: Sub_0001_dat_wlk_01_R_knee_X.txt.

3.6.2. Motion Capture

For the motion capture data to be usable, it must be converted to either positional data in <x,y,z> or rotational data $<\theta_x, \theta_y, \theta_z>$. The current marker setup cannot provide us a direct positional or rotational data of the joints required. Therefore a reconstruction of the human skeleton is required, and is processed through the use of Vicon Blade (version 1.7.0).

The process used in this database is closer to that used in the entertainment and gaming industry than the way it is traditionally dealt with in biomechanics. In most biomechanical based studies, the markers just focus on lower limb movement, while the setup used in this database involves lower and upper limbs, as well as spine movement. The data is first processed for what is called ROM (Range of motion), in which the range of motion of the subject is identified. It is followed by a calibration, in which the generic skeleton in Blade is adjusted according to the subject's body size. Figure 25 shows the generic skeleton and how it is matched to the markers from the ROM recording. Finally, the new skeleton is used as a base for solving all the gait samples. Solving the gait samples involves fitting the calibrated skeleton to the recorded markers on the suite during a walk. Figure 26 further illustrates the calibrated skeleton solved for one of the gait samples. The solution results rotational values for all the joints available in the used marker setup. Rotational information matches state of the art information extracted in gait recognition techniques using dynamic features. Positional data will be indirectly inferred via the measurements extracted from the 3D scans. Some joints are constrained on their degrees of freedom, such as the knee joint, which rotates only around one axis (X). The data is then exported as an ASCII file containing the rotational data of all the joints and is saved according to the following naming convention:

Sub_####_dat_mcp_xxx_yy_.txt

Where #### is the subject ID, xxx is the gait form, and yy is sequence number.

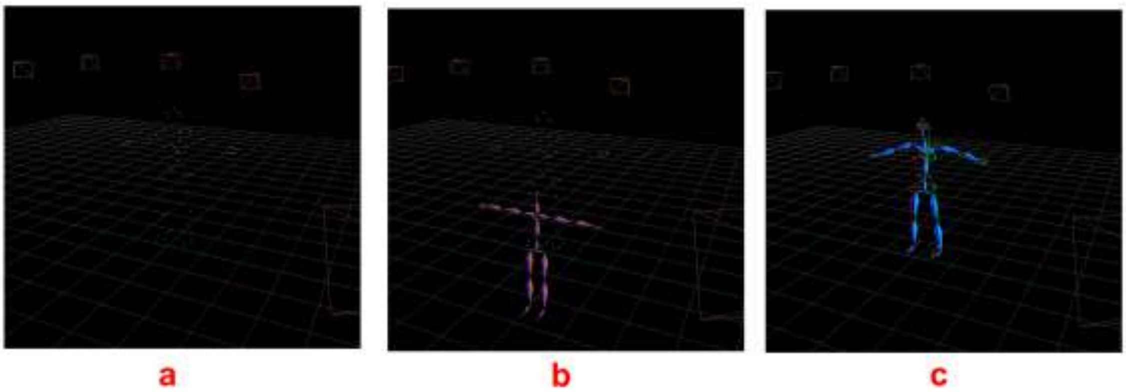

Figure 25: An illustration of the character calibration process in Vicon Blade. a) The points reconstructed from the motion capture session. b) The non-calibrated character is imported into the file. c) The character is calibrated to fit the points captured from the motion capture.

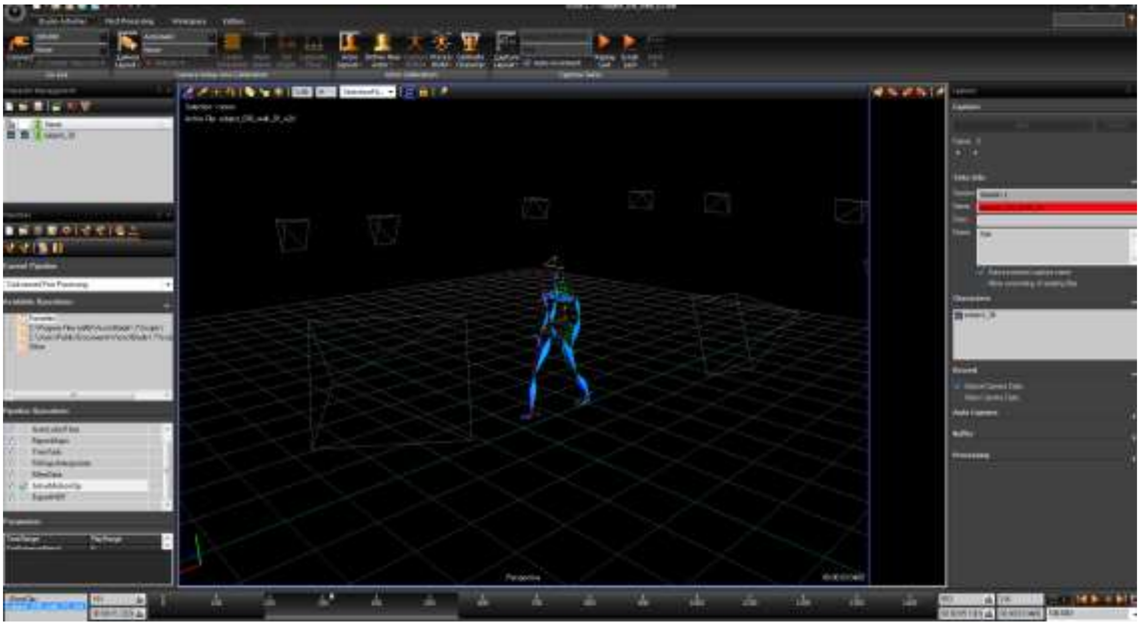

Figure 26: An example of a calibrated character that has been solved for the motion capture sessions of the subject walking.

3.6.3. 3D Laser Scan

The aim of recording an accurate 3D representation of the subject was for two reasons:

1- To be able to accurately provide scalar data in regards to 2D measurements of the human body (length of leg, width of arm, etc.…)
2- To be able to study the body from a 3D point of view (volume, surface distribution, etc.…)

In regards to the first aim, direct measurements using the point-measuring tool in Faro Scene is utilised. Within Faro Scene, the points to measure between were manually chosen. This involves choosing the 2D measuring tool, and clicking between two points on surface to perform the measurement. Automatic division of the body was not applicable, therefore' manual labeling of the joints was used. The specific parameters chosen to measure will be discussed in later chapters.

For the purposes of studying the body in 3D space, the two separate scans were merged together. Because there was very minimal overlap between the two scans of every subject, Polyworks software was not capable of automatically aligning the scans. Therefore, it was required for this step to be done manually. Same procedure was applied for the second set of scans, in which four sides of a subject were captured. The processing of the 3D laser scans involves: point cloud conversation to a 3D surface or mesh, manual alignment of scans, and finally manually fitting a 3D human mesh. The first step involves creating a 3D mesh from the point cloud using InnovMetric Polyworks (version 10). This step would convert the dispersed point clouds into a 3D surface in the OBJ format. The two or four separate OBJ files were then imported into Autodesk Maya (2011 version). Using Autodesk Maya's 3D move and rotation tool, each scan was manually aligned to fit all the different captured sides. Figure 27 illustrates how the different sides are aligned together.

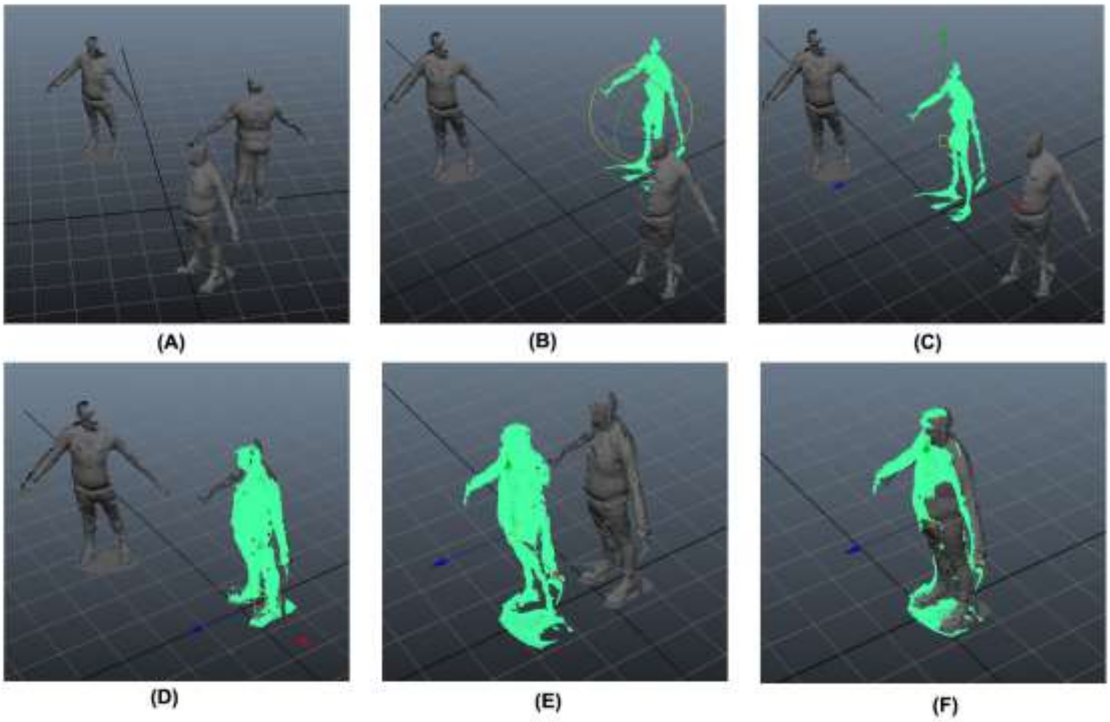

Figure 27: General steps in manually merging the 3D scans in Autodesk Maya (A) the different scans unaligned, (B-C) rotate and move the first scan to the origin(centre) , (D) move and rotate the following scanned side to match the first scan, (E-F) rotate and move the last piece to match the remaining aligned scans.

It is important to notice that there are holes present, especially on both sides. Therefore; 4 scans were recorded of the second batch of 18 participants, which included front, back, right, and left side of the subject. The resultant files were saved in the /inf folder using the following naming convention:

Sub_####_inf_3dp.obj,

where #### is the subject ID number.

3.7. Database availability

The database has been mentioned in paper that will be published in the British Journal of Applied Science and Technology. The database will also be made available online to the research community through the Centre of Visual

Computing at the University of Bradford website. To gain access to the information, they are required to fill in a form available online, and upon approval; user name and password will be provided for a one time download of the data. The data that will be provided will only contain the volume and surface area measurements, and rotational data of the joints. For anonymity, the subjects will only be named using numbers (1,2,3…etc.).

3.8. Conclusion

This database is the first known example of a database that includes accurate 3d gait parameters of 3d body measurements. As such it is the first truly 3D gait database of its kind, and sets the benchmark for future databases. In the remainder of the thesis, we will use the data to investigate possible correlations between static and dynamic gait measurements and features.

Chapter 4: Relationship between 2d static and dynamic features

4.1. Introduction

The overall goal of this thesis is to investigate the relationship between static measurements of the body and dynamic features of gait. This is done with the aim of investigating the potential of using partial gait data, which will be defined in the following section, to model and predict full gait cycles. In this chapter we build the foundation for the thesis by exploring the relationship between 20 static features and dynamic features.

Although various gait recognition techniques take into consideration both static and dynamic features, there are no studies that attempt to describe a detailed relationship between both types of features. On the contrary to gait recognition related research, in biomechanics there is a particular interest in the relationship between static measurements and their ability to predict gait dynamics in order to diagnose abnormalities of a person's gait. In 1989, Hamill et al conducted a test to study the relationship of static physical(Hamill et al., 1989) measurements of the lower extremity and dynamic features. The outcome of the research proved that there is a limited canonical correlation from using measurements taken solely from the lower extremities. In more recent studies, other static measurements were used to predict either dynamic motion or disabilities (Hunt et al., 2000)(Cornwall and McPoil, 2011). They share similar conclusions that some measurements are a good predictor of motion, but not disabilities. Although these results might seem discouraging in the area of medical biomechanics, they carry great potential in gait recognition studies.

Based on the mentioned studies, there are two points that need to be taken into consideration. First, it is very clear that no study has taken into consideration a comprehensive set of static features that would include measurements of the upper and lower body. Secondly, previous research indicates the existence of a correlation between certain static and dynamic features, but these results were disregarded because of their irrelevance to the objectives of those studies.

4.2. The chosen features and post processing

In most gait recognition techniques, the static features are extracted from the 2D or 3D model used to describe the subject's gait (Wang et al., 2004, Ioannidis et al., 2007a, Huang and Boulgouris, 2010, Guo and Nixon, 2009, Johnson and Bobick, 2001, Niyogi and Adelson, 1994, Zhao et al., 2006, Ariyanto and Nixon, 2011). In this study, the purpose is to study the relationship of the body and its relationship to gait; therefore, it was a necessity to acquire all the information using a tool that can provide the most accurate result.

4.2.1. Static features

Computer vision based static features extraction techniques can have a considerable amount of error, especially when it comes to upper body dynamics. Therefore; in order to acquire data that is as accurate as possible, the features were manually extracted from the three dimensional point cloud data of the 3d scan mentioned in chapter 3. The measurements were taken from specific static features using the Faro Scene software. All measurements were manually extracted.

The choices of features were based on logical landmark physical characteristics as well as static features mentioned in Guo and Nixon's work in which feature selection was examined to find the most influential features in recognition(Guo and Nixon, 2009). The static features are based on the assumption of a video being recorded from a frontal view. There are 19 2D static features. The features that were used from the study conducted by Guo and Nixon are: torso height(H2), length of thigh(H3), length of shin(H4), foot length(FL), length of head(HL), width of head(HW), width of leg at top of the thigh(L1), and width of leg at the knee joint(L2). The other features that were introduced in this thesis are logical landmarks that included: total height(H1), length of shoulder to elbow(A1), length of Elbow to wrist(A2), length of hand(A3), arm thickness at shoulder joint(A4), arm thickness at elbow(A5), arm thickness at wrist(A6), torso width at shoulder level(T1), torso width at waist level(T2), torso width at hip level (T3), and width of the leg at the ankle joint(L3). It was also taken into consideration that only the right side of the subjects would be used for two main reasons. First, because the dynamic features were extracted from a 2D video, the left side of the body was occluded behind the body of the subject. Second, we carry out the study based on the notion of symmetry of motion dynamics between the right and the left sides of the body, which is a practice commonly conducted in 2d video based gait recognition. Two other factors were included from the information provided by the subject, which included: age (Ag) and weight (Wg). Figure 28 illustrates subject's static features used.

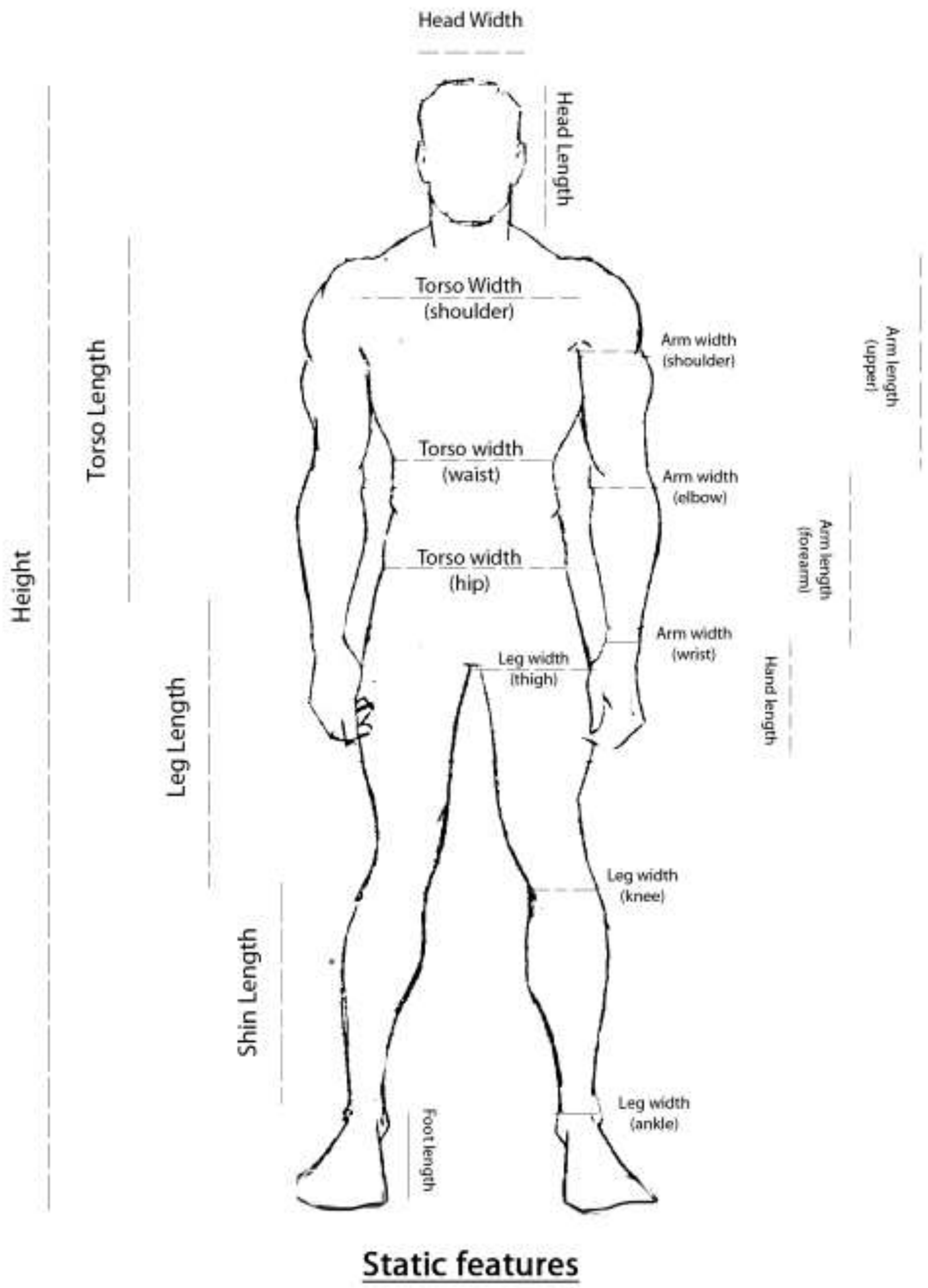

Figure 28: An illustration of the static features extracted from every subject in the database

4.2.2. Dynamic features

The dynamic features used in the correlation study were the phase-weighted magnitude (PWM) of the different joint rotations of a subject. This method is driven from a technique developed by Cunado et al. In this method the phase and magnitude component of the Fourier transform applied on the thigh and knee rotations from the gait sample, are used(Cunado et al., 1997). Magnitude provides the range of motion a joint goes through, while the phase component describes the time component of the movement. It was used in later studies and applied to both 2D and 3D models(Yam et al., 2002, Ariyanto and Nixon, 2011). A major difference in this conducted study is that the same technique is also applied to the upper and lower arm temporal rotational data. The angles are extracted from the manually labeled joint 2D pixel location in a single image.

The final feature is formed by multiplying the magnitude component by its corresponding phase component. Therefore; PWM is defined as;

$$x_{l,k}^{i} = \left|\Theta\,(e_{l,i}^{j\omega k})\right| \bullet \arg\left(\Theta\left(e_{l,i}^{j\omega k}\right)\right), \qquad \textbf{(1)}$$

$$k = 1,2,...,N\,,$$

where $x_{l,k}^{i}$, is the Phase-Weighted magnitude signature for the l^{th} sequence of subject i and the k^{th} Fourier transform component. The $\left|\Theta\,(e_{l,i}^{j\omega k})\right|$ represents the absolute value of the k^{th} Discrete Fourier Transform magnitude component, while $\arg\left(\Theta\left(e_{l,i}^{j\omega k}\right)\right)$ is the complex form representation of the phase component. The $\bullet$ implies the multiplication of each component in the first vector by its corresponding component in the second vector.

Only the lower order components are used to avoid noise and irrelevant data. The first two components are used in the thigh rotation, while the first three components in the knee rotations were used. This decision was based on a study by Yam et al, in which the mentioned components were found to be highly discriminatory while other components consisted of noise, which could not be used for recognition(Yam et al., 2004). The outcome result showed that in most gait samples the magnitude spectrum produced by a Fourier Transform algorithm converged to a zero value beyond the fifth harmonic. It was also proven that a phase-weighted magnitude, in which the phase component is multiplied by the magnitude component, provides stronger discriminatory potential then the use of the phase or magnitude component independently. This is likely to be related to the fact that gait is not defined only by the range of movements, but also with timing.

Based on the mentioned gait signature, a total of 10 dynamic features were used and were extracted from the right side of the subjects. As mentioned earlier, the left side was disregarded because it would be occluded from the camera view. Since the camera was placed perpendicular to the walking path, the left arm was always behind the torso of the subject. Because it is not visible to the camera, it was not included. The same structure used for the leg was used for the arm in this study. Since the first two harmonics were used for the thigh, only the two harmonics were used for the shoulder. They are both the first joint in their respective joint chain. The three harmonics of the elbow were used, which is similar to the harmonics used for the lower leg rotations. Therefore; the 2D dynamic features include: second and third phase-weighted components of the right shoulder (PSa,PSb), second and third phase-weighted components of the right thigh (PTa, PTb), second, third, and fourth phase-weighted components of the right lower leg(PKa, PKb, PKc) and elbow(PEa, PEb, PEc)..

4.3. Correlation analysis and results

There were a total of 21 static features and 8 dynamic features. All the features and their abbreviations are listed in Table 3.

Table 3: A list of all the dynamic and static features used in the study

abbreviation	feature description	type
H1	Total height	Static
H2	Torso length	Static
H3	Thigh length	Static
H4	Shin length	Static
FL	Foot length	Static
A1	Length between shoulder and elbow	Static
A2	Length between elbow and wrist	Static
A3	Hand length	Static
HL	Head length	Static
HW	Head width	Static
A4	Width of arm at shoulder	Static
A5	Width of arm at elbow	Static
A6	Width of arm at wrist	Static
T1	Width of torso at shoulder level	Static
T2	Width of torso at waist level	Static
T3	Width of hip	Static
L1	Width of upper thigh	Static
L2	Width of knee	Static
L3	Width of ankle	Static
PSa	1st component PWM of the Shoulder rotation	Dynamic
PSb	2nd component PWM of the shoulder rotation	Dynamic
PEa	1st component PWM of the elbow rotation	Dynamic

PEb	2nd component PWM of the elbow rotation	Dynamic
PEc	3rd component PWM of the elbow rotation	Dynamic
PTa	1st component PWM of the thigh rotation	Dynamic
PTb	2nd component PWM of the thigh rotation	Dynamic
PKa	1st component PWM of the knee rotation	Dynamic
PKb	2nd component PWM of the knee rotation	Dynamic
PKc	3rd component PWM of the knee rotation	Dynamic
Wg	Weight of subject	static
Ag	Age of subject	static

The aim of the study was to investigate the relationship between static and dynamic features. This was achieved through the use of the correlation coefficient. The correlation coefficient matrix; $R(i, j)$ is defined as;

$$R(i,j) = \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}}, \quad \textbf{(2)}$$

where C is the covariance, and i, j are the features extracted. The covariance was calculated using the following formula;

$$C(i,j) = E[(i - E[i])(j - E[j])], \quad \textbf{(3)}$$

where E is the expected value; or weighted average.

Only features with a p-value smaller than 0.05 ($p<0.05$) were considered to be significant. Out of the possible relationships, eleven correlations fit this criterion. The eleven relationships are listed below in table 4.

Table 4: A list of the top 11 significantly correlated 2D static and dynamic features

Dynamic Feature	Static Feature	Correlation Coefficient	P-value
1st comp elbow PWM	foot length	0.48	0.0429
1st comp elbow PWM	length forearm	0.50	0.0365
2nd com shoulder PWM	shoulder width	0.68	0.0020
2nd comp thigh PWM	elbow width	0.55	0.0194
3rd comp knee PWM	wrist width'	0.50	0.0365
2nd com shoulder PWM	width torso-shoulder	0.49	0.0409
2nd comp thigh PWM	width torso-shoulder	0.48	0.0434
2nd com shoulder PWM	width torso – hip	0.55	0.0180
2nd com shoulder PWM	width of upper thigh	0.50	0.0349
1st comp shoulder PWM	Weight	0.55	0.0186
2nd com shoulder PWM	Weight	0.78	0.0001

The results show that there are static measurements that relate to the dynamics of gait. Specifically, the 2nd component of the shoulder's PWM is significantly correlated to 5 static features. Even though an arm static feature would seem to be the ideal static feature relating to the arm related dynamic feature, yet, weight in this analysis has shown to have the highest correlation coefficient. It has a correlation coefficient of (0.7799) with the 2nd component of the shoulder's PWM. Figure 29, represents the plotted data of the PSb (2nd Component of Shoulder's PWM) against the weight of subjects analyzed in the sample. Figures 29-33 are a visual plot of the highest five correlations in the study.

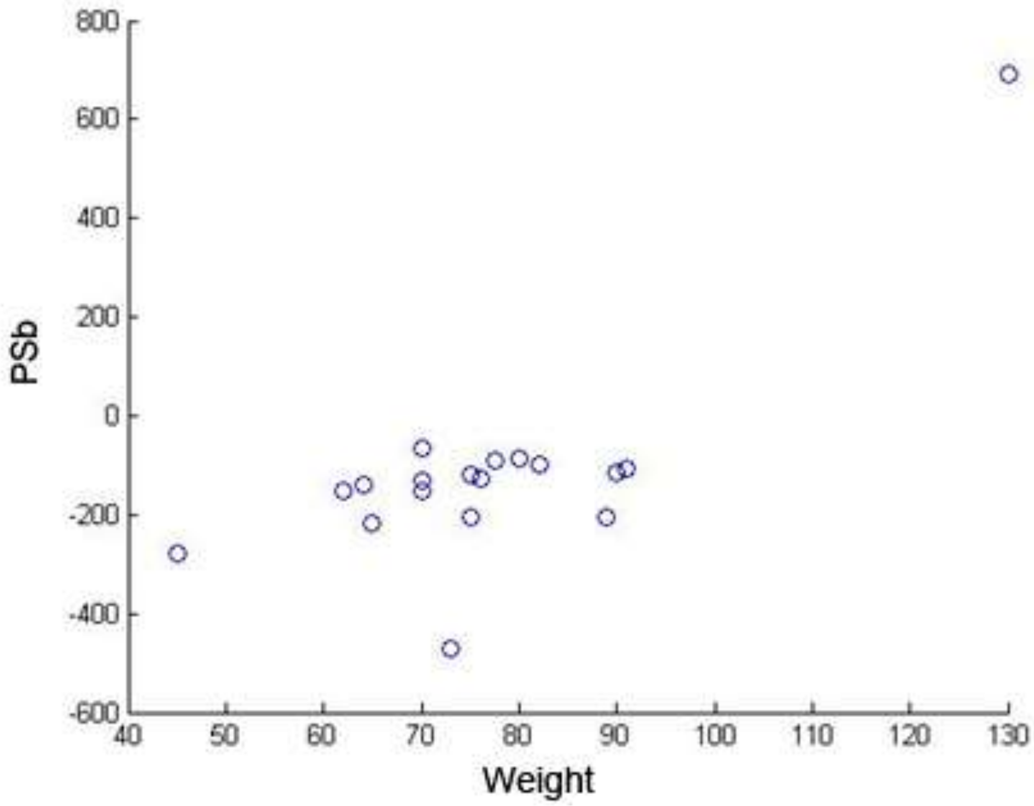

Figure 29: Plot of 2nd component of the shoulder's PWM against a subject's weight

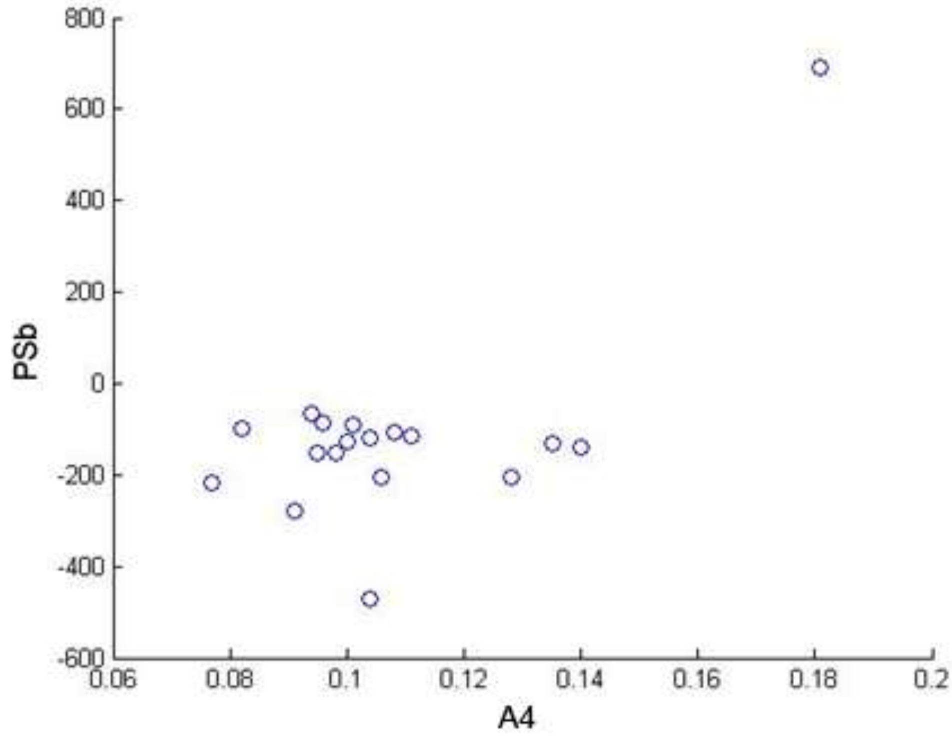

Figure 30: Plot of 2nd component of the shoulder's PWM against A4

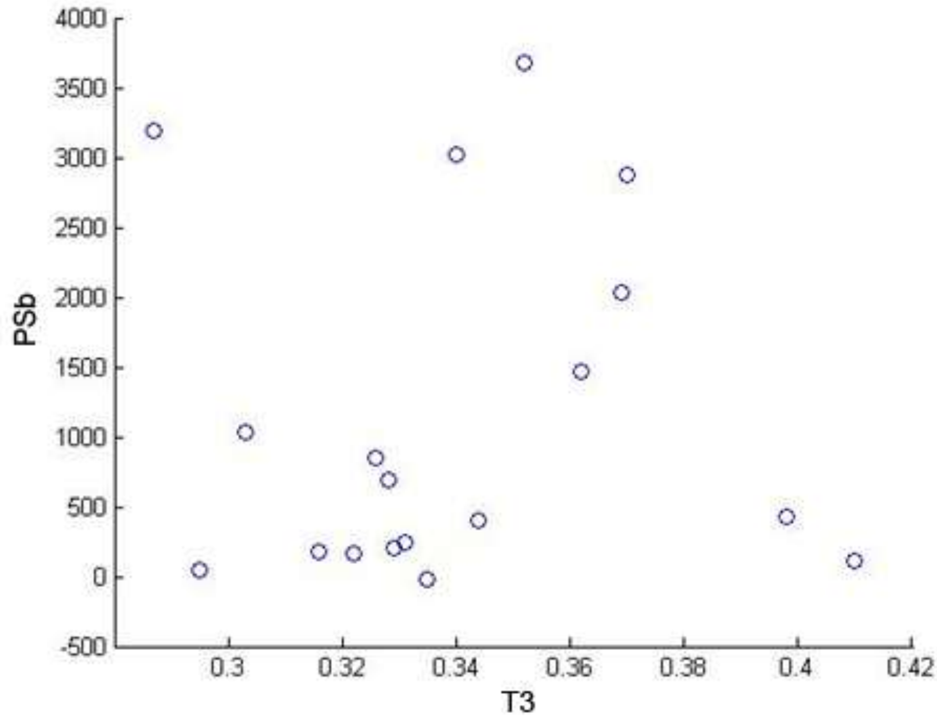

Figure 31: Plot 2nd component of the shoulder's PWM against T3

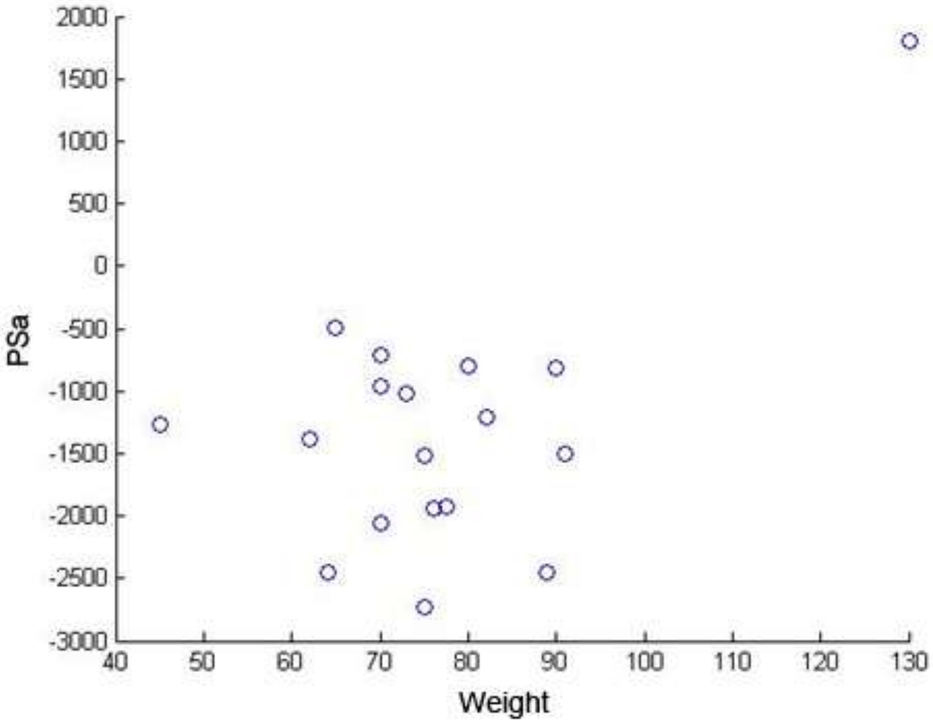

Figure 32: Plot of 1st component of the shoulder's PWM against subject's weight

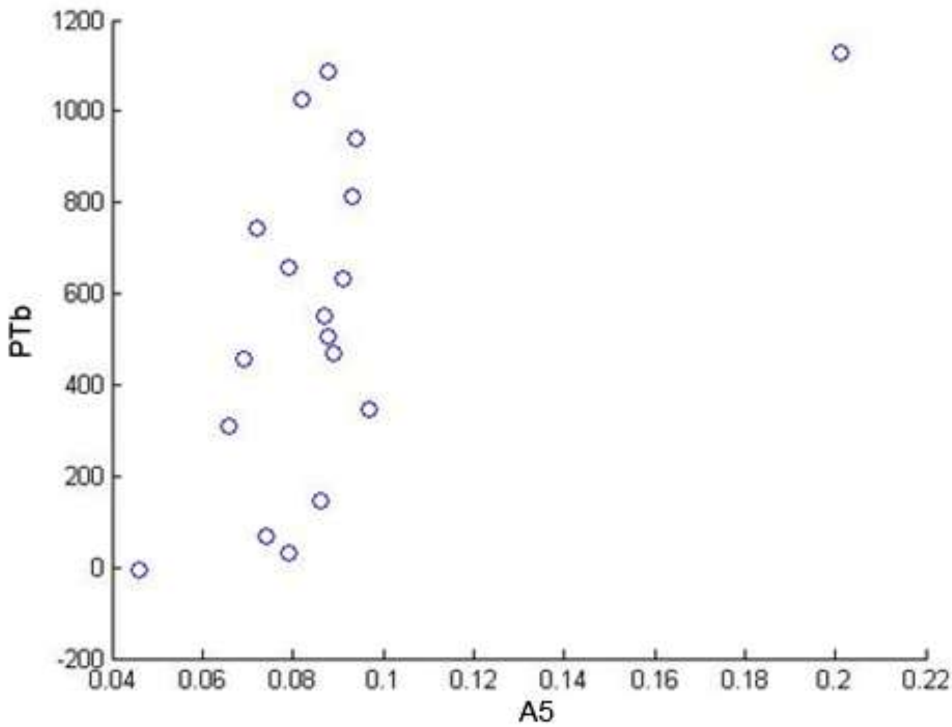

Figure 33: Plot of 2nd component of the thigh's PWM against A5

To further provide an insight on the correlation analysis, the top 5 correlated static features with each dynamic features is shown in tables 5-14.

Table 5: Top 5 correlated features to 1st component shoulder PWM

Static feature	Correlation coefficient	p-value
Weight	0.548	0.019
width torso-shoulder	0.417	0.085
shoulder width	0.394	0.105
Age	0.301	0.225
width torso – hip	0.293	0.238

Table 6: Top 5 correlated features to 2nd component shoulder PWM

Static feature	Correlation coefficient	p-value
'weight'	0.780	0.0001
'shoulder width'	0.678	0.002
'width torso - hip'	0.550	0.018
'width of upper thigh'	0.499	0.035
'width torso-shoulder'	0.486	0.041

Table 7: Top 5 correlated features to 1st component elbow PWM

Static feature	Correlation coefficient	p-value
'length forearm'	0.496	0.036
'foot length'	0.482	0.043
'age'	-0.461	0.054
'hand length'	0.405	0.096
'thigh length'	0.340	0.167

Table 8: Top 5 correlated features to 2nd component elbow PWM

Static feature	Correlation coefficient	p-value
'weight'	-0.370	0.131
'torso length'	-0.342	0.165
'total height'	-0.328	0.184
'shoulder width'	-0.328	0.184
'width torso - hip'	-0.301	0.225

Table 9: Top 5 correlated features to 3rd component elbow PWM

Static feature	Correlation coefficient	p-value
'head width'	0.370	0.130
'head length'	0.313	0.206

'foot length'	0.283	0.255
'width of knee'	0.225	0.370
'width torso - waist'	-0.208	0.407

Table 10: Top 5 correlated features to 1st component thigh PWM

Static feature	Correlation coefficient	p-value
'head length'	-0.456	0.057
'head width'	-0.392	0.108
'width of knee'	0.391	0.108
'shin length'	-0.371	0.129
'width torso-shoulder'	-0.371	0.130

Table 11: Top 5 correlated features to 2nd component thigh PWM

Static feature	Correlation coefficient	p-value
'elbow width'	0.545	0.019
'width torso-shoulder'	0.481	0.043
'shin length'	0.454	0.059
'head length'	0.432	0.073
'width of ankle'	0.425	0.079

Table 12: Top 5 correlated features to 1st component knee PWM

Static feature	Correlation coefficient	p-value
'thigh length'	-0.443	0.065
'shoulder width'	-0.376	0.124
'shin length'	-0.286	0.250
'width of knee'	0.232	0.354
'width torso - waist'	0.229	0.361

Table 13: Top 5 correlated features to 2nd component knee PWM

Static feature	Correlation coefficient	p-value
'shin length'	-0.448	0.062
'thigh length'	-0.430	0.075
'head length'	-0.350	0.154
'width of ankle'	-0.305	0.218
'shoulder width'	-0.276	0.268

Table 14: Top 5 correlated features to 3rd component knee PWM

Static feature	Correlation coefficient	p-value

'wrist width'	0.495	0.037
'width torso - waist'	0.432	0.073
'age'	-0.340'	0.168
'length forearm'	0.338	0.170
'head width'	-0.327	0.185

There are certain measurements in which the difference in measurement between subjects is relatively similar to the potential error in measurement. Measurements such as width of ankle, wrist width, and foot width are very small measurements. The resolution, at which the scan was taken and the angle at which the scanning was set to; can potentially introduce errors in measurement. To a lesser extent measurement such as width of thigh, knee, shoulders and elbows are close to the potential error.

Although weight is one of the top correlated static features, yet one subject has a weight of 130kg (an outlier), that is creating a favorable situation for a stronger correlation as in figures 29 and 32. To assess the influence of the outlier information, that subject (subject_03), was removed from the correlation analysis. Instead of resulting in 11 correlations with a P-value less than 0.05, it resulted in a total of 5 correlations fitting the criterion. The five correlated features are listed in table 15**.**

Table 15: A list of the significant correlations between static and dynamic features after removal of outlier (weight outlier)

	Dynamic Feature	Static Feature	Correlation Coefficient	P-value
1	1st comp elbow PWM	length forearm	0.515	0.034
2	1st comp knee PWM	shoulder width	-0.544	0.024
3	2nd comp thigh PWM	elbow width	0.552	0.022
4	3rd comp knee PWM	wrist width	0.511	0.036
5	3rd comp knee PWM	width torso - waist	0.567	0.018

Although the previous tables show that certain upper body static measurements are correlated with lower body dynamic features, there is the constant question of whether there is a stronger correlation between the lower body dynamic features and its lower body static measurements. Table 16 quantifies the correlation coefficient and P-values between lower limb dynamic features and lower limb static features only.

Table 16: Coreelation coefficient and P-values between lower limb 2D static and dynamic features

Static feature	Dynamic feature	Correlation coefficient	p-value
Thigh length(H3)	'1st comp knee PWM'	' -0.44296'	' 0.065621'
	'2nd comp knee PWM'	' -0.42971'	' 0.075118'
	'3rd comp knee PWM'	' 0.29137'	' 0.24076'
	'1st comp thigh PWM'	' -0.13178'	' 0.60219'
	'2nd comp thigh PWM'	' -0.057351'	' 0.82117'

Shin length (H4)	'2nd comp thigh PWM'	' 0.4538'	' 0.058542'
	'2nd comp knee PWM'	' -0.44838'	' 0.062005'
	'1st comp thigh PWM'	' -0.3709'	' 0.1297'
	'1st comp knee PWM'	' -0.2858'	' 0.25028'
	'3rd comp knee PWM'	' -0.23872'	' 0.34009'
Width of upper thigh (L1)	'2nd comp thigh PWM'	' 0.42249'	' 0.080697'
	'1st comp knee PWM'	' 0.22166'	' 0.37672'
	'1st comp thigh PWM'	' -0.21153'	' 0.39944'
	'3rd comp knee PWM'	' 0.058431'	' 0.81786'
	'2nd comp knee PWM'	' 0.010435'	' 0.96722'
Width of knee (L2)	'1st comp thigh PWM'	' 0.39115'	' 0.10847'
	'2nd comp thigh PWM'	' 0.3514'	' 0.15275'
	'1st comp knee PWM'	' 0.23218'	' 0.35389'
	'3rd comp knee PWM'	' 0.23093'	' 0.35654'
	'2nd comp knee PWM'	' 0.2069'	' 0.41008'

Although none of the correlations in the table above fit the P-value criterion of 0.05, yet the average of the correlation coefficients and the P-values can give us some an insight into the relationship and influence of certain type of measurements (width versus length) over the other. The average absolute correlation coefficient for the thigh length is 0.2706 and P-value of 0.361, and the shin length had a 0.35952 and P-value of 0.1681. On the other hand, the width of the thigh had an average absolute correlation coefficient of 0.1849092 and a P-value of 0.528; and the width of the knee had a 0.283 and a P-value of 0.276. In both cases, the length of the leg segment had a stronger correlation then the width. It was also clear that the shin measurements, both length and width, had a stronger correlation with the dynamic features of the lower limbs than the thigh measurements. This finding can be explained by the various models such as the pendulum model, in which the length of the lower limb is a major part of the motion model of the leg(Yam et al., 2004).

In conclusion, the correlation analysis conducted to study the relationship between 2d static and dynamic features resulted in several key results. There were 11 feature correlations that were considered statistically significant ($p<0.05$). There were static features that need to be evaluated because of the existence of an outlier in the data sample, which has shown to influence the correlation analysis. Static features such as weight were removed from a follow up analysis to see the influence of certain outlier containing subject data can have a great effect on the results. Removing the subject with the outlying weight static feature reduced the correlation coefficient and became statistically insignificant. Further insight into the influence of lower limb static measurements directly to its dynamic feature revealed that length of limbs were more related to the dynamics of the lower limb movement. Within the whole leg, the shin measurement shows a stronger relationship then the thighs.

In a study by Hanlon and Anderson, a r^2 value between 0.49-0.64 was regarded to be a moderate indication of prediction(Hanlon and Anderson, 2006). The r^2 values in the current study have a higher value, indicating a higher potential of strong predictions, therefore based on the correlation analysis conducted, prediction of some of the dynamic features is potentially possible.

4.5. Conclusion

There are numerous literatures supporting the existence of a relationship between the physical characteristics of a person to the main gait dynamics. Although several studies suggest that there are no clear relationships in the features they chose, yet the specific dynamic features covered are not the dynamic features that gait recognition focuses on(Hamill et al., 1989, McPoil and Cornwall, 1996, Cavanagh et al., 1997, Hunt et al., 2000, Cornwall and McPoil, 2011). Our study suggests that there is a relationship between some static features and dynamic features.

Further dynamic features and static features must be considered, as well as other advanced statistical tools must be explored to study the relationship between the two types of features, which will further enhance the understanding of gait. Future results will hold great benefits to several fields including: computer vision based gait recognition, biomechanical medical gait analysis, and the entertainment based computer animation application.

Although the criteria used in this study to define which features could be considered correlated is high, there were correlated static and dynamic features. Therefore, based on these indicators, the goal of this chapter was to use a more comprehensive approach to include more static and dynamic features using a unique set of data available, described in the previous chapter. The results of this study hold great potential for several reasons. Once an understanding of the relationship between the two set of features is defined, static features will enable us to predict the dynamic features and vice versa. In the field of biometrics and security, this would imply that less information would be needed to acquire a signature of a suspect or a criminal, which would benefit future criminal investigations that use gait as a source of identification. In biomechanics, physical measurements will allow the analysis of one's gait without resorting to the use of expensive systems. It will also have potentially great importance in further enhancing the knowledge about the specific mechanics of a human's gait. These results hold great potential for further studies in modelling the relationship between a human's static and dynamic gait features, and help in modelling the prediction, which will be explored in chapter 6.

There are certain factors that can be taken into consideration in future research.

1- Although the study has captured various aspects of the human body, there are other valuable factors to consider, for example, 3D volume static data extracted from the 3D point clouds.

2- The inclusion of additional 2D static features could potentially provide further insight into other possible relationships.

3- The correlation coefficient was used in this study to investigate if a relationship exists. Other statistical tools must be considered to interpret this relationship further. There is potential in the usage of non-linear statistical tools, as well as the use of autocorrelation and cross correlation with temporal data.

Chapter 5: Relationship Between 3d Static and Dynamic Features

5.1. Introduction

As mentioned in the previous chapter, although various gait recognition techniques take into consideration both static and dynamic features, there are no studies that attempt to describe a detailed relationship between both types of features.

Previous research indicates the existence of a correlation between certain static and dynamic features, but was disregarded because of their irrelevance to the objectives of those studies. In the previous chapter, two dimensional static and dynamic features where examined using a correlation coefficient analysis. The study concludes that there were eleven significantly correlated features. Therefore, based on these indications, the current chapter; first, looks at three dimensional static and dynamic features; and second, uses a high accuracy data capture method that includes motion capture and three dimensional laser scanned subjects, instead of 2d video object tracking and 2d measurements.

5.2. Review of related literature

There are several studies that have looked at volume or mass related static measurements. In a study by Van Den Bogert et al.,adding mass to the limb contributes directly to effort and stride length(van den Bogert et al., 2012b). This indirectly suggests that a change in mass can contribute to a change in kinematics. In another study, Wong et al’s study looked at how static parameters or features of a human can effect body kinematic and improve tennis serves(Wong et al., 2014). The relationship between body fat composition and gait speed was the focus of a study that aimed to understand which body part contributes most to gait speed (Beavers et al., 2013). Although the mentioned studies use mass related measurements, yet they are not measurable by image or video based sensors. The use of volume, rather than weight, is a more pragmatic static feature to be considered when using vision-based medium in capturing gait.

Since the subjects were captured using the Faro Ls laser scanner, it is possible to measure the volume and surface area of each individual segment of the body. Hence, following a similar methodology in studying the relationship between features, volume based static features and 3d dynamic features will be studied using a correlation analysis. Volume based static features were extracted from the 3d scans as described in chapter 3, while the 3d dynamic features were extracted from the motion capture data in the same mentioned database.

5.3 Feature choices and processing

In this correlation study, phase-weighted magnitude (PWM) of the different joint rotations of a subject was used as dynamic features. The joints used include: waist spine joint, upper spine joint, neck, shoulders, elbows, wrists, thigh joints, knees, ankles, ball of the foot, and shoulder traps. Each joint has three rotational axes[x, y, z], except for the knee which a hinge joint; therefore, has only one axis. The method is driven from a technique developed by Cunado et al. which was also used in chapter 4's correlation analysis(Cunado et al., 1997). In this method the phase and magnitude component of the Fourier transform applied on the rotations of every individual joint in a gait sample are used. The final feature is formed by multiplying the magnitude component by its corresponding phase component. Therefore, PWM is defined as,

$$x^{i}_{l,k,\sigma} = \left|\Theta\left(e^{j\omega k}_{l,i,\sigma}\right)\right| \bullet \arg\left(\Theta\left(e^{j\omega k}_{l,i,\sigma}\right)\right), \qquad \textbf{(4)}$$

$$k = 1,2,\ldots,N$$

where $x^{i}_{l,k}$, is the Phase-Weighted magnitude signature for the l^{th} sequence of subject i on the σ axis (because angle rotations are represented in three dimensions *x, y, and z*), the $\left|\Theta(e^{j\omega k})\right|$ represents the absolute value of the k^{th} Discrete Fourier Transform magnitude component, while $\arg(\Theta(e^{j\omega k}))$ is the complex form representation of the phase component. The "•" implies the multiplication of each component in the first vector by its corresponding component in the second vector. N is the number of subjects in the database, which in this analysis is 38.

Similarly to what was mentioned in the previous chapter, anything beyond the fifth phase harmonic can be ignored because of the insignificance of its magnitude component. In the mentioned study, only the first two harmonics in the thigh rotational data and the first three harmonics in the lower leg rotational data were used because of their highly discriminative properties(Yam et al., 2004). Therefore, only the 2nd to 5th components were used in the analysis to avoid noise and irrelevant data (Yam et al., 2004).

With most gait recognition techniques, the static features are extracted from the 2D or 3D model used to describe the subject's gait (Guo and Nixon, 2009). Computer vision based static features extraction techniques applied to video or two dimensional images carry a considerable amount of error, therefore; in order to acquire data that is accurate, a reconstruction of the subject's three dimensional body volume was created from the four 3D laser scans using Geomagic Polyworks to reverse engineer the point cloud to a mesh, and Autodesk Maya to combine the various meshes. The choice of features and the manner in which the subject's 3D volume was divided was based on logical physical landmarks of discriminative static features mentioned in the study by Guo and Nixon as well as in chapter 4(Guo and Nixon, 2009). Each individual part's volume and surface area was then calculated using Autodesk Maya's MEL commands ('computePolysetVolume' and 'polyEvaluate –area'). There were a total of 42 3D static features used. A visual representation of the division map of the body is show in Figure 34, while table 17 lists all body segments used, in which each segment was represented as a volume and surface area.

Table 17: A list of the 3D static features extracted from the 3D laser scanned subjects

Body segment	Description
Left leg	Starts from the top of the left thigh and ends at the left ankle
Right leg	Starts from the top of the right thigh and ends at the right ankle
Left thigh	Starts from the top of the left thigh and ends at the left knee
Right thigh	Starts from the top of the right thigh and ends at the right knee
Left shin	Starts from the left knee and ends at the

	left ankle
Right shin	Starts from the right knee and ends at the right ankle
torso	It includes the whole torso from the hip to the neck, without the arms
Left arm	Starts from the left shoulders to the left wrist
Right arm	Starts from the right shoulders to the right wrist.
Left shoulder	Starts from the left shoulder to the left elbow
Right shoulder	Starts from the right shoulder to the right elbow
Left forearm	Starts from the left elbow to the left wrist
Right forearm	Starts from the right elbow to the right wrist
Body	Includes the whole body without the hands, feet, and head.
Upper body	Include the torso and arms, without the head or hands.
Lower body	Includes the legs only without the feet
Left body	Includes the left arm, left leg, and the left half of the torso
Right body	Includes the right arm, right leg, and the right half of the torso
Hip	From the top of the leg to the waist
chest	From the waist to the beginning of the neck
No arms body	Similar to the body segment but without both arms

Figure 34: a visual representation of the 3D body segments

5.4. Correlation analysis

The correlation coefficient was used to serve the study's main aim at examining the relationship between the static and dynamic features. The correlation coefficient matrix $R(i,j)$ is defined as,

$$R(i,j) = \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}} \quad \textbf{(5)}$$

where $C(i,j)$ is the covariance, i and, j are the extracted features. The covariance was calculated using the following formula,

$$C(i,j) = E[(i - E[i])(j - E[j])], \quad \textbf{(6)}$$

where E is the expected value or weighted average.

5.5. Results

Based on the previous chapter, the correlation was considered to be significant if it met the criterion of having a p-value less than 0.05($p<0.05$). With this criterion there were 1196 pairs of features that expressed significant correlation. All significantly correlated features are listed in a table in appendix 5.1. The 20 strongest correlated feature pairs are listed in Table 1 *(In the dynamic feature's name, "L" or "R" define if it is a joint from the right(R) or left (L) side (some features do not have a right or left such as the head, root, and spine). The second word specifies the name of the joint (as an example: hand, thigh, elbow…). The last portion of the name describes the axis(x, y, z) and the Fourier component (1-4). Therefore L_hand_Yrotation1 represents the 1st PWM component of the left hand y-axis rotation*).

Table 18: A list of the top 20 correlated 3D static and dynamic features.

	Dynamic Feature	Static Feature	Correlation Coefficient	P-value
1	L_hand_Yrotation1'	Right forearm volume	0.982	0.0004
2	Root_Yposition4'	Lower body volume	-0.979	0.0007
3	R_elbow_Yrotation4'	Left Forearm surface area	-0.980	0.0006
4	head_Xrotation4'	Right shoulder volume	-0.979	0.0007
5	R_hand_Yrotation3'	Left body volume	0.976	0.0009
6	R_foot_Yrotation3'	Right body surface area	-0.972	0.001
7	L_hand_Yrotation4'	Right forearm volume	0.973	0.001
8	R_foot_Zrotation2'	Right body volume	-0.971	0.001
9	L_shoulder_Xrotation2'	Right Leg volume	0.970	0.001
10	L_shoulder_Xrotation3'	Right Leg volume	0.970	0.001
11	L_shoulder_Xrotation4'	Right Leg volume	0.970	0.001
12	L_shoulder_Xrotation1'	Right Leg volume	0.970	0.001
13	R_hand_Xrotation2'	Left arm Surface	-0.969	0.001

		area		
14	L_hand_Yrotation4'	Left forearm surface area	0.964	0.002
15	head_Xrotation4'	Right thigh volume	-0.964	0.002
16	L_hand_Yrotation4'	Left forearm volume	0.963	0.002
17	R_elbow_Zrotation2'	Total body surface area	-0.963	0.002
18	R_foot_Yrotation4'	Right body volume	-0.961	0.002
19	Spine_1_Yrotation2'	Right thigh surface area	0.959	0.002
20	L_hand_Yrotation3'	Right forearm volume	0.959	0.002

Based on the results above, there are certain correlations that exhibit a high correlation coefficient. On the contrary to the dynamic features used in chapter 4, the dynamic features used in this correlation analysis include the three axes (X, Y, and Z). The findings that there is a relationship between static and dynamic features in chapter 4 are echoed in these results, and furthermore provide a more detailed insight into the contribution of each individual rotational axis in a joint to the correlation. The dynamic features in table 18 include features extracted from hands, elbows, spine, head, shoulder, and foot rotations, while the static features included those of the forearm, thigh, body, arm, leg, shoulder, and whole body measurements. The features mentioned vary differently in regards to which body region they come from; therefore, to simplify the understanding of this huge dataset, the next set of analysis will look at specific regions of the body. Lower body or leg based dynamic features are the most commonly used features for gait recognition, therefore the next set of analysis will look specifically at contribution of different regions' static features to lower body dynamic features.

First, Similar to the analysis in chapter 4, the lower limbs dynamic features is compared to two different sets of static features: upper limbs static features and lower limbs static features. This initial comparison was conducted to compare the statistically based influence on the way legs move in a human's gait. Based on the two analyses, it is clear that both the upper and lower limbs static features are correlated to the movement of the legs. A list of all statistically significant correlated lower limb static to lower limb dynamic features are listed in appendix 5.2, and appendix 5.3 lists all the significant correlations between upper limb static features to lower limb dynamic features.

Secondly, to further simplify the analysis, a specific correlation analysis was conducted to investigate the correlation between lower limb dynamics and over all general regions of the body such as: overall body, upper body, lower body, right side of the body, and left side of the body. This analysis would offer us an insight into whether there is a stronger correlation to the general mass of the body to the dynamics of the legs, rather than specific body parts such as forearm or shoulder. Table 19 lists statistically significant correlations that fit the criterion of having a P-value less than 0.05.

Table 19: A list of all significantly correlated 3D torso and body static measurements and lower limb dynamic features.

Dynamic feature	Static feature	Correlation coefficient	P-value
'R_thigh_Zrotation2'	'body_vol'	' 0.51113'	' 0.021264'
'L_knee_Xrotation3'	'body_vol'	'-0.54426'	' 0.013102'

'L_foot_Yrotation3'	'body_vol'	' 0.46351'	' 0.039557'
'R_thigh_Zrotation3'	'body_vol'	' 0.49566'	' 0.026255'
'L_thigh_Zrotation4'	'body_vol'	' 0.44425'	' 0.049717'
'L_knee_Xrotation4'	'body_vol'	'-0.47719'	' 0.033373'
'L_foot_Yrotation4'	'body_vol'	' 0.44607'	' 0.048681'
'R_thigh_Zrotation4'	'body_vol'	' 0.63293'	' 0.0027421'
'R_thigh_Zrotation5'	'body_vol'	' 0.45002'	' 0.046484'
'R_thigh_Zrotation2'	'body_sur'	' 0.46956'	' 0.036719'
'R_thigh_Zrotation3'	'body_sur'	' 0.48156'	' 0.031566'
'L_thigh_Yrotation4'	'body_sur'	'-0.48449'	' 0.030399'
'L_thigh_Zrotation4'	'body_sur'	' 0.54975'	' 0.012037'
'L_foot_Yrotation4'	'body_sur'	' 0.46927'	' 0.036854'
'R_thigh_Zrotation4'	'body_sur'	' 0.62486'	' 0.0032228'
'L_thigh_Yrotation5'	'body_sur'	'-0.53959'	' 0.014068'
'R_thigh_Zrotation1'	'upper_vol'	' 0.47283'	' 0.035254'
'R_thigh_Zrotation2'	'upper_vol'	' 0.51944'	' 0.018914'
'Root_Xposition3'	'upper_vol'	' 0.45971'	' 0.041423'
'L_knee_Xrotation3'	'upper_vol'	'-0.59852'	' 0.0053038'
'L_foot_Yrotation3'	'upper_vol'	' 0.47963'	' 0.032355'
'R_thigh_Zrotation3'	'upper_vol'	' 0.49362'	' 0.026977'
'L_knee_Xrotation4'	'upper_vol'	'-0.53565'	' 0.014928'
'R_thigh_Zrotation4'	'upper_vol'	' 0.61064'	' 0.0042398'
'R_thigh_Zrotation5'	'upper_vol'	' 0.45836'	' 0.042098'
'Root_Xposition2'	'upper_sur'	' 0.46077'	' 0.040893'
'R_thigh_Zrotation2'	'upper_sur'	' 0.52785'	' 0.016752'
'Root_Xposition3'	'upper_sur'	' 0.54693'	' 0.012576'
'L_knee_Xrotation3'	'upper_sur'	'-0.49779'	' 0.025517'
'R_thigh_Zrotation3'	'upper_sur'	' 0.45753'	' 0.042521'
'Root_Xposition4'	'upper_sur'	' 0.47987'	' 0.032254'
'L_knee_Xrotation4'	'upper_sur'	'-0.56485'	' 0.0094606'
'R_thigh_Zrotation4'	'upper_sur'	' 0.60421'	' 0.0047797'

'Root_Xposition5'	'upper_sur'	' 0.49971'	' 0.024866'
'R_thigh_Xrotation5'	'upper_sur'	' -0.5611'	' 0.010055'
'Root_Zposition1'	'lower_vol'	' 0.4912'	' 0.027851'
'L_thigh_Zrotation1'	'lower_vol'	' 0.70624'	'0.00050104'
'L_thigh_Zrotation2'	'lower_vol'	' 0.61834'	' 0.0036603'
'L_foot_Yrotation2'	'lower_vol'	'-0.53507'	' 0.015057'
'L_thigh_Zrotation3'	'lower_vol'	' 0.48539'	' 0.030048'
'R_foot_Xrotation3'	'lower_vol'	'-0.46198'	' 0.0403'
'R_toe_Xrotation3'	'lower_vol'	' 0.46152'	' 0.040526'
'L_thigh_Zrotation4'	'lower_vol'	' 0.51999'	' 0.018767'
'R_thigh_Zrotation4'	'lower_vol'	' 0.45536'	' 0.04364'
'R_foot_Xrotation4'	'lower_vol'	'-0.46885'	' 0.037042'
'L_thigh_Zrotation1'	'lower_sur'	' 0.56183'	' 0.0099362'
'L_thigh_Zrotation2'	'lower_sur'	' 0.52742'	' 0.016858'
'L_foot_Yrotation2'	'lower_sur'	' -0.5547'	' 0.011137'
'L_thigh_Zrotation3'	'lower_sur'	' 0.50934'	' 0.0218'
'L_thigh_Zrotation4'	'lower_sur'	' 0.52076'	' 0.018561'
'L_thigh_Yrotation5'	'lower_sur'	'-0.45275'	' 0.045014'
'L_thigh_Zrotation5'	'lower_sur'	' 0.51483'	' 0.02019'
'L_knee_Xrotation2'	'left_vol'	' -0.5005'	' 0.024602'
'R_thigh_Zrotation2'	'left_vol'	' 0.45515'	' 0.043749'
'L_knee_Xrotation3'	'left_vol'	'-0.48721'	' 0.029345'
'R_thigh_Zrotation3'	'left_vol'	' 0.48407'	' 0.030566'
'L_thigh_Zrotation4'	'left_vol'	' 0.44858'	' 0.047279'
'L_knee_Xrotation4'	'left_vol'	'-0.50591'	' 0.022856'
'R_thigh_Zrotation4'	'left_vol'	' 0.59732'	' 0.0054194'
'L_thigh_Yrotation5'	'left_vol'	'-0.45329'	' 0.044728'
'Root_Yposition2'	'left_sur'	'-0.45514'	' 0.043751'
'L_knee_Xrotation2'	'left_sur'	'-0.61527'	' 0.003883'
'R_thigh_Zrotation3'	'left_sur'	' 0.44511'	' 0.049226'
'L_knee_Xrotation4'	'left_sur'	'-0.44768'	' 0.047774'

'R_thigh_Zrotation4'	'left_sur'	' 0.508'	' 0.022208'
'L_thigh_Yrotation5'	'left_sur'	'-0.49219'	' 0.027491'
'L_knee_Xrotation2'	'right_vol'	' -0.4781'	' 0.03299'
'R_thigh_Zrotation2'	'right_vol'	' 0.48691'	' 0.02946'
'L_knee_Xrotation3'	'right_vol'	'-0.52524'	' 0.017399'
'L_foot_Yrotation3'	'right_vol'	' 0.45478'	' 0.04394'
'R_thigh_Zrotation3'	'right_vol'	' 0.46646'	' 0.038153'
'L_knee_Xrotation4'	'right_vol'	'-0.57969'	' 0.0073853'
'R_thigh_Zrotation4'	'right_vol'	' 0.59694'	' 0.0054574'
'R_thigh_Zrotation5'	'right_vol'	' 0.47544'	' 0.034119'
'L_knee_Xrotation2'	'right_sur'	'-0.61833'	' 0.0036615'
'L_knee_Xrotation4'	'right_sur'	'-0.50586'	' 0.022871'
'R_thigh_Zrotation4'	'right_sur'	' 0.46905'	' 0.036954'
'R_thigh_Zrotation1'	'noArms_vol'	' 0.45903'	' 0.041763'
'R_thigh_Zrotation2'	'noArms_vol'	' 0.5062'	' 0.022764'

The table above indicates that overall there is correlation between the body static measurements and the dynamics of a gait. The whole body volume and surface area display a significant correlation to the rotation of the right and left thigh, knee, and foot rotations on all axes. The same results were also achieved when correlating the leg dynamic features to the static features: the upper and lower body volumes, and the right and left volume and surface area. It is also important to note that volume of the whole body with no arms showed the least number of significant correlated features, which can potentially indicate the importance of the volume and surface area of the arms in influencing the leg dynamics.

In addition to looking specifically at only the significantly correlated features, the third analysis looked at the overall correlation between the body regions and the leg dynamics. Table 20 shows the average absolute value of correlation coefficients of all correlations, alongside the average P-value.

Table 20: The average absolute correlation coefficient and average P-value of body and torso static features to lower limb dynamic features

Static feature	Average absolute correlation coefficient	Average p-value
Whole body volume	0.171	0.548
Whole body surface area	0.188	0.511
Upper body volume	0.177	0.532
Upper body surface area	**0.203**	**0.473**
Lower body volume	0.174	0.549
Lower body surface area	0.166	0.551
Left side volume	0.173	0.540
Left side surface area	0.183	0.507
Right side volume	0.165	0.556
Right side surface area	0.168	0.536
Body volume with no arms	0.167	0.557
Body surface area with no arms	0.170	0547

All the average absolute correlations above range between 0.165-0.203. It is clear from these results that the upper body surface area has the strongest correlation with lower limb dynamic features. It is also clear that when we compare between the whole body to the body without the arm, the correlation strength decreases in both volume and surface area. This can be contributed to the upper limb's relationship with lower limb dynamics, although the effect is relatively small.

Of particular concern is the volume of the body with no arms, as it was intended to study the actual contribution of arms to the lower extremities of gait. To get further indications of whether upper or lower body has a stronger correlation to lower limb dynamics, we calculated the average of the absolute value of the correlation coefficient and the p-values of the correlations with a P-value less than 0.05 of static feature of lower limbs and upper limbs. Results can be found in table 21.

Table 21: Average absolute correlation coefficients and average P-values of significant correlations between upper or lower limbs static features to lower limbs' dynamic features.

Static features	Dynamics feature	Average absolute correlation coefficients	Average p-values
Lower limb	Lower limb	0.5101	0.0258
Upper limb	**Lower limb**	**0.5398**	**0.0194**

The table above takes into consideration the statistically significant correlations. But for an overall understanding of the other static features that don't fit the criterion, are listed in table 22.

Table 22: Average absolute correlation coefficients and average P-values of all correlations between upper or lower limbs static features to lower limbs' dynamic features.

Static features	Dynamics feature	Average absolute correlation coefficients	Average p-values
Lower limb	Lower limb	0.1833	0.5135
Upper limb	**Lower limb**	**0.2199**	**0.4394**

In both cases in the two tables above, the upper limb static features show a slightly stronger correlation to lower limb dynamic features than lower limb static features.

More importantly, it was critical to focus on the contribution of the volume of each segment of the body, to its dynamic counterpart. We have seen previously that the strongest correlation to lower limb dynamic features was with the upper limbs' static features. To evaluate if such a correlation observation is present between right and left parts of the body, the average absolute correlation coefficient and average p-values of each side's static feature to the of one side to the opposite side's dynamic features. The results can be found in table 23.

Table 23: Average absolute correlation coefficients and average P-values of significant and all correlations between right and left static features to right and left dynamic features.

Static features	Dynamic features	Average absolute correlation coefficient	Average p-value
Right side	Right side	0.5008 ($p<0.05$) 0.2073	0.028($p<0.05$) 0.4582
Right side	Left side	0.5134($p<0.05$) 0.1992	0.0251($p<0.05$) 0.4746
Left side	Right side	0.5377($p<0.05$) 0.2215	0.0202($p<0.05$) 0.4416

Left side	Left side	0.5390(p<0.05) 0.2148	0.0197(p<0.05) 0.4540

Looking at the results above at first sight, there is not an obvious difference in strength of correlation between opposite sides or same side. When comparing the correlation between the right side dynamic, and it’s counterpart static features on right or left, the difference is approximately 0.014, with the left side (opposite) bearing a stronger correlation. The correlation between the left side dynamic features to the right and left static features, the difference is approximately 0.016. On the contrary to the right side dynamic features, the left side dynamic feature favored a stronger correlation to left side static features (same side). The difference between the correlations are minimal, and is not consistent, therefore; on the contrary to the results for top versus bottom static features correlating to their opposite dynamic features, horizontally opposite features do not appear to correlate more strongly than features on the same side of the body.

Two different types of static measurements were used in the correlation study: volume and surface area. Since they both represent different aspects of a body volume’s characteristic, it is important to measure their contribution to correlation strength. Therefore to measure the average absolute correlation coefficient was measured for two sets: between surface static features and dynamic features; as well as between volume static features and dynamic features. The results are show in table 24.

Table 24: Average absolute correlation coefficients and average P-values of significant and all correlations between surface area and volume static features to all dynamic features.

Dynamic features	Static features	Average absolute correlation coefficient	Average p-value
All dynamic features	Surface areas	0.536(P<0.05) 0.224	0.021(P<0.05) 0.437
All dynamic features	volumes	0.518(P<0.05) 0.217	0.024(P<0.05) 0.446

In both cases, surface area presented a stronger correlation to dynamic features. The difference though is very small; therefore it does not form a clear cut difference between surface area and volumes. Although in the general outlook there were no clear differences, further analysis was done to see the difference between correlations of volumes and surfaces areas, but divided into upper and lower body, instead of considering them as a whole. The results of upper static features are presented in table 25, and the results of lower static features analysis are presented in table 26.

Table 25: Average absolute correlation coefficients and average P-values of significant and all correlations between surface areas and volumes of upper body static features to all dynamic features.

Dynamic features	Static features	Average absolute correlation coefficient	Average p-value
All dynamic features	Surface areas upper body	0.554 (P<0.05) 0.252	0.019 (P<0.05) 0.395
All dynamic features	Volumes upper body	0.516 (P<0.05) 0.234	0.024 (P<0.05) 0.413

Table 26: Average absolute correlation coefficients and average P-values of significant and all correlations between surface areas and volumes of lower body static features to all dynamic features

Dynamic features	Static features	Average absolute correlation coefficient	Average p-value
All dynamic features	Surface areas lower body	0.509 ($P<0.05$) 0.197	0.026 ($P<0.05$) 0.476
All dynamic features	Volumes lower body	0.519 ($P<0.05$) 0.197	0.024 ($P<0.05$) 0.477

Although the differences are small between the correlations to surfaces and volumes, yet the surface area of the upper body shows a relatively stronger correlation with the dynamic features than the volume of the upper body. The difference between the correlation coefficient when using surface areas and volumes of the upper body, is approximately 0.018. This is not the same case with the results of the lower body static measurements. In the lower body static features, the average absolute correlation coefficient is approximately the same for both surface areas and volumes. Although the upper body shows a greater correlation between surface areas and dynamic features than volumes, yet the difference is not large enough to show a clear effect.

5.6. Discussion

Although there were a considerable number of significantly correlated features, the majority of static features did not contribute directly to their body part's dynamic features. On the contrary, correlated features displayed a relationship between dynamic features and their vertically opposite corresponding static feature. Such findings support studies that relate weight and size and their mirror influence on gait kinematics. Yen et al. describe the effect of load on carriage on the temporal relationship between the trunk and the leg (Yen et al., 2011). Another study by Collins et al. describes the contribution of arm movement to the reaction moment from the ground (Collins et al., 2009). The study compared a gait cycle in which arm movement was restricted, and was found to directly contribute to greater reaction moment from the ground, hence requiring the human body to adapt and increase energy expenditure and muscle usage. Therefore, the motion of the arms directly contributes to the effort of the legs during gait. David et al. conducted a study on the effect of carrying a bag on static posture and gait dynamics(Pascoe et al., 1997). It describes a direct influence of an increase in size and weight in the upper extremities (carrying a bag), on gait dynamics relating to lower extremities, such as stride length and frequency.

Therefore, firstly, there is a clear stronger relationship between the upper body static features and the leg dynamics, than the lower body static features to the leg dynamics. Although intuitively, one might think that the size of the legs would influence the leg's dynamic more strongly, yet the analysis showed that the upper body had a stronger correlation to the dynamics of the leg. Based on previous studies mentioned above, this can be explained as the weight or size of the upper body is continuously balanced by the legs, hence influencing the way it moves more.

Secondly, surface areas have displayed a stronger correlation to the dynamics of the legs rather than volumes. Although larger volumes tend to have bigger surfaces areas, yet it is not always true. There are subjects in the database that share very similar volumes, yet vary proportionally in surface areas. Surface areas potentially provide more information in regards to the shape of the body rather than size, which indicates in some case the obesity or fitness of a person.

Thirdly, arms' volume and surface area are strongly correlated to the leg dynamics and contribute greatly to gait. Within the results section, the two static features: surface area of the whole body, and the surface are of the whole body without the arm; were compared in regards to their correlation to the dynamics of the leg. The body's volume without the arms had a weaker correlation with leg dynamics, than with the arms included. This once again can also be contributed to the legs balancing the weight of the arms as shown in the study by Collins et al. in which arm movement was restricted.

5.7. Conclusion

On the contrary to the findings of biomechanics studies of the relationship between static features and dynamic(kinematics) features, this study exhibits strong correlation between 1196 pairs of features with ($P<0.05$). These results bare great potential for further investigation in the relationship between dynamic and static features, which would contribute to various applications such as: clinical gait analysis, security related gait recognition application, and 3D computer animation.

The results direct towards several future directions for further research is required and can be summarized in three main points:

1. There is potential in investigating the ability of the correlated features in creating a prediction model to allow the visualization and simulation of gait using only static features.

2. It is important to note that the work here is based on a single gait cycle for each of the observers. It is well known that there is some within-individual variability and we would need to take this into account to help establish which correlations might be due to noise rather than any causal link. In particular we would investigate significant correlations involving higher Fourier components, which we expect to contain a higher noise component than the lower components.

3. Considering phase and magnitude independently could provide a detailed understanding of the relationship of each component to static data.

4. Although the study took in consideration numerous features, including other dynamic and static features could prove to provide more insight into the nature of the correlation between the two sets of data

The results of this study hold great potential for several reasons. Once an understanding of a more detailed relationship between the two sets of features is defined, static features will enable us to predict the dynamic features and vice versa. This would potentially allow physical measurements to predict the kinematics of a gait without resorting to the use of expensive systems. It will also bear great importance to further enhancing the knowledge about the specific mechanics of a human's gait.

Chapter 6: Prediction of gait signature

6.1. Introduction

In the previous chapter, some static features portrayed strong relationships with dynamic features. Lower limbs dynamic and static features are especially important, because they are the main focus of most clinical biomechanics studies and analysis, as well as being most commonly used in model based gait recognition techniques mentioned in previous chapters. Since the main aim of the correlation study was to study the potential of using static features to predict dynamic features, this chapter focuses upon the prediction aspect. This chapter will cover an overview of dynamic gait prediction in other past and present studies, and the prediction methodology used in this study and its results. The understanding of this relationship and being able to predict dynamic features from static features can greatly contribute to both forensic and biomechanics applications.

6.2. Definition and scope

Gait prediction is an area that has interest from different disciplines, such as clinical gait analysis and robotics. Gait prediction (or gait pattern prediction) can be defined as calculating or defining an optimized motion model or dynamic gait features or parameters using limited or static gait features or parameters (Yun et al., 2014).

6.2.1. Biomechanics gait prediction

Prediction studies relating to gait are not only oriented towards building a motion model necessarily for gait recognition, but also contribute to clinical analysis for pathological gait problems, gait simulation, sport sciences, and robotics.

A major part of human gait simulation is prediction (Xiang et al., 2011) . In clinical gait analyses, simulations (or models) are used to predict or accurately estimate certain values such as muscle forces. Predictions or simulations based on energy cost and efficiency have been used for over 20 years. In 1995, a study by Chou et al. based their algorithm for estimating a limb swing by choosing the most energy efficient trajectory(Chou et al., 1995). Understanding the muscle forces and the kinetics of a gait, facilitate in the diagnosis of a person’s gait, as well as building an understanding for enhancing footwear and athletes’ training (van den Bogert et al., 2012a). It is also used to model the effect of prosthetics or medical interventions on human gait (Millard et al., 2008). Not limiting prediction to gait, a study was conducted to test whether certain body parameters can predict if a person has the potential to be a more athletic cross-country sprint skier(Stöggl et al., 2010)

Most clinical gait analyses use model based techniques(Yun et al., 2014). These techniques utilize energy cost theories in gait biomechanics to build mathematical models of predicting or simulating the optimum solution for limb kinematics(Yun et al., 2014). Energy cost theories simply state that for any speed or distance traveled, the human body attempts to move in a way that exerts the least amount of energy. There are two most commonly used model-based optimization approaches in simulation which are: forward dynamic optimization and inverse dynamics-based optimization (Xiang et al., 2011). Inverse dynamic simulation is not a kinematic predictive approach. It is best described as an approach that predicts the forces (or gait kinetics) that are in place based on a specific motion, gait kinematics or pose(Millard et al., 2008). Inverse dynamic approaches are often used in gait analysis laboratories to evaluate the moments and forces effecting a joint(Kiernan et al., 2014) . Forward dynamic optimization on the other hand, looks at forces and their influence on gait kinematics; therefore, making it predictive. Forward dynamic approaches can be optimized using various techniques. An example would be the use of metabolic efficiency, in which the model is constructed to choose the metabolically efficient simulation of human like gait kinematics and mechanism(Millard et al., 2008). Forward dynamic optimization approaches are usually computationally heavy(Ackermann and van den Bogert, 2010). Others approaches include the collocation method, predictive dynamic approaches, and the temporal finite element method(Yun et al., 2014).

Other than predicting the kinetics of a human's gait, prediction is also involved in the analysis of the effect of certain parameters or influencing factors on gait. For example, in (Predicting peak kinematic and kinetic parameters from gait speed) an equation was developed to express the influence in change of speed on the peak sagittal angles. Furthermore, a study by Hanlon et al. examined the effect of speed on the whole gait cycle(Hanlon and Anderson, 2006). In this study, the gait cycle was divided into 22 parts, 11 in the stance period and 11 in the swing period. This approach according to the study provided a method to measure kinematic values. At each point, an angle was extracted. These angle measurements along with the minimum and maximum angles of the swing and stance phase, a total of twenty-six points in a gait cycle were correlated against gait speed. Because most gait databases used to drive gait simulation data are captured from healthy subjects, both mentioned studies studied the relationship and influence of speed to help in the analysis of pathological gait problems, in which the patients usually walk at a slower pace than healthy subjects(Lelas et al., 2003).

Although most prediction or gait simulation techniques are model-based, a statistical approach better handles the deviations and uncertainties in gait(Yun et al., 2014). In the study by Hanlon and Anderson, angle measurements were taken at 11 points in swing, 11 points in stance, and the minimum and maximum angles in both phases for five joints (Hanlon and Anderson, 2006). A correlation study was conducted between the angle measurements for the three gait speeds. The results stated that there were significant correlations between the two sets of data, therefore; biomechanical gait prediction models should take speed into consideration. At the same time as this study was conducted, another study took a similar approach. The aim of the study by Yun et al. was to build a statistically based function that predicts 14 joints' gait kinematics from 14 gait static parameters (Yun et al., 2014). The study used gait parameters (stride length and cadence) and static features (ASIS breadth, thigh length, calf length, and foot length) to predict the Fourier coefficient vector, which would provide a stochastic model for the motion of the subject(Yun et al., 2014).

In (Yun et al., 2014) , gait parameters and anthropometric measurements were used to predict Fourier coefficient vectors, which were used to simulate the kinematic and dynamic motion of the subject.

Prediction is vital to robotic applications as it provides the basis on which walk simulations are executed. Specifically, creating or predicting gait patterns is important in robotic assisted gait rehabilitation(Yun et al., 2014).

6.2.2. Gait prediction from a forensic perspective

Although several previously mentioned studies have proved that gait can be used as a biometric using computer vision based techniques, the majority was tested in favorable conditions. Yet in forensic based approaches several challenges arise and must be studied and overcome for a practical application of gait recognition techniques. Some of these challenges are being addressed by other studies such as different lighting conditions, angle variance, shoe type, time passage between gait capture, and flooring. But there are other challenges more specific to forensic applications of gait recognition that are less addressed. These challenges can be summarized as: low temporal and spatial resolution, and partial temporal and spatial gait cycles as mentioned in chapter 2.

For gait to be used in forensic applications, the source of the gait signature would usually be extracted from CCTV footage. CCTV footage’s spatial and temporal resolution can greatly vary. Spatial resolution can be described as the number of pixels representing the person in focus in a single frame. Temporal resolution on the other hand is the number of frames representing a certain period of time, which is usually measured in frames per second (fps). Partial temporal gait cycle is an incomplete gait cycle, which can be caused by the subject leaving the field of view of the camera, or being totally occluded by an object in the foreground. Partial spatial gait cycle is the condition when only part of the body appears in a gait cycle because of an object hiding part of the body, as in when a subject walks behind a fence, and only the upper body appears on camera.

In certain situations, the CCTV camera footage is of a low frame rate or low resolution. Most model based gait recognition studies extract gait signatures using videos that are 60, 30, or 25 frames per second (fps). Some CCTV cameras record as low as 1 fps (Akae et al., 2012). Depending on how far the subject is from the camera, the amount of pixel data available to extract model based gait features can vary. Potential approaches to tackle low frame rate videos have been conducted other studies (Mori et al., 2010, Akae et al., 2012).

Therefore in this chapter we propose gait predication as a solution for some of the presented challenges. In all of the above-mentioned challenges, the only common characteristic is the presence of one single image of the subject. Whether low resolution, slow frame rate, incomplete gait cycle, or body occlusion; certain measurements using photogrammetry can be extracted from the images. Therefore our aim is to be able to translate such measurements to a gait signature representing the extra dimension of time. This chapter will investigate the potential of using static measurements to predict dynamic gait signature features.

6.3. Prediction methodology

To critically look at the potential of static features to predict dynamic features, several aspects of the workflow have to be taken into consideration. The common prediction workflow involves four major factors: the regression model, what to predict, choice of predictors, and the assessment of the prediction. Because the goal of prediction in this study is to use the predicted dynamic features as a gait signature, classification assessment must be included as a fifth factor. Figure 39 illustrates the workflow of the prediction methodology used.

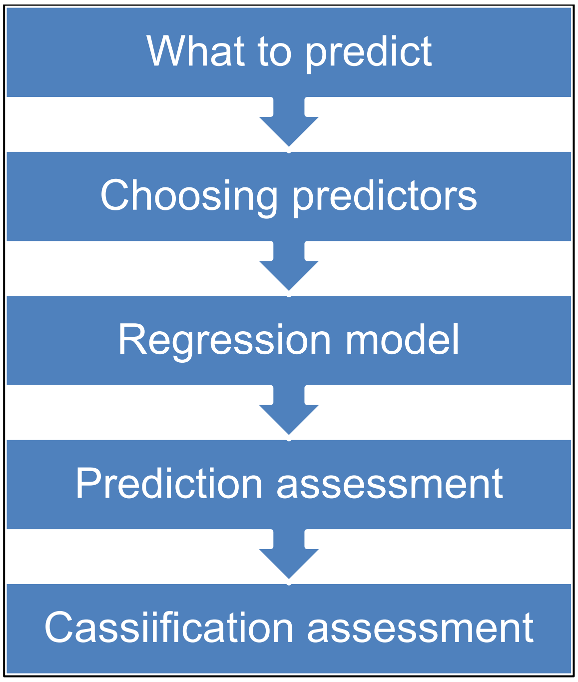

Figure 35: A diagram of the prediction methodolgy implemented in the prediction of the dynamic gait signature

Linear regression is used in this study to create a model to predict dynamic features from static features. Linear regression was used to predict gait kinematics or the influence of certain factors on gait kinematics(Hanlon and Anderson, 2006) (Lelas et al., 2003). The choice of the predicted and predictors will be discussed further in the next two subsections.

6.3.1. The predicted

The Fourier transform is commonly used in gait recognition applications and studies to represent the cyclic gait motion(Yun et al., 2014). Although in the study by Yun et al, the Fourier transform was used to extract the Fourier coefficients vectors, in this study phase and magnitude were extracted instead.

The results of the correlation study conducted in the previous chapter suggest that there needs to be a focus on specific dynamics features. Since the aim is to predict a gait signature, the thigh and knee joints were used. They are the most commonly used joints for the creation of a dynamic signature in model based gait recognition techniques. As mentioned in the previous section, the knee and thigh dynamic features were extracted through the magnitude and phase components extracted by the use of the Fourier transform. MatLab FFT was used. There Fourier transform components are based on the three axis of the thigh rotation, and only a single (x) axis of the knee rotation. Based on the model used to extract the motion capture data discussed in chapter 3, the knee had only one degree of freedom. The magnitude and phase components were multiplied to form the phase-weighted magnitude (PWM), which was discussed in previous chapters. Unlike the previous chapter, only the 2^{nd}, 3^{rd}, and 4^{th} components' PWM were used in prediction. To further understand and explore the effect of each component; a second correlation study was conducted in which magnitude and phase were considered independently as individual dynamic features. Since magnitude and phase represent different aspects of the gait signal, it would be logical to consider them independently. Using the Pearson coefficient and the p-value as a mean of ranking statistical significant relationships, tables 27-39 list the significantly correlated features between all static features, and only the right lower limb *(In the static feature's name, "L" or "R" define if it is a segment from the right(R) or left (L) side (some features do not have a right or left such as the head, root, and spine). The second word specifies the name of the segment (e.g. arm, thigh, body…). The last portion of the name describes whether it is a volume measurement (vol) or a surface area measurement (surf). Therefore L_arm_vol is the left arm's volume measurement*).

Table 27: 2nd component Magnitude of the thigh X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_arm_vol'	0.198	0.300
'L_shoulder_vol'	0.256	0.267
'upper_sur'	0.346	0.222
'L_shoulder_sur'	0.375	0.209
'R_shoulder_sur'	0.461	0.175

Table 28: 2nd component Magnitude of the thigh Y-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_arm_sur'	0.0002	-0.734
'L_forearm_sur'	0.0004	-0.712
'L_shoulder_sur'	0.0009	-0.683
'L_forearm_vol'	0.0026	-0.635
'R_arm_sur'	0.0069	-0.583

Table 29: 2nd component Magnitude of the thigh Z-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_arm_sur'	0.0035	-0.621
'L_shoulder_sur'	0.0049	-0.603
'L_forearm_sur'	0.0086	-0.570
'body_sur'	0.0303	-0.485
'L_forearm_vol'	0.0320	-0.480

Table 30: 2nd component Magnitude of the knee X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'R_leg_vol'	0.0423	0.458
'R_thigh_vol'	0.0476	0.448
'lower_vol'	0.1328	0.348
'R_shin_vol'	0.1342	0.347
'L_thigh_vol'	0.1640	0.324

Table 31: 3rd component Magnitude of the thigh X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shin_sur'	0.0129	-0.545
'L_leg_sur'	0.0264	-0.495
'lower_sur'	0.0305	-0.484
'R_leg_sur'	0.0396	-0.463
'R_forearm_sur'	0.0407	-0.461

Table 32: 3rd component Magnitude of the thigh Y-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'R_forearm_sur'	0.0910	-0.388
'L_shin_sur'	0.1186	-0.360
'R_forearm_vol'	0.1210	-0.358
'L_leg_sur'	0.2302	-0.281
'L_shin_vol'	0.2330	-0.279

Table 33: 3rd component Magnitude of the thigh Z-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shoulder_sur'	0.0209	-0.512
'L_arm_sur'	0.0394	-0.464
'body_sur'	0.0531	-0.439
'R_thigh_sur'	0.0704	-0.413
'noArms_sur'	0.0705	-0.413

Table 34: 3rd component Magnitude of the knee X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_forearm_vol'	0.0208	0.513
'L_forearm_sur'	0.0435	0.456
'L_arm_sur'	0.0660	0.419
'L_shoulder_sur'	0.1038	0.375
'hip_sur'	0.1136	0.365

Table 35: 4th component Magnitude of the knee X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shin_vol'	0.0182	0.522
'L_arm_vol'	0.0471	0.449
'right_vol'	0.0538	0.437
'upper_sur'	0.0566	0.433
'right_sur'	0.0683	0.416

Table 36: 2nd component phase of the thigh X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_forearm_sur'	0.0558	0.434
'L_shin_vol'	0.1171	0.362
'R_arm_sur'	0.1193	0.360
'L_arm_sur'	0.1340	0.347
'R_shoulder_sur'	0.1411	0.341

Table 37: 2nd component phase of the thigh Y-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'chest_sur'	0.0137	0.541
'R_forearm_sur'	0.1786	-0.313
'L_shin_vol'	0.1896	-0.306
'L_leg_vol'	0.2099	0.293
'L_thigh_sur'	0.2258	0.284

Table 38: 2nd component phase of the thigh Z-axis rotation’s correlation to static features

Static feature	P-value	Correlation Coefficient
'lower_vol'	0.0039	0.615
'L_leg_vol'	0.0080	0.575
'L_thigh_vol'	0.0083	0.573
'R_leg_vol'	0.0147	0.537
'R_thigh_vol'	0.0197	0.517

Table 39: 2nd component phase of the knee X-axis rotation’s correlation to static features

Static feature	P-value	Correlation Coefficient
'left_sur'	0.0018	-0.654
'right_sur'	0.0024	-0.640
'left_vol'	0.0039	-0.615
'right_vol'	0.0046	-0.607
'L_arm_vol'	0.0063	-0.589

Table 40: 3rd component phase of the thigh X-axis rotation’s correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shoulder_sur'	0.0008	0.688
'L_arm_sur'	0.0022	0.643
'L_arm_vol'	0.0069	0.584
'L_forearm_vol'	0.0175	0.525
'L_forearm_sur'	0.0313	0.482

Table 41: 3rd component phase of the thigh Y-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shoulder_sur'	0.0392	-0.464
'L_shoulder_vol'	0.0422	-0.458
'L_arm_sur'	0.0477	-0.448
'L_arm_vol'	0.0535	-0.438
'R_forearm_sur'	0.0586	-0.430

Table 42: 3rd component phase of the thigh Z-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'lower_vol'	0.0109	0.556
'R_leg_vol'	0.0179	0.523
'L_thigh_vol'	0.0194	0.518
'R_shoulder_sur'	0.0210	0.512
'L_leg_vol'	0.0269	0.494

Table 43: 3rd component phase of the knee X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'L_shin_vol'	0.1406	0.341
'L_thigh_vol'	0.2246	-0.284
'L_leg_vol'	0.3150	-0.237
'right_sur'	0.3222	-0.233
'R_thigh_vol'	0.3321	-0.229

Table 44: 4th component phase of the knee X-axis rotation's correlation to static features

Static feature	P-value	Correlation Coefficient
'hip_vol'	0.0070	-0.583
'torso_vol'	0.0076	-0.579
'upper_vol'	0.0089	-0.568
'chest_vol'	0.0092	-0.567
'noArms_vol'	0.0103	-0.559

Although both correlation studies show different correlation coefficients and p-values, their prediction potential can only be compared through a classification assessment of the predicted dynamic features, which will be described in following sections

6.3.2. Choosing predictors

The first step in the proposed workflow is the choice of predictors. Previous studies vary in their choice of predictors, but they can be categorized as either: static features, limited temporal dynamic features, upper body dynamic features, or a mixed module of features.

In Yun et al's study, static features such as: ASIS breadth, thigh length, calf length, and foot length were used as part of the prediction inputs(Yun et al., 2014). While the use of limited temporal data in dynamic features is evident in a study by Findlow et al., in which acceleration and angular data from motion sensors placed on the leg were used to predict gait kinematics(Findlow et al., 2008). Sensors were placed on the shank and feet on each leg.

Other predictor choices such as gait speed are used in the study by Hanlon et al(Hanlon and Anderson, 2006). Gait speed was used to predict the changes in the lower extremities' kinematic parameters. A relationship between two dynamic features was explored to answer clinical based questions in diagnosing abnormal gaits. Some methods merge the use of static and non-static features. In Yun et al's study, static features were used alongside non-static features such as: stride length and cadence(Yun et al., 2014).

The mentioned studies that use linear regression deal with a small number of predictors compared to this study's 42 static features. Therefore, a major challenge in building the prediction model was predictor choice. Three proposed methods in predictors (static features) choice were used: statistical significance, top-x correlated features, and a mixed method. The statistical significance method depends on p-values in selecting the predictors. For example, the predictors can be chosen based on their statistical significance, where significant features are defined as those for which ($p<0.05$). With such a threshold, static features that fit this criterion will be included as predictors. Unfortunately not all dynamic features have correlated static features, which meet this criterion. Based on the results from the previous chapter and the results of the correlation analysis with phase and magnitude independently, to allow each dynamic feature to have at least one correlated static feature, a threshold of $p<0.19$ must be used. Although this would give every dynamic feature a minimum of one correlated static feature, it would also include too many predictors for other dynamic features.

As an alternative solution, the second method proposed; top-x method is used. In this method the correlated predictors (static features) were ranked based on the p-value. Based on the rank, the static features with lowest p-value were used as the explanatory variables (or predictors). To decide the number of static features used, the study assessed the result of using five, four, three, two, or one variable as a predictor.

Each of the two mentioned methods of choosing an explanatory variable has an advantage. The first method only includes highly significant correlated features, but leaves some dynamic features with no predictors, or if the threshold is changed to accommodate all, some dynamic features will have too many predictors. Secondly, although the second method (top-x method) provides every dynamic feature with a predictor, yet some static features that are not considered highly significant are included. Therefore a third method is suggested, in which each dynamic features uses only the highly significant correlated static features($P < 0.05$), and if none exist, then the highest correlated feature method is used. In this manner we combine the logical benefits of both methods. To measure which method produces the better results, a quantifiable assessment tool is developed, which will be explained further in the next section.

6.3.3. Assessment of Quality and Accuracy

To conclude which predictor choice method is most suitable, a unified assessment tool and method must be set. Assessing a prediction model depends on the application of the prediction data. Yun et al's assessment of the quality of a prediction was conducted using the correlation coefficient, mean absolute deviation and threshold absolute deviation(Yun et al., 2014). Findlow et. al used the same methods as well as the percentage of variance unexplained(Findlow et al., 2008). The Leave-one-out cross-validation technique is commonly used in various gait recognition or gait pattern simulation methods to validate and test a model (Yun et al., 2014).

In this study, a leave-one-out cross validation method was used. The assessment for the prediction quality was expressed using three measurements: Cumulative difference, Standard scores based difference, and correlation coefficient.

Cumulative difference is the sum of the absolute differences between the predicted and actual features.

$$CumDiff = \sum_s^n \sum_f^{19} |\mathrm{A}_s^f - \mathrm{B}_s^f| \; ; \qquad \textbf{(6)}$$

where $CumDiff$ is the cumulative difference, A is the predicted value, B is the actual value, s is the subject number (n, number of subjects), and f is the dynamic features.

While standardized score difference is defined as

$$SS_{score}(x) = \frac{x - \mu}{\sigma} \; ; \qquad \textbf{(7)}$$

where SS_{score} , is the standard score, x is the actual value, σ is the standard deviation, and μ is the mean of the x values which is defined as

$$\mu = \frac{\sum_s^n \mathrm{B}_s^f}{n} \qquad \textbf{(8)}$$

Therefore the standard score difference can be described as;

$$SS_{diff} = \sum_{s}^{n} \sum_{f}^{19} |SS_{score}(\mathrm{A})_{s}^{f} - SS_{score}(B)_{s}^{f}| \qquad \textbf{(9)}$$

Where SS_{diff} is the standard score difference, A is the predicted value, B is the actual value, s is the subject number (n , number of subjects), and f is set of the 19 dynamic features.

6.3.4. Assessment of Classification potential

In this study's application the aim is to use the predicted values as a gait signature. Because gait signatures are used to recognize the identity of a subject, there is a more crucial need to assess the results from a classification perspective rather than the previously mentioned manner.

The testing was done initially using the general measurement of each feature predicted from its actual feature value. The sum of all the absolute values of these differences, summed over all features created a distance score between the template and the database for each subject. Since the previous mentioned method does not take into consideration the variance in the feature space of each individual component, another method was also used in which each feature was normalized based on its variance. The standard score method used earlier to asses prediction quality, was used as a classification method, but a different score is again generated for each subject rather than summing over all subjects. The classification is then done by choosing the subject with the lowest score.

6.4. Results and discussion

Based on the mentioned predictor's selection, an assessment is conducted on the prediction quality using the difference method, standard score method, and the correlation method. The two-predictor selection methods: Top-x method and the mixed method will first be assessed predicting the PWM as one variable, and later assessed when phase and magnitude are independently predicted. The results will be concluded by the assessment of the predicted dynamic feature's classification quality; first as PWM and secondly as Phase and magnitude independently.

6.4.1 PWM prediction assessment

Initially, the model is designed to predict the PWM dynamic feature as one component. The assessment on prediction quality is first conducted based on using the top-x method. The results of assessment are shown in 45.

Table 45: Assessment of PWM prediction quality using the top-x method

Predictor selection method	The difference method ($CumDiff$)	Standard score (SS_{diff})	Mean correlation coefficient
Top-5	50799.31	0.8994	0.9268
Top-4	51158.33	0.6401	0.9316
Top-3	50283.41	0.6368	0.9332
Top-2	48842.48	0.6249	0.9412
Top-1	48629.99	0.6252	0.9370

The results show that in general the fewer predictors we use the better the quality of the prediction. Using the $CumDiff$ values, it would seem that using one predictor would produce the optimum results. On the contrary, the other two assessment tools show that using two predictors produces a slightly better result than using one. The better results displayed when using the $CumDiff$ assessment can be explained by the non-normalized features representation, with the 2nd component magnitude being very big when compared to the other features, and therefore dominating the overall score.

The second assessment is based on predicting the PWM dynamic features, using the mixed model as a predictor selection method. The mixed method here used a p value of 0.05 ($p<0.05$). It was assessed with the 6 different thresholds. In the first test, there was no limit to the number of predictors as long as they fit the criterion. This was followed by five tests in which the threshold was set to 10, 5, 4, 3, and 2; where the threshold would state the maximum number of predictor's to use if the number exceeds the threshold. Using a threshold of one, would give us the same results as using the Top-1 method; hence, it was ignored. The threshold was used in order to see the influence of the number of the predictors even when the statistical significance is high. The mixed method results are shown in 46.

Table 46: Assessment of PWM prediction quality using the mixed method

Method used	The difference method ($CumDiff$)	Standard score (SS_{diff})	Mean correlation coefficient
Mixed(no limit)	745911.28	12.9680	0.1625
Mixed (lim 10)	287974.49	4.2938	0.4863
Mixed (lim 5)	59529.56	0.9918	0.9131
Mixed (lim 4)	59087.92	0.9854	0.9129

Mixed (lim 3)	57837.57	0.9264	0.9155
Mixed (lim 2)	55800.88	0.8670	0.9179

The trend is similar to the previous assessment, in which the prediction quality is improved when using fewer predictors, although the change from using a threshold of 5 to a threshold of 1 is minimal.

6.4.2. Phase and Magnitude prediction assessment

As mentioned earlier, the need to predict the phase and magnitude components independently is motivated by the need to understand the predictability of each component, as well as assessing their effect on classification.

Following the same methodology in assessing the predictability of PWM dynamic features, the top-x method is first assessed in choosing predictors for the phase and magnitude component separately. The results are presented in table 47.

Table 47: Assessment of phase and magnitude prediction quality using the top-x method

Method used	The difference method $(CumDiff)$	Mag. Standard score (SS_{diff})	Phs. Standard score (SS_{diff})	Mean correlation coefficient
Top 5	21415.97	1.0536	1.0484	0.9623
Top 4	20313.78	0.9819	1.0086	0.9654
Top 3	18952.61	0.8818	0.9548	0.9707
Top 2	18334.58	0.8510	0.8814	0.9721
Top 1	17590.57	0.8145	0.8416	0.9731

The results of the prediction quality are similar to predicting PWM in that the fewer features used, the better the prediction. Comparing the numbers directly would not provide a fair comparison because they belong to two different feature spaces. They will be compared in their classification potential in the next section.

The top-x method in predictor choice is also assessed in its prediction quality for phase and magnitude separately, with table 48 illustrating the results.

Table 48: Assessment of phase and magnitude prediction quality using the mixed method

Method used	The difference method $(CumDiff)$	Mag. Standard score (SS_{diff})	Phs. Standard score (SS_{diff})	Mean correlation coefficient
Mixed(no limit)	150679.92	4.7962	23.8798	0.4064
Mixed (lim 10)	94030.91	3.6060	4.0313	0.4999
Mixed (lim 5)	25967.25	1.4611	1.5962	0.9280
Mixed (lim 4)	25537.64	1.4308	1.0570	0.9286
Mixed (lim 3)	22868.91	1.2588	1.0118	0.9582
Mixed (lim 2)	21158.10	1.1127	0.9319	0.9617

The mixed method predictor selection, as in the case of predicting PWM, performs better with a lower threshold. The best results are computed when using a threshold of a maximum of 2 predictors. Although using a threshold of 2 predictors produced the best results, yet there isn't a big difference between using 5, 4, 3, or 2 in prediction quality.

It is clear that if quality assessment is dependent on how close the prediction value is from the actual value, that using a top-x method in choosing predictors is better. To illustrate the difference between each, figures 40-43 compare the two methods using each assessment measurement.

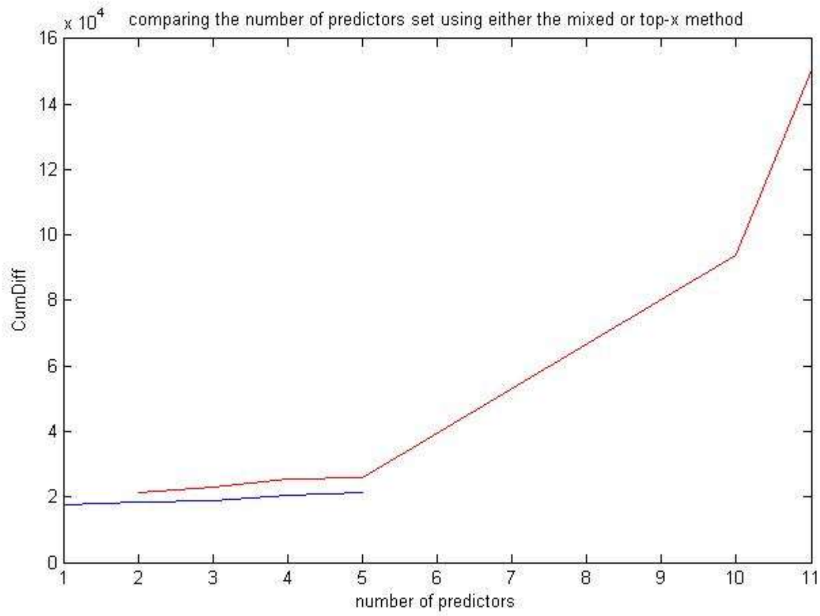

Figure 36: A graph comparing the number of predictors used in a mixed method to a top-x method based on CumDiff assessment tool.

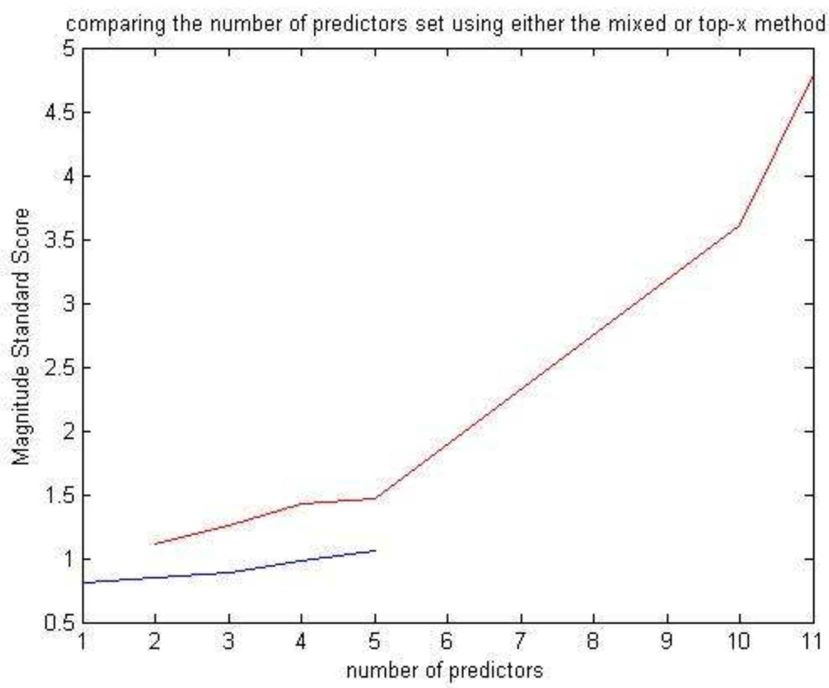

Figure 37: A graph comparing the number of predictors used in a mixed method to a top-x method based on Magnitude Standard Score tool.

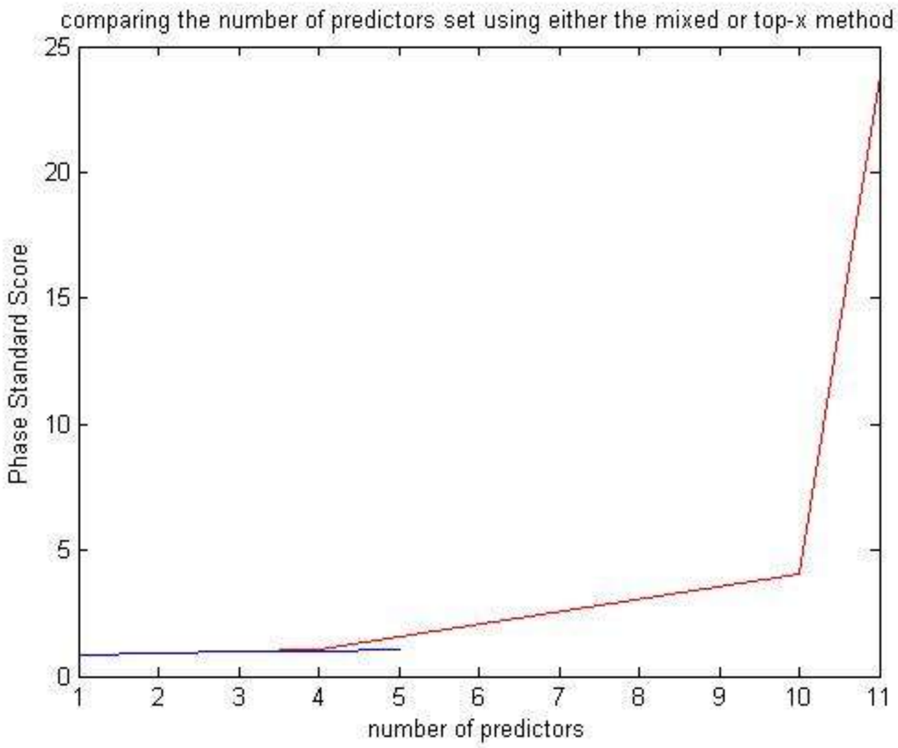

Figure 38: A graph comparing the number of predictors used in a mixed method to a top-x method based on Phase Standard Score tool.

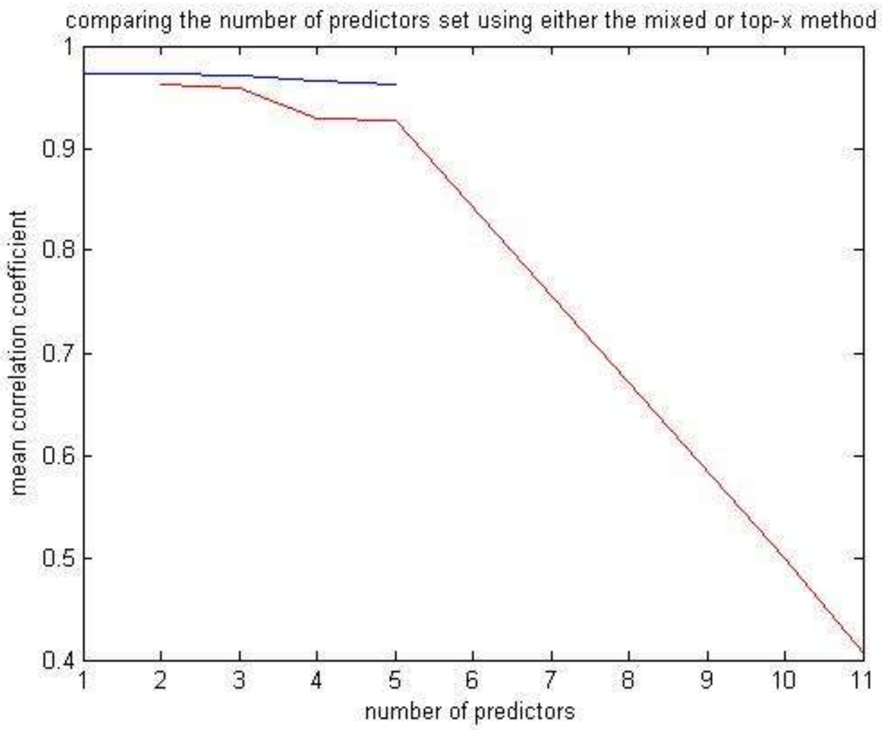

Figure 39: A graph comparing the number of predictors used in a mixed method to a top-x method based on mean correlation coefficient assessment tool.

6.5. Classification assessment

In the previous section, an assessment was done to measure how close the predicted value is to the actual value for features based on Fourier components. Nevertheless, since the main aim was to establish whether classification can be achieved using these predicted values; therefore a classification assessment was required.

Two classification methods were used: the nearest neighbor and a standard score based method. The K-nearest neighbor was used in which the linear distance between the predicted feature and the same feature from within the database of each subject is calculated, and ranked accordingly. The method can be defined as

$$DisDiff(P, A) = \sum_{f}^{19} |\mathrm{P}^{f} - \mathrm{A}^{f}| \; ; \qquad \textbf{(10)}$$

Where P is the predicted gait signature, A is the one of the actual gait signatures in the database, f is the f th feature, and the number of features in the signature that are being used is 19.

The second classification method used is based on the standardized score method The standardized score based classification method is based on calculating a match score between the predicted dynamic features and each subject in the database using the standard score difference. The standardized score based classification method can be defined as:

$$SS_{class}(P_{t,s}, A_s) = \sum_{f}^{19} |SS_{score}(P_{t,s})_f - SS_{score}(A_s)_f| \qquad \textbf{(11)}$$

Where P_t is the predicted gait signature for subject t,the test subject, A_s is one of the actual gait signtures in the database for subject s , and f is the f th feature.

6.5.1. Ranking percentile

The leave-one-out cross validation is used in evaluating the classification potential of the predicted gait signatures. Where the left out subject's predicted gait signature is matched with the full database of gait signatures. Based on the sorting of the matched score, the predicted subject's correct match will be on the n^th rank. Using the n-rank, a mean match percentile score can be calculated for each of the predictor selection methods used in section 3. The mean matching percentile ($\widetilde{Per_{rank}}$) can be defined as:

$$\widetilde{Per_{rank}} = \frac{\frac{n-r_s}{n-1} \times 100}{n} \quad \textbf{(12)}$$

; where n is the number of subjects in the test, and $r_s$is the rank score of the s^th subject. A score of 100 represents a perfect match, where the test subject is always ranked first in the classification. A score of zero means that the test subject is always ranked last. Chance performance is obtained at a 50% match percentile.

6.5.2. Classification assessment results

The standard score based classification method is used to rank the best match for a test subject. A mean percentile score is calculated for each. Based on these assessment tools, the following sections will assess the classification quality of predicting a PWM as a single variable, and the classification quality of predicting phase and magnitude independently. Finally, the independent phase and magnitude component will be multiplied together to form the PWM; therefore reconstructing the PWM instead of predicting it immediately as in the first case. These assessments will illustrate which method, regardless of quality of prediction assessment, produces better results in a classification scenario.

The study calculated the classification quality of the predicted PWM using the Standard score classification method. The results are presented in table 49.

Table 49: The mean matching percentile for predicted PWM

	Mean matching percentile (%)	AUC
Top 5	55%	0.5452
Top 4	52.89%	0.5262
Top 3	53.68%	0.5333
Top 2	51.05%	0.5095
Top 1	53.68%	0.5333
Mixed(no limit)	44.21%	0.4476
Mixed (lim 10)	42.37%	0.4310
Mixed (lim 5)	51.56%	0.5143
Mixed (lim 4)	50.26%	0.5024
Mixed (lim 3)	51.58%	0.5143
Mixed (lim 2)	52.11%	0.5190

The average percentile for all the tests performed using the predicted PWM was 50.76%, with a mean matching percentile ranging between 42.37-55.00%. The majority of the predictor choice methods resulted in a mean matching percentile close to chance, which is 50%. The only exception is when the top-5 method is used to choose predictors. In this method the mean match percentile was 55%, which is 5% better than chance.

The top-x method produced a better total mean matching percentile of 53.26%, while the mixed method resulted in a total mean matching percentile of 48.68%.

Table 50: The mean matching percentile for independently predicted phase and magnitude

	Mean matching percentile (%)	AUC
Top 5	49.21%	0.4929
Top 4	43.68%	0.4429
Top 3	50%	0.5000
Top 2	50.26%	0.5024
Top 1	50.79%	0.5071`
Mixed(no limit)	52.11%	0.5190
Mixed (lim 10)	51.84%	0.5167
Mixed (lim 5)	49.29%	0.4929
Mixed (lim 4)	50.79%	0.5071
Mixed (lim 3)	49.74%	0.4976
Mixed (lim 2)	48.95%	0.4905

The average percentile for all the mean matching percentile performed using the prediction of phase and magnitude independently, as shown in table 50, was 49.70%, 1.06% less than the PWM test. The matching percentile ranged from 43.68-52.11%, with the mixed method with no thresholds scoring the highest matching percentile. The majority of the scores were within 1-4 % of one another (with the exception of the percentile obtained when using top-4 method in choosing the predictors).

When comparing the methods used, the top-x method had a total mean matching percentile of 48.79%, while the mixed method scored a 50.45% total mean matching percentile. In both cases when predicting phase and magnitude independently, and using them in that state for classification produces a classification that is regarded as equal as or less than the probability of classification with pure chance.

Finally, the independent phase and magnitude component will be multiplied together to form the PWM; therefore reconstructing the PWM instead of predicting it immediately as in the first case. The mean matching percentile is presented in table 51.

Table 51: The mean matching percentile for PWM produced using the independently predicted phase and magnitude

	Mean matching percentile (%)	AUC
Top 5	52.11%	0.5190
Top 4	52.37%	0.5214
Top 3	53.95%	0.5357
Top 2	54.47%	0.5404
Top 1	56.05%	0.5548
Mixed(no limit)	58.16%	0.5738
Mixed (lim 10)	59.21%	0.5833
Mixed (lim 5)	55.26%	0.5476
Mixed (lim 4)	56.32%	0.5571
Mixed (lim 3)	57.63%	0.5690
Mixed (lim 2)	55.00%	0.5452

The average of all the mean matching percentiles when multiplying the predicted phase and magnitude components to be used in classification was 55.50%. This score is 4.74% higher than the total mean score of using the predicted PWM, and 5.8% higher than when using the predicted phase and magnitude components separately. The increase in mean matching percentile further supports the connotation that when phase and magnitude components are multiplied to form a PWM, a better classifier is created.

When comparing both methods used in predictor choices, the top-x method produced a total mean of 53.79% mean matching percentile, while the mixed method produced a total mean of 56.93% mean matching percentile. It is also clear that the highest matching percentile is achieved by using the mixed method, with a high threshold of 10. The mean matching percentile is reduced when the threshold is reduced from 5 to 2.

6.6. Conclusion

Gait prediction methods are used in various fields. Depending on their objectives, they vary in the predictors they choose, what they predict, and the method in which the prediction takes place. Gait prediction in the field of forensic and criminal investigation cases can potentially be used in several manners such as, predicting lower dynamic gait features from upper dynamics, predicting gait dynamics of low-frame rate video footage, or providing a dynamic gait signature from static 2d or 3d measurements. In this study, we examined the possibility of using 3d static volume based measurements in predicting dynamic gait signatures; specifically the 2nd ,3rd, and 4th phase and magnitude

Fourier analysis components of the three rotational axis of the knee and thigh joints. The predictions were performed in two manners: predicting PWM as one variable, predicting the phase and magnitude independently. Each of these methods were assessed in their prediction quality using CumDiff, stand score based difference, and the correlation coefficient. They were also assessed in their classification potential. A third method for classification was used in which the independently predicted phase and magnitude were multiplied by their counterpart to form the PWM, which was then used for classification. The classification potential was assessed through the quantification of their mean matching percentile.

First, in regards to the prediction quality assessment, the best results in predicting PWM were achieved by using the top-2 method in choosing predictors. Although the top-1 scored better using the Cumdiff assessment, yet the standard score based score reveals the top-x to be slightly better mainly because of the normalization of each feature according to the standard deviation, which dilutes the influence of the 2nd magnitude component of the thigh rotations. When predicting phase and magnitude independently, the top-1 method produces the best results using the quality assessment tools used. In both cases when predicting PWM or phase and magnitude independently, the fewer predictors used the better quality assessment tools score.

Secondly, when it came to the assessment of classification potential, the prediction quality did not directly forecast their classification potential. When directly predicting PWM, the top-5 method in choosing predictors provided the highest mean matching percentile of 55%, while the top-2 method, which scored best in the prediction quality assessment, scored 51.05%. When using the independently predicted phase and magnitude for classification, the mixed method with no threshold scored best with a mean matching percentile of 52.11%, while the top-1 method which scored best in the prediction quality assessment, scored 50.79%.

The use of predicted PWM or the independently predicted phase and magnitude did not create a considerable difference. Rather, the creation of a PWM using the independently predicted phase and magnitude, performed better in classification then when predicting PWM directly. The highest mean matching percentile achieved in all tests was using the mixed method with a threshold of 10, with a mean matching percentile of 59.21%. In most cases, this method increased the mean matching percentile, with an average increase of 4.74%. The change is illustrated in table 53.

Table 52: The difference in classification assessment between directly predicting PWM and creating PWM from the independently predicted phase and magnitude.

	PWM directly predicted	PWM from independently predicted phase and magnitude	difference
Top 5	55%	52.11%	- 2.89
Top 4	52.89%	52.37%	- 0.52
Top 3	53.68%	53.95%	+ 0.27
Top 2	51.05%	54.47%	+ 3.42
Top 1	53.68%	56.05%	+ 2.37
Mixed(no limit)	44.21%	58.16%	+ 13.95
Mixed (lim 10)	**42.37%**	**59.21%**	**+ 16.84**
Mixed (lim 5)	51.56%	55.26%	+ 3.7
Mixed (lim 4)	50.26%	56.32%	+ 6.06

Mixed (lim 3)	51.58%	57.63%	+ 6.05
Mixed (lim 2)	52.11%	55.00%	+ 2.89

The PWM created from the independently predicted phase and magnitude managed to achieve a mean matching percentile of 59.21% which is better than the probability of pure chance. This is the current baseline for the classification potential using predicted dynamic gait signatures from static features. Although such a result is achieved, yet there are several factors to consider that would provide further insight, and might potential provide a better prediction.

First, there are static features and body measurement that effect gait kinematics that are not considered. Body fat percentage has been shown to effect gait speed, especially thigh inter-muscle fat (Beavers et al., 2013). The length measurement of various body segments was not included as part of the static features used to predict the dynamic gait features. Second, although the methods of choosing the predictors was chosen on the overall effectiveness, further study looking at each feature individually and its optimum number of static features used for prediction would potentially build a better predicting model. Third, Lelas et al used quadratic regression was used, and was a more effective method to describe the relationship between gait speed and gait parameters(Lelas et al., 2003). Findlow et al. , used the generalized regression neural networks(GRNN) algorithm(Findlow et al., 2008). This regression method was used based on a test they conducted using several regression models, in which GRNN proved to be more robust in predicting gait kinematics from motion sensor data. Such findings suggest that the use of non-linear methods in prediction may be more appropriate for gait.

Chapter 7: Conclusion

7.1. Introduction

Gait recognition can potentially be a great biometric to be used for surveillance and forensic use for several reasons, most importantly is its ability to be captured at a distance using non-invasive methods. Different cameras and sensors have been used to capture gait, which include; floor sensors, wearable sensors, and video cameras. From this data captured using these sensors, gait recognition is achieved either through using appearance-based methods (non-model), or model-based methods. Appearance based methods depend on pixel information or silhouettes and shapes; while model based methods rely on extracting the kinematics of a gait. Although appearance based methods are computationally cost effective, we chose to base this thesis study on model based methods because they are resistant to changes in lighting conditions or clothing, as they rely on the underlying dynamics rather than appearance and shape. Although in theory model based approaches would be the ideal method to use; yet it still has to simulate a motion model based on an extracted silhouette from the data captured by the sensor. The challenges they face are similar, because both have to use the same source of data. The main challenges in gait recognition include recognizing aspects of gait that are invariant to: angle variance, the capture device, clothing, carrying of objects, surfaces, shoes, time passage, and partial (latent) information in forensic cases. To do this requires the availability of high quality databases. In this thesis, we focused on two challenges: databases and the issue of limited or latent (partial) information, which is common in forensic applications.

7.2. Future Gait Recognition Research

The journey of going through the steps in this thesis has brought great insight and thought to the manner in which gait recognition and gait analysis are being carried out. Although the ultimate goal of the thesis was to assess the potential of predicted dynamic gait features to be used in gait recognition, yet the steps taken to reach to that point have provided an alternative approach and perspective to gait recognition and gait analysis.

First, the process of creating a database has provided great insight of several aspects other than looking at the relationship between static and dynamic features. The process of capturing gait in itself through the use of video cameras, motion capture, or laser scanning is very crucial. Understanding its limitation and strength is equally important. Motion capture provides a dynamic signature with minimal errors. Although in the a practical application of gait recognition a camera would be the ideal medium to use, yet to overcome and understand the changes that happen due to the many factors mentioned in previous chapters, motion capture is the ideal tool. Motion capture data can provide the ground truth to all gait techniques. Once all challenges are understand and addressed using motion capturing, then individual aspects can be looked at such as the introduction of noise and error when using video or other mediums.

Although gait is regarded as an emerging biometric, yet it is moving towards the direction of being validated and more robust. It is a new area of interest when compared to the years in which fingerprints have been used. For gait to progress from the emerging stage to becoming an independent robust biometric of its own right, it will require two major directions: validating the uniqueness of gait in very large databases, and building a gait signature that is robust to changes of clothing, time passage, shoes , and potential spoofing. These two aspects can be approached by either building bigger databases, or unique modalities to investigate other features. The Bradford multi-modal database fits the unique criterion in accuracy and availability of three rotation axis on every joint. While in regards to size, the current Osaka University gait database is becoming a standard in the last year in validating and benchmarking video based gait recognition techniques.

Features from the axis other than the obvious one to the more subtle ones which involve twists and sways of right and left. Therefore, 3D approach provides more details that can be more robust against attempted changes to one's gait. Especially with the technology of cameras with the extra information of depth develop, this does not seem to be part of the very far future.

The whole process of conducting this research has covered several aspects of gait recognition as an emerging biometric or forensic tool. Even though gait has been studied as an emerging biometric from the 1990s, yet it faces certain challenges that need to be overcome in order for it to be used as a robust biometric. There are four main aspects that need to be taken into consideration to facilitate the implementation of gait as a usable practical robust biometrics: precision of data, gait features, future of capturing mediums, and time passage.

7.3. Contribution and results

The aim of this thesis was to study the relationship between 2D and 3D dynamic and static features, and assess the potential of using the predicted dynamic features in gait recognition. The relationship was studied through the Bradford Multi-Modal Gait database that was created using motion capture and 3D laser scanning systems. The major contributions of this thesis can be divided into four main areas: gait databases, gait features, forensic biometric gait application, and biomechanics.

7.3.1. Gait Databases

A first of its type, the Bradford Multi-Modal Gait Database is the only database to offer 3D scans of a subject and gait samples that are relevant to gait recognition application, and motion capture data of the gait. Many databases provide several covariates, but they are captured using 2D video camera sensors. The other databases that do use motion capture to record a subject's gait, offer a limited variation of gait samples. Therefore the Bradford Multi-Modal Gait database offers several unique and novel contribution to the gait databases available for gait recognition studies. These unique aspects include:

1- Accurate 3D volume representation of subjects
2- Accurate 3D motion representation of a subject's gait.
3- Accurate 3D motion representation of a subject's run

4- Accurate 3D motion representation of a subject's walk carrying a bag
5- Accurate 3D motion representation of a subject's run
6- Accurate 3D motion representation of a subject's transition from a walk to a run
7- Accurate 3D motion representation of the same subject over a one year's period.

Therefore the database's novelty resides in the accurate medium used, as well as the covariates and gait representations recorded.

7.3.2. Gait Features

Features used in gait recognition started as appearance based. As gait recognition evolved, it was clear that the use of model based features are more robust against occlusion, angle variance, and change of clothes. Most gait recognition techniques used 2D based dynamic and static features. As mentioned earlier, the techniques that use 3D based gait capturing, convert the end features to a 2D based feature. This thesis has produced a novel set of 3D static and dynamic features.

First of all, this thesis introduced the usage of novel 2D and 3D static features. The 2D static features include: length of shoulder to elbow, length of Elbow to wrist, length of hand, arm thickness at shoulder joint, arm thickness at elbow, arm thickness at wrist, torso width at shoulder level, torso width at waist level, torso width at hip level ,width of the leg at the ankle joint, age, and weight. From those static features, several of them exhibited a strong correlation to gait dynamic features which include: torso width at shoulder level, torso width at the hip level, and weight. In addition to the use of novel 2D static features, this thesis introduced a new set of 3D static features which are: volume and surface area. To the best of our knowledge, no previous 3D based gait recognition technique used such static features. Both volume and surface area were found to correlate to many dynamic features as explained previously in chapter 5.

Secondly, the 3D dynamic features in this thesis are novel as well. In most gait recognition techniques, the rotation axis with the biggest range of movement is usually used as dynamic features, such as the rotation of the thigh back and forth as a subject walks. Yet, many gait recognition techniques do not use the other axes because of the difficulty in measuring such subtle movement with current standard technology. In the processing of the motion capture data, accurate 3D representation of the rotation of most joints across three axes, provided a different approach, which potentially can provide a dynamic gait feature that would be harder to spoof.

7.3.3. Biometric Gait Prediction

As mentioned before, the final aim of this thesis was to assess the potential of using the predicted dynamic features in gait recognition. The results presented in chapter 6 have put forth several major contributions to several aspects of predicting dynamic gait features, which include: a method of assessing prediction quality and accuracy, choice of predictors, and baseline for recognition rate.

In regards to assessment, to our best of knowledge, this thesis introduces the use of a standard score based difference to evaluate how close a predicted dynamic features is to the actual dynamic feature. The score was also later used for in classification for recognizing the subject from the predicted dynamic features and performed better than use a non-normalized difference measurement between the actual dynamic features and the predicted dynamic features.

This thesis also introduces a new approach to choosing the predictors from the static features: the mixed method. This approach is carried out in a computationally efficient manner, in which the choice of predictors is based on the P- value from the correlation analysis between the specified dynamic feature and all other static features. If dynamic features have one or more correlated static features with a P-value less than 0.05, then those will be used as a predictor. If that is not the case, then a top-x method is used, as explained in chapter 6. This mixed method is the method that produced the best predicted dynamic features to be used for recognition.

In the classification potential assessment, using a predicted PWM or an independently predicted phase and magnitude did not create a considerable difference. The performance improved significantly when a new PWM was created using the independently predicted phase and magnitude. The highest mean matching percentile achieved in all tests was using the “mixed method” with a threshold of 10, which produced a mean matching percentile of 59.21%. In most cases, creating a PWM from an independently predicted phase and magnitude produced an increase in the mean matching percentile by an average increase of 4.74%. The improvement of the highest matching percentile is shown in table 53.

Table 53: Improvement of the mean matching percentile using a PWM created from independently predicted phase and magnitude

	PWM directly predicted	PWM from independently predicted phase and magnitude	difference
Mixed (lim 10)	42.37%	59.21%	+ 16.84

Two prediction approaches were used: predicting PWM as one variable, and predicting the phase and magnitude components of the Fourier transform independently. Each of these methods were assessed in their prediction quality, as mentioned in chapter 6, using CumDiff, standard score based difference, and the correlation coefficient. Their classification potential was also assessed comparing with a third method in which the independently predicted phase and magnitude components were multiplied together to form the PWM. The classification potential was assessed through the quantification of their mean matching percentile. We evaluated different methods for selecting predictors by assessing their ability to predict dynamic features. In accuracy and quality assessment, the "top-2" method performed best at predicting a PWM, while the top-1 method produced the best results when predicting phase and magnitude independently. Therefore, to produce prediction that closer to the actual values, an adaptive approach to choosing predictors is recommended, were a different number of predictors are used depending on what dynamic feature is being predicted. We call this a "top-x" method.

These experiments are the first attempt, to the best of our knowledge, to evaluate gait recognition performance on dynamic features that are predicted from static feature rather than measured directly. Therefore, these results act as a baseline for the classification potential using predicted dynamic gait signatures from static features that can be used as a benchmark for future research.

7.3.4. Biomechanical based contributions

In biomechanical based studies, most concluded that there is no significant relationship between static and dynamic features. In these studies the definitions of static and dynamic features differ from the definition of these features in computer vision based gait recognition. In the biomechanical studies, the static features consisted of measurements of the feet, while the dynamic features were represented using measurements such as: stride length, max rotations, and range of motion. In this thesis, the correlation analysis similar to the ones conducted in biomechanical based studies was used. Although the analysis was conducted in that manner, yet the choice of features was based on computer vision based gait recognition studies as well as other features introduced in this thesis. The static features involved a more holistic set including upper and lower body measurements. They dynamic features also described motion in a better manner than the dynamic features used in biomechanical studies. The Phase weight magnitude dynamic features describe both the manner and timing in which a specified joint rotates.

Therefore on the contrary to biomechanical studies, the first 2D analysis this thesis study conducted suggests that there is a relationship between some of the static features and dynamic features. Eight dynamic features and twenty-one static features were used. The static features included width and length measurements of body segment. Eleven pairs of features were found to be significantly correlated, using a P-value of less than 0.05. It was also found that the length of a body segment is more correlated to dynamic features than width measurements.

Although the first analysis has captured various aspects of the human body, yet there are other valuable factors to consider. Therefore 3D volume static data extracted from the 3D point clouds were used in the second analysis, which included 42 static features. The static features consisted of volumes and surface area measurement of predefined body segments. The second analysis exhibited a strong correlation between 1196 pairs of features with a P-value less than 0.05, with surface area having a stronger correlation to dynamic features than volume measurements. The majority of the static features did not directly contribute to their dynamic counterpart, as an example the thigh volume is not the strongest correlated static feature to the dynamic features related to the thigh. On the contrary, there was a common strong correlation between vertically opposite static to dynamic features, where lower limb (leg) dynamic features were strongly correlated to upper body static features.

7.4. Forensic application relevance

The indications from the correlation analysis and prediction assessment provided a good indication of enabling static features to predict dynamic features and vice versa. This would potentially allow physical measurements to predict the dynamic features of a gait, providing a great benefit to forensic cases with latent (partial) information.

This thesis used as accurate as possible mediums to record the dynamics and static measurements of a subject and the gait, to work as ground truth. Because no previous studies attempted to predict dynamic features from static features, this thesis was set to provide a proof of concept in ideal conditions. Since previous studies concluded that there were no relationship between static and dynamic features, in our analysis we attempted to conduct this study with a more holistic set of features, with the least amount of noise and error. Both the correlation analysis of 2D and 3D features and the results of the prediction assessment provide a sound base for using dynamic features predicted from static features.

The prediction carried out in this thesis was performed using 3D static features. For such results to be implemented in forensic applications, two approaches are suggested. First, if multiple cameras captured a suspect, then a 3D reconstruction of the person can be created. Using this reconstruction, 3D measurements similar to the ones used in this thesis can be used to create a dynamic gait signature. Therefore, with multiple cameras, even if the footage is of a low frame rate, a dynamic gait signature can be predicted. This dynamic gait signature can be compared to other video footage available, or compared to a suspect in custody in an investigation.

Second, the results can also be used when a suspect refuses to provide the investigators with a sample gait cycle performed in front of the camera. In that case a 3D representation of the suspect, either by using multiple camera laser scanner, can be used to predict a dynamic gait signature, which can then be compared to a video footage from the actual crime scene.

Ultimately, gait can be used as a form of direct identification of a person in a criminal investigation, but can provide great support to the body of evidence, and provide leads in an investigation. This thesis focused on the possibility of using 3d static volume based measurements in predicting dynamic gait signatures. The results bare great potential for other approaches in using gait in forensic cases: such as, predicting lower dynamic gait features from upper dynamics, predicting gait dynamics of low-frame rate video footage, or providing a dynamic gait signature from static 2d or 3d measurements.

7.5. Limitations and Future work

Although the results are promising, there are several aspects that could be taken into consideration to provide better results and a better understanding of the relationship between the two sets of features. Further dynamic features and static features must be considered, as well as using other advanced statistical tools must be explored to study the relationship between the two types of features, which will further enhance the understanding of gait. In the following, recommendations are made as to what future directions should be explored. These recommendations are grouped according to the component they influence, which includes recommendations to: database improvements, feature choices, alternative relationship analysis and prediction tools, and scope of applications. Each subsection below will describe the limitation, as well as suggest the future steps and direction for that specific challenge.

7.5.1. Database improvements

The database was recorded over two phases. The only modification to the procedures in the second phase, was taking four laser scans of each subject, instead of three scans. There are several other recommendations that can further enhance the database's capture procedures and recording techniques in two manners: first by increasing accuracy, and secondly by maintaining consistency in recording quality and information. These limitations and recommendations cover both the 3D laser scanning and the motion capture system.

Motion capture

The motion capture procedure used a marker set used for real time gaming and animation based results and setup. This setup was used for two main reasons. First, the setup provided a fast and efficient way of recording motion data. Secondly, the use of the marker set in this thesis study was based on the tools available under the current system and support at the University of Bradford. There are other marker sets used by biomechanical and clinical gait analysis systems that attempt to capture more accurate joint information, while set ups used for animation, aim to achieve life-like movement rather than accurate information.

Secondly, the placement of the markers themselves, were placed on a suite. The markers attempt to represent the position of a joint as accurate as possible, yet there are two factors that continually to provide slight bias to the data. First of all, the underlying muscle and fat movement cause a general sliding that happens between the surface skin and the joint underneath. Second of all, the clothing also acts as a second layer of movement. The clothes tend to slide across the skin, introducing slight movement to the markers. Although muscle and skin movement is unavoidable, yet in many biomechanical studies, markers are placed directly on the skin. This extra step avoids any extra movement the cloth might introduce.

Finally, recording and instructions procedures that would also introduce bias are speed of gait, and shoe variance. The subjects were asked to walk at their own pace. Changes in speed of 1 to 2 m/s can cause changes in the peak sagittal angles between (1.8-11.1 degrees)(Hanlon and Anderson, 2006). Such a change can potentially change the PWM used to represent dynamic gait features. As well as the effect of speed, shoes have been discussed as a one of the main challenges of gait recognition in chapter 2. Shoes can change a gait to a certain degree. In the current database, footwear was not controlled, and subjects were given the freedom to wear what they feel is suitable.

To resolve the challenges mentioned, an analysis should be done on the effect of slight change of speed in gait, in changing phase weight magnitude, and whether that would affect the classification. In addition to this analysis, the potential to unify shoe types, by providing subjects with the same type shoes might also remove unwanted noise to the gait data. This would further provide better ground truth data for correlation and prediction analysis.

3D Laser scanning

Although the second stage included four scans of a subject, yet there were still areas of occlusion. Secondly, the alignment of the three and four scans can be improved by using other technologies. Currently, every scan is taken at a different point of time. It is therefore very difficult to maintain the same position and pose of a subject to perfectly align the 3d scans. Even though a chair and markers were used when scanning the subjects, there was movement between the two or four scans. This is caused for several reasons which include: movement of spine, breathing, head movement, and adjusting centre of balance. Using technologies that allow the capturing of the 3d surface from all sides at the same moment would be able to avoid such a problem. There are current technologies that use multiple cameras around a body that can achieve these results such as IR's 3D full body scanning system which uses 150 DSLR cameras, and the Ten24's full body scanning which uses 80 DSLR cameras.

Subject Sampling

The gender sampling is currently unbalanced. The database currently has 7 females and 31 males. This is common in most gait database. The only large database that has a more even male to female ratio is the University of Osaka gait database. The addition of more females to balance the gender distribution can provide a better understanding of the difference between genders in gait..

7.5.2. Features

The two stages of the correlation analysis extracted different types of static measurements. The first included 2D features: heights and widths, while the second involved 3D features: volumes and surfaces areas. This thesis focused on the mentioned features for their novelty, yet the inclusion of other features can provide additional insight not covered by the current thesis. There are features that can be considered that can be extracted from the current data, and there are other features that require additional information not accessible from current data.

2D Features

The 2D static features used in the correlation analysis in chapter 4 are based on the assumption that they were extracted from a frontal viewing camera of a subject. The width was measured from a frontal view. While the 2D dynamic features were based on a model based recognition feature extraction technique in which angles of the rotation of joints were measured. Therefore, appearance and pixel based dynamic features were disregarded, as well as other model based dynamic features that are used by other gait recognition technique.

To provide a wider analysis, other static features can be extracted which include measuring the width of the body static features used in chapter 4, but from a side viewing camera. This would provide two different measurements to predict dynamics of a gait, whether a frontal or side viewing cameras is used. This would also provide further insight into which measurement displays a stronger relationship between that specific static measurement and the dynamic features used in the analysis. As well as using the mentioned static features, other dynamic features not covered in the analysis could provide an alternative approach, such as: stride length, and other biomechanical based dynamic features that include max angle rotation, and range of rotation of a joint.

3D Features

The 3D static features used in this thesis included volume and surface area. They have provided results that have positively indicated the presence of a relationship between static and dynamic features, yet they do not describe certain other information about a subject's physical build. Volume of a torso of two people can be the same, but one would be more muscular built than the other. Secondly, two subjects can share the same volume yet a different length. For example, two might share the same volume thigh, yet one subject is taller than the other. In the correlation analysis and prediction, they would appear the same without the length measurement, yet in reality their build is different.

Therefore, including other features in future analysis would provide a better understanding and create a better representation of the build of a subject. This addition can be conducted through different approaches. First, the addition of a length measurement to the set of static features, as in chapter 4 of the 2D set of features, would provide a variable that is missing from the 3D set of features. Second, although surface area provides size information of the surface, yet it does not convey information about the curvature of the surface. Such information would provide a variable that indicates how fit and healthy a person is, without resorting to fat and muscle percentage measurements. Finally, the dynamic features extracted involve several components of the fast Fourier Transform. Although previous studies have mentioned that the important information are in the second, third, and fourth , components of the Fourier transform, yet they were conducted on results extracted from a 2D video. The data in this thesis is more accurate than 2D video data, as well as dynamic features are available in more than one axes. A analysis of the discriminatory characters of each component on the axes is to be conducted in the future to determine exactly at which Fourier component, noise presence exceeds actual information of the dynamic features.

There are other features that would require additional information not currently available in the Bradford Multi-Modal Gait Database. First, static features and body measurement that effect gait kinematics that are not considered, such as body fat percentage can be crucial. It has been shown that such static features can effect gait speed, especially the thigh inter-muscle fat (Beavers et al., 2013). Finally, considering the correlation of static features to appearance based features can also provide an alternative perspective.

7.5.3. Relationship analysis and prediction

The thesis studied the relationship between static and dynamic features using a correlation analysis, and addressed the challenge of gait signature prediction by using linear regression. Firstly, this thesis used linear regression as a simplified tool to examine the existence of a relationship between static and dynamic features, since more studies in biomechanics concluded otherwise. Yet the nature of motion from the signal created by the rotation of individual joints over time to pace of a walk and run, are nonlinear in nature. Secondly, it is important to note that the study is based on a single gait cycle for each of the observers (subjects). It is well known that there is some within-individual variability and we would need to take this into account to help establish which correlations might be due to noise rather than any causal link. Thirdly, there are significant correlations involving higher Fourier components, which we expect to contain a higher noise component than the lower components. Fourthly, the correlation coefficient was used in this study to investigate if a relationship exists. Similar to linear regression, the correlation coefficient examines the statistically linear relationship between two sets of variables. Finally, the methods of choosing the predictors were chosen on the overall effectiveness. When evaluating the prediction quality in chapter 6, the assessment number produced an average difference between the actual and predicted variable in all dynamic features. Potentially, certain dynamic features might perform better using one method of choosing predictors, while the opposite happens when using another method. There was no individual analysis and comparison of each dynamic feature and which predictor choice method worked best with it.

To further investigate the relationship between static and dynamic features and its prediction, there are there different approaches to tackling the above mentioned challenges: adjustments to features and predictors used, adjustment to relationship and prediction tools, or using a different prediction model.

Adjustments to the features and predictors used involve modification to the feature representation as well as a change of the method used in predictors' choices. Further study looking at each feature individually and its optimum number of static features used for prediction would potentially build a better predicting model and individual performance measurement for each predictor choice method instead of the currently used method mention in chapter 6. Multiple gait samples must be taken into consideration for each subject. This modification will allow the investigator to look into the inter and intra-variability in the feature set, and also allow for a better differentiate between what is an outlier in a subject’s gait sample, from its average counterpart.

Based on the current results and other parallel emerging relevant studies, other tools can be used to both: study the relationship between static and dynamic features, and perform prediction.. Because both the correlation analysis and the prediction were linear in nature, similar recommendations can be suggested for both problems. Other statistical tools must be considered to interpret this relationship further. There is potential in the usage of non-linear statistical tools, as well as the use of autocorrelation and cross correlation with temporal data. Non-linear regression needs to be considered for the study of the relationship between the two sets of data, since studies that explore the area of the relationship between features in gait often result in better bond when using non-linear methods(Yun et al., 2014). Lelas et al. have found that some gait features have a quadratic relationship with gait speed(Lelas et al., 2003). In the study by Lelas et al, quadratic regression was used, and was a more effective method to describe the relationship between gait speed and gait parameters (Lelas et al., 2003). In regards to prediction, Findlow et al., used the generalized regression neural networks(GRNN) algorithm (Findlow et al., 2008). This regression method was used based on a test they conducted using several regression models, in which GRNN proved to be the most robust in predicting gait kinematics from motion sensor data. Therefore, the use of non-linear methods in prediction needs to be assessed for analyzing and predicting gait signatures.

7.5.4. Forensic application

One of the main hypotheses in this thesis has been inspired by forensic challenges in using gait recognition, particular latent information. The notion of the existence of a relationship between static and dynamic features was opposed to by many studies in the field of biomechanics. In this study, optimum accuracy was used to provide ground truth data, to evaluate if the relationship exists or not, as such a relationship would serve the future of using gait recognition in forensic application.

Although the results show there is a relationship between static and dynamic features and that predicting dynamic features can produce a recognition higher than chance, yet there are certain limitations with its application in the current technological state of most cameras used in investigations. First of all, the current predictions in this thesis are done using an accurate 3D laser scanner. Using video cameras or even multiple cameras will potentially create and lower resolution 3D representation. The volume and surface area static features would be hard to replicate using single 2D cameras. Secondly, the 2D measurements used in chapter 4 are based on the assumption that it is a frontal camera. Although frontal viewing cameras are a potential camera angle in forensic cases, yet others exist, such as top, side, or back camera views. Thirdly, the choice of predictors in the current model includes a large number of different measurements and segments, some of which might be hard to measure or unavailable in certain criminal cases. Finally, predicting dynamic features from only static features is only one method of approaching latent information. Other approaches can be tackled and will be described.

Since the study provided a ground truth to whether a relationship exists, its practical application will require certain future steps and assessments to take place and build upon the findings in this thesis. First of all, a future study using the same methodology in prediction and same set of features used can be conducted using video data from the database. A comparison between the current predictions in this thesis to the ones from the video only data would provide an insight into usability of such a method in in standard 2D CCTV videos

Secondly, a case study of an actual case would provide insightful challenges and limitations of a practical application of such a prediction methodology. The chosen case study should be based on a case that has been concluded with evidence such DNA or fingerprint, used to confirm the identity. Such a criterion would provide the ground truth information based on the evidence. In the current thesis study, the choice of predictive static features was based on the one with the highest correlation. In certain criminal cases, the possible measurements to extract would be limited. Using a limited set of static features to predict dynamic features should be conducted and assessed. A ranking system to evaluate the accuracy of the prediction dependent on the static features used should be established.

Thirdly, although the thesis concentrate on the relationship and predictions from static to dynamic features, yet features other static features can be used to predict a full dynamic gait signature. Using dynamic features to predict other dynamic features would be beneficial. In cases where only the upper body is visible, predicting lower dynamic features from upper dynamic features would be useful. Furthermore, such an analysis would provide more insight into the contribution of the arms to the movement of the legs. In chapter 5, the arms displayed a high correlation with the dynamic of the legs.

Finally, although current CCTV cameras are 2D based, yet there are more studies being conducted on the usage of cameras that carry 3D depth information. Such a medium would be able to replicate the kind of static features used in this thesis. Therefore, an analysis used such cameras like the Microsoft Kinect, would also be a beneficial in providing an alternative approach to using standard 2D CCTV video cameras.

In conclusion, the results in this thesis built a basis for the ground truth that there is a relationship between static and dynamic features. To facilitate the practical application of this information to forensic and police work, certain approaches must be taken into consideration. First comparing between dynamic features predicted from 2D measurements to ones predicted from 3D measurements would provide the appropriateness of using the current methodology. Secondly, a case study would provide insight into the practical challenges than need to be focused upon in further research. Finally, different combinations of predictors, such as upper body dynamic features, can be used to execute predictions, depending on the forensic case in hand. As technology advances and available at a consumer level, the closer the data will be to the current static features used in this thesis.

7.6. Potential application

The results in this thesis provided a counter argument to the previous studies that say there is no relationship between static and dynamic features. Using simple and efficient linear regression, the study was able to produce similar predicted dynamic features to the actual dynamic features. Such findings provide potential future implementation in various fields that include: forensics, clinical gait analysis, and entertainment based 3D computer animation.

In this thesis, the static features were predicted as a Phase weight magnitude, and not the rotations of the joints. Potentially, since phase and magnitude were predicted for each component, a signal can be reconstructed using an inverse form of the Fourier Transform. Therefore, predicting the rotational values from static measurements. This prediction can serve both clinical gait analysis, as well as 3D computer animation.

Clinical gait analysis is currently conducted using high-speed cameras or extensive gait laboratories that consist of a motion capture system fused with surface sensors. This captured information provides details of the kinetic and kinematic measurements. Unfortunately such systems are expensive. Therefore, predicting how a person walks from basic physical measurements can provide details otherwise only available using a motion capture system. ….

While in computer animation, animating 3D characters involves intensive work and numerous hours depending on the complexity. It requires both a skilled person as well as time. Currently in 3D video games, characters have to be pre-animated by an animator. With the proposed predicted gait, characters in animations and video games will be able to walk using the predicted gait. This gait manner will change based on body size and proportion. Therefore, reducing the time and type of labour needed to execute the task.

7.7. Summary

This thesis has provided a novel database that was used to understand the relationship between static and dynamic features. The correlation analysis provided evidence that there is a relationship between static and dynamic features, both in two and three dimensions. Specifically, the upper body static features tend to influence the lower body dynamics. Prediction from static to dynamic features using linear regression from has provided gait signatures that perform at a 59% recognition rate. Such a result provides a baseline for any future work in gait signature prediction and its use in gait recognition. Further studies and alternative approaches to the database, feature selection, prediction and correlation tools, and classifier choices can provide further insight and potentially better results.

The benefits of understanding the nature of this relationship is not limited to biometric and forensic based applications, but can also contribute to biomechanics, clinical gait analysis, and 3d animation. In biometrics and security applications, this would imply that latent (partial) information will be acceptable to create a signature of a suspect or a criminal. The relationship between static and dynamic measurements from a computer vision point view, can provide an alternative insight into biomechanical human motion modeling. Being able to predict the dynamics of a gait from static measurements can potentially reduce the cost of gait analysis by taking away the need of using expensive gait motion capturing systems. Finally, predicting the motion component of gait through static measurement can provide an automatic method of creating walk cycles for 3d animations and games.

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Appendices

Appendix 3.1: Example of the Consent Form

University of Bradford
School of Computing, Informatics and Media
Multi-Modal Gait Database

Hamad Alawar, Prof. Hassan Ugail, Dr Mumtaz Kamala and Dr David Connah.

This consent form outlines my rights as a participant in the multi-modal gait database conducted by Hamad Alawar ,Prof. Hassan Ugail, Dr Mumtaz Kamala, and Dr David Connah, School of Computing, Informatics and Media, University of Bradford.

The database you are contributing to will be a recording of your gait cycle (the manner in which you move, walk, or run). The database will be used to test gait recognition algorithm conducted by this research, as well as future research in the University of Bradford only. It will be recorded through several mediums and recording methods:

1- Regular video:

There will be one camera recording your walk from a horizontal point of view

2- Multiple view cameras:

There will be another set of cameras that will record your gait from several angles (front, back, corner)

3- Thermal camera

This device will be thermally recording your gait, through the camera’s ability to sense heat radiating from the human body.

4- Motion capture:

This will capture the 3D motion data of your gait.

5- 3D Laser scanner:

This will be used to capture an accurate measurement of your total height, leg length, and arm length, as well as the dimensions of the room.

During the course of this sample you will be asked to do the following in this order:

1- Conduct a walk

2- Conduct a run

3- Conduct a walk

4- Conduct a walk carrying a heavy bag

5- Conduct a walk

6- Conduct a run

7- Conduct a walk to run transition

8- Conduct a run

All the information will be kept confidential. There will be no record in the final database of names. The data will be stored in a secure location. Only the parties conducting the research will be allowed access to this information.

Participant's Agreement:
I am aware that my participation in this data sample is voluntary. I understand the intent and purpose of this research. If, for any reason, at any time, I wish to stop the data capture, I may do so without having to give an explanation.

The project team has reviewed the individual and social benefits and risks of this project with me. I am aware that the data will be used for testing pattern and gait recognition and those results will be published. I understand the risks of laser usage, and will be following the guidelines through the use of safety goggles that will be provided in this session. The data gathered in this study is confidential with respect to my personal identity, but will be used solely by the researchers mentioned above. In case images from the video will be published, the face part of the image will be blurred and pixelated to prevent any identification of the participant. I understand if I say anything that I believe may incriminate myself, the relevant potentially incriminating information will be destroyed at my wish. The engineer will then ask me if I would like to continue the data sample.

In the case of my intention to remove my data from the database, I will submit a written request to remove all the data related to myself. The researchers will delete my data within 2 weeks from receiving the written request.

If I have any questions about this study, I am free to contact the project team (contact information given above).

I have read the above form and, with the understanding that I can withdraw at any time and for whatever reason, I consent to participate in today's gait recording session.

I am happy for my images and videos to be used according to what I have agreed upon

______________________________ ________________________

Participant's signature Date

Printed name: _______________________

Appendix 3.2: Example of the information sheet.

Multi-Modal Gait Database - Information sheet

Biometrics:

There are certain sources of information that can help identify people. These identifiers can be classified into three types:

1- **objects**

2- **knowledge**

3- **biometrics**

Object based identifiers allow access to other objects, computer-based systems, or physical areas. Examples include, Keys, ID cards, credit cards etc. .

Knowledge based identifiers are what we know as passwords or pin numbers. In some cases only one identifier type is used, while presently a lot of systems use two identifiers, like the systems used with cash machines, in which a bank card and pin number are used.

The third type of identifier, are biometrics. Biometrics are considered to be unique to one person only. Examples of biometrics are fingerprints or DNA. Biometrics have been heavily researched in the last 20 years, and new biometrics have started to surface, such as facial, iris, hand, and gait recognition.

Gait is defined as the manner in which one walks or moves. In regards to Gait as a biometric, a subject's walk is analysed and certain key elements of the walk are regarded as discriminatory information that differentiate one person to another. Gait is a very promising biometric because it can be recorded and detected from distance using standard CCTV cameras. It also does not require the voluntary cooperation of a subject, therefore it is viewed as a possible solution for security surveillance for recognising wanted criminals or offenders.

Gait as a biometric is still evolving, and a critical requirement for testing this technique is to have a database of gaits. The database recorded here will be used as a test bed for new Gait-based techniques. In this multi-modal database, gait will be captured using several mediums listed below:

1- **Motion Capture**: White markers will be placed on the subject to help capture the exact movement of the subject.

2- **Infrared camera**: A camera that can detect infra-red (in the thermal range) emissions from objects will be used to detect temperature changes in a person's walk.

3- **Multiple camera setup**: The subject's Gait will be captured using more than one camera placed at different angles to the subject (e.g. side-view and front-view).

4**- 3D Laser scanning**: The 3d laser scanner will be used to capture measurements related to gait analysis such as the subject's thigh, shin, height, width, arm length, torso length. The laser used in this device if classified as a 3R Laser class which is regarded as a non-visible laser of low risk. Although there is a very minimal risk of using laser, precautions will be taken by using a safety goggle worn by the participant.

All of these mediums will then be integrated together within an automatic computer-based analysis program which will attempt to recognise the subject based on their recorded Gait signatures.

The database will be solely used in research conducted in the University of Bradford, for continuous gait recognition algorithm testing and analysis. The regular 2d video will only be used in published research with written consent from the participant.

Appendix 5.1

Table 54: Appendix 5.1: A list of the statistically significant correlations between 3d static and dynamic features.

	Dynamic Feature	Static Feature	Correlation Coefficient	P-value
1	'L_leg_vol'	'Root_Zposition1'	' 0.53102'	' 0.015989'
2	'R_leg_vol'	'Root_Zposition1'	' 0.46975'	' 0.036634'
3	'L_thigh_vol'	'Root_Zposition1'	' 0.7219'	' 0.00032615'
4	'R_thigh_vol'	'Root_Zposition1'	' 0.56926'	' 0.0088004'
5	'lower_vol'	'Root_Zposition1'	' 0.4912'	' 0.027851'
6	'L_shin_vol'	'Root_Zrotation1'	'-0.44528'	' 0.049129'
7	'L_forearm_sur'	'L_thigh_Xrotation1'	'-0.45788'	' 0.042343'
8	'L_arm_vol'	'L_thigh_Yrotation1'	'-0.53389'	' 0.015325'
9	'L_arm_sur'	'L_thigh_Yrotation1'	'-0.63148'	' 0.0028238'
10	'L_shoulder_sur'	'L_thigh_Yrotation1'	'-0.61853'	' 0.0036472'
11	'L_forearm_vol'	'L_thigh_Yrotation1'	'-0.48672'	' 0.029531'
12	'L_forearm_sur'	'L_thigh_Yrotation1'	'-0.56044'	' 0.010162'
13	'L_leg_vol'	'L_thigh_Zrotation1'	' 0.65158'	' 0.0018554'
14	'L_leg_sur'	'L_thigh_Zrotation1'	' 0.53255'	' 0.015632'
15	'R_leg_vol'	'L_thigh_Zrotation1'	' 0.62524'	' 0.0031988'
16	'R_leg_sur'	'L_thigh_Zrotation1'	' 0.47872'	' 0.032733'
17	'L_thigh_vol'	'L_thigh_Zrotation1'	' 0.64315'	' 0.0022207'
18	'L_thigh_sur'	'L_thigh_Zrotation1'	' 0.54915'	' 0.012149'
19	'R_thigh_vol'	'L_thigh_Zrotation1'	' 0.6004'	' 0.0051255'
20	'R_thigh_sur'	'L_thigh_Zrotation1'	' 0.48822'	' 0.028961'
21	'R_shin_vol'	'L_thigh_Zrotation1'	' 0.52853'	' 0.016586'
22	'R_arm_vol'	'L_thigh_Zrotation1'	' 0.54276'	' 0.013407'
23	'R_arm_sur'	'L_thigh_Zrotation1'	' 0.5066'	' 0.022641'
24	'R_shoulder_vol'	'L_thigh_Zrotation1'	' 0.62092'	' 0.0034815'
25	'R_shoulder_sur'	'L_thigh_Zrotation1'	' 0.57975'	' 0.0073783'
26	'L_forearm_sur'	'L_thigh_Zrotation1'	' 0.47919'	' 0.032535'
27	'lower_vol'	'L_thigh_Zrotation1'	' 0.70624'	' 0.00050104'

28	'lower_sur'	'L_thigh_Zrotation1'	' 0.56183'	' 0.0099362'
29	'L_arm_vol'	'L_foot_Yrotation1'	' 0.49477'	' 0.026568'
30	'L_shin_vol'	'L_foot_Zrotation1'	'-0.46406'	' 0.03929'
31	'torso_vol'	'R_thigh_Zrotation1'	' 0.49076'	' 0.028012'
32	'torso_sur'	'R_thigh_Zrotation1'	' 0.51109'	' 0.021277'
33	'upper_vol'	'R_thigh_Zrotation1'	' 0.47283'	' 0.035254'
34	'hip_vol'	'R_thigh_Zrotation1'	' 0.55885'	' 0.010425'
35	'hip_sur'	'R_thigh_Zrotation1'	' 0.52299'	' 0.017976'
36	'noArms_vol'	'R_thigh_Zrotation1'	' 0.45903'	' 0.041763'
37	'R_forearm_sur'	'R_foot_Xrotation1'	' 0.53883'	' 0.014232'
38	'R_forearm_sur'	'R_foot_Yrotation1'	' 0.47581'	' 0.033962'
39	'L_thigh_vol'	'R_foot_Zrotation1'	'-0.45046'	' 0.046244'
40	'L_shin_sur'	'R_foot_Zrotation1'	' 0.46914'	' 0.036911'
41	'R_forearm_sur'	'R_foot_Zrotation1'	' 0.49431'	' 0.026729'
42	'L_thigh_vol'	'R_toe_Xrotation1'	'-0.57457'	' 0.008054'
43	'L_shin_vol'	'R_toe_Xrotation1'	' 0.44404'	' 0.049841'
44	'R_forearm_sur'	'R_toe_Xrotation1'	' 0.47186'	' 0.035683'
45	'L_leg_vol'	'Spine_0_Yrotation1'	' 0.46936'	' 0.03681'
46	'R_leg_vol'	'Spine_0_Yrotation1'	' 0.65433'	' 0.0017476'
47	'R_leg_sur'	'Spine_0_Yrotation1'	' 0.55092'	' 0.011819'
48	'L_thigh_sur'	'Spine_0_Yrotation1'	' 0.44455'	' 0.049547'
49	'R_thigh_vol'	'Spine_0_Yrotation1'	' 0.62736'	' 0.003067'
50	'R_thigh_sur'	'Spine_0_Yrotation1'	' 0.57988'	' 0.0073616'
51	'R_shin_vol'	'Spine_0_Yrotation1'	' 0.6274'	' 0.0030647'
52	'torso_sur'	'Spine_0_Yrotation1'	' 0.49876'	' 0.025186'
53	'body_vol'	'Spine_0_Yrotation1'	' 0.45348'	' 0.044626'
54	'body_sur'	'Spine_0_Yrotation1'	' 0.53289'	' 0.015554'
55	'upper_sur'	'Spine_0_Yrotation1'	' 0.4712'	' 0.035978'
56	'lower_vol'	'Spine_0_Yrotation1'	' 0.56368'	' 0.0096426'
57	'lower_sur'	'Spine_0_Yrotation1'	' 0.49842'	' 0.025303'
58	'left_vol'	'Spine_0_Yrotation1'	' 0.46856'	' 0.037178'
59	'left_sur'	'Spine_0_Yrotation1'	' 0.54039'	' 0.0139'
60	'right_vol'	'Spine_0_Yrotation1'	' 0.50832'	' 0.022111'
61	'right_sur'	'Spine_0_Yrotation1'	' 0.58921'	' 0.0062629'

62	'hip_vol'	'Spine_0_Yrotation1'	' 0.48821'	' 0.028963'
63	'hip_sur'	'Spine_0_Yrotation1'	' 0.51411'	' 0.020398'
64	'noArms_vol'	'Spine_0_Yrotation1'	' 0.45953'	' 0.04151'
65	'noArms_sur'	'Spine_0_Yrotation1'	' 0.55952'	' 0.010314'
66	'L_shin_vol'	'Spine_0_Zrotation1'	' 0.59718'	' 0.0054336'
67	'torso_vol'	'Spine_0_Zrotation1'	' 0.46282'	' 0.039887'
68	'L_arm_vol'	'Spine_0_Zrotation1'	' 0.57329'	' 0.008229'
69	'L_shoulder_vol'	'Spine_0_Zrotation1'	' 0.50098'	' 0.024444'
70	'upper_vol'	'Spine_0_Zrotation1'	' 0.44738'	' 0.047947'
71	'chest_vol'	'Spine_0_Zrotation1'	' 0.53607'	' 0.014835'
72	'L_arm_vol'	'Spine_1_Yrotation1'	'-0.56134'	' 0.010015'
73	'L_arm_sur'	'Spine_1_Yrotation1'	'-0.61231'	' 0.0041078'
74	'L_shoulder_sur'	'Spine_1_Yrotation1'	'-0.63062'	' 0.0028731'
75	'L_forearm_vol'	'Spine_1_Yrotation1'	'-0.46987'	' 0.036579'
76	'L_forearm_sur'	'Spine_1_Yrotation1'	'-0.51878'	' 0.019094'
77	'L_shin_vol'	'neck_Xrotation1'	' 0.54518'	' 0.012918'
78	'L_shin_sur'	'neck_Xrotation1'	' 0.55829'	' 0.010519'
79	'R_forearm_sur'	'neck_Xrotation1'	' 0.45017'	' 0.046401'
80	'torso_vol'	'neck_Yrotation1'	'-0.48398'	' 0.030598'
81	'torso_sur'	'neck_Yrotation1'	'-0.52364'	' 0.017808'
82	'L_arm_vol'	'neck_Yrotation1'	'-0.65155'	' 0.0018564'
83	'L_arm_sur'	'neck_Yrotation1'	'-0.78978'	'3.4495e-005'
84	'R_arm_vol'	'neck_Yrotation1'	'-0.51748'	' 0.019448'
85	'R_arm_sur'	'neck_Yrotation1'	'-0.62283'	' 0.0033542'
86	'L_shoulder_vol'	'neck_Yrotation1'	'-0.50698'	' 0.022522'
87	'L_shoulder_sur'	'neck_Yrotation1'	'-0.74073'	' 0.00018729'
88	'R_shoulder_vol'	'neck_Yrotation1'	' -0.4776'	' 0.033202'
89	'R_shoulder_sur'	'neck_Yrotation1'	'-0.54842'	' 0.012289'
90	'L_forearm_vol'	'neck_Yrotation1'	'-0.67669'	' 0.0010509'
91	'L_forearm_sur'	'neck_Yrotation1'	'-0.73454'	' 0.00022592'
92	'R_forearm_vol'	'neck_Yrotation1'	'-0.54387'	' 0.013181'
93	'R_forearm_sur'	'neck_Yrotation1'	'-0.55313'	' 0.011415'
94	'body_vol'	'neck_Yrotation1'	'-0.53173'	' 0.015822'
95	'body_sur'	'neck_Yrotation1'	'-0.61522'	' 0.003887'

96	'upper_vol'	'neck_Yrotation1'	'-0.54991'	' 0.012007'
97	'upper_sur'	'neck_Yrotation1'	'-0.68351'	' 0.00089226'
98	'left_vol'	'neck_Yrotation1'	'-0.52111'	' 0.018469'
99	'left_sur'	'neck_Yrotation1'	'-0.46756'	' 0.037638'
100	'right_vol'	'neck_Yrotation1'	'-0.44982'	' 0.046593'
101	'hip_vol'	'neck_Yrotation1'	'-0.50289'	' 0.023818'
102	'hip_sur'	'neck_Yrotation1'	'-0.58094'	' 0.0072291'
103	'chest_vol'	'neck_Yrotation1'	'-0.45698'	' 0.042801'
104	'noArms_vol'	'neck_Yrotation1'	'-0.49649'	' 0.025964'
105	'noArms_sur'	'neck_Yrotation1'	'-0.52714'	' 0.016926'
106	'L_leg_vol'	'neck_Zrotation1'	' 0.47933'	' 0.03248'
107	'L_leg_sur'	'neck_Zrotation1'	' 0.52004'	' 0.018752'
108	'R_leg_vol'	'neck_Zrotation1'	' 0.57378'	' 0.0081616'
109	'R_thigh_vol'	'neck_Zrotation1'	' 0.4747'	' 0.034436'
110	'L_shin_vol'	'neck_Zrotation1'	' 0.57154'	' 0.0084739'
111	'L_shin_sur'	'neck_Zrotation1'	' 0.66815'	' 0.0012826'
112	'R_shin_vol'	'neck_Zrotation1'	' 0.59487'	' 0.0056637'
113	'R_shin_sur'	'neck_Zrotation1'	' 0.50967'	' 0.021699'
114	'R_arm_sur'	'neck_Zrotation1'	' 0.53411'	' 0.015274'
115	'R_shoulder_sur'	'neck_Zrotation1'	' 0.45921'	' 0.041671'
116	'R_forearm_vol'	'neck_Zrotation1'	' 0.57101'	' 0.0085482'
117	'lower_vol'	'neck_Zrotation1'	' 0.53603'	' 0.014843'
118	'lower_sur'	'neck_Zrotation1'	' 0.49735'	' 0.025667'
119	'right_sur'	'neck_Zrotation1'	' 0.44823'	' 0.047472'
120	'L_leg_sur'	'head_Xrotation1'	'-0.47811'	' 0.032986'
121	'L_shin_sur'	'head_Xrotation1'	'-0.50351'	' 0.023618'
122	'R_arm_vol'	'head_Xrotation1'	'-0.52961'	' 0.016326'
123	'R_arm_sur'	'head_Xrotation1'	'-0.53375'	' 0.015355'
124	'L_forearm_sur'	'head_Xrotation1'	'-0.47566'	' 0.034025'
125	'R_forearm_vol'	'head_Xrotation1'	'-0.65873'	' 0.0015863'
126	'R_forearm_sur'	'head_Xrotation1'	' -0.6592'	' 0.0015698'
127	'lower_sur'	'head_Xrotation1'	'-0.45301'	' 0.044872'
128	'R_arm_sur'	'head_Yrotation1'	' 0.46453'	' 0.039064'
129	'R_shoulder_vol'	'head_Yrotation1'	' 0.47007'	' 0.036487'

130	'R_shoulder_sur'	'head_Yrotation1'	' 0.46826'	' 0.037317'
131	'L_shoulder_vol'	'L_shoulder_Xrotation1'	' 0.46912'	' 0.036922'
132	'L_arm_vol'	'L_shoulder_Zrotation1'	'-0.49827'	' 0.025353'
133	'L_arm_sur'	'L_shoulder_Zrotation1'	'-0.68308'	' 0.00090177'
134	'R_arm_sur'	'L_shoulder_Zrotation1'	'-0.45604'	' 0.043287'
135	'L_shoulder_sur'	'L_shoulder_Zrotation1'	'-0.65423'	' 0.0017514'
136	'L_forearm_vol'	'L_shoulder_Zrotation1'	' -0.4855'	' 0.030006'
137	'L_forearm_sur'	'L_shoulder_Zrotation1'	' -0.6171'	' 0.0037492'
138	'body_sur'	'L_shoulder_Zrotation1'	'-0.45467'	' 0.043999'
139	'L_arm_sur'	'L_elbow_Zrotation1'	' 0.59661'	' 0.0054898'
140	'L_shoulder_sur'	'L_elbow_Zrotation1'	' 0.60773'	' 0.0044773'
141	'L_forearm_sur'	'L_elbow_Zrotation1'	' 0.47596'	' 0.033897'
142	'L_shin_vol'	'L_hand_Yrotation1'	' 0.44666'	' 0.048347'
143	'R_forearm_sur'	'L_hand_Yrotation1'	' 0.4438'	' 0.049977'
144	'L_shoulder_vol'	'L_hand_Zrotation1'	' 0.47144'	' 0.035874'
145	'L_shoulder_sur'	'L_hand_Zrotation1'	' 0.48183'	' 0.031456'
146	'L_arm_vol'	'R_shoulder_Yrotation1'	'-0.46106'	' 0.040748'
147	'L_shoulder_vol'	'R_shoulder_Yrotation1'	'-0.46132'	' 0.04062'
148	'L_shoulder_sur'	'R_shoulder_Yrotation1'	'-0.47345'	' 0.034984'
149	'R_forearm_vol'	'R_shoulder_Zrotation1'	' 0.47723'	' 0.033357'
150	'R_forearm_sur'	'R_shoulder_Zrotation1'	' 0.45748'	' 0.042547'
151	'R_leg_vol'	'R_elbow_Xrotation1'	' 0.44536'	' 0.049083'
152	'lower_vol'	'R_elbow_Xrotation1'	' 0.4534'	' 0.044666'
153	'torso_vol'	'R_forearm_Xrotation1'	' 0.49898'	' 0.025113'
154	'torso_sur'	'R_forearm_Xrotation1'	' 0.48792'	' 0.029075'
155	'upper_vol'	'R_forearm_Xrotation1'	' 0.47489'	' 0.034358'
156	'chest_vol'	'R_forearm_Xrotation1'	' 0.53943'	' 0.014102'
157	'L_leg_sur'	'R_hand_Xrotation1'	'-0.47022'	' 0.036422'
158	'R_leg_vol'	'R_hand_Xrotation1'	'-0.46898'	' 0.036986'
159	'R_leg_sur'	'R_hand_Xrotation1'	'-0.55013'	' 0.011965'
160	'L_thigh_sur'	'R_hand_Xrotation1'	'-0.51818'	' 0.019257'
161	'R_thigh_vol'	'R_hand_Xrotation1'	' -0.4726'	' 0.035358'
162	'R_thigh_sur'	'R_hand_Xrotation1'	'-0.52584'	' 0.01725'
163	'R_shin_vol'	'R_hand_Xrotation1'	'-0.51348'	' 0.020578'

164	'R_shin_sur'	'R_hand_Xrotation1'	'-0.45931'	' 0.041623'
165	'torso_vol'	'R_hand_Xrotation1'	'-0.48635'	' 0.029676'
166	'torso_sur'	'R_hand_Xrotation1'	' -0.5085'	' 0.022053'
167	'L_arm_vol'	'R_hand_Xrotation1'	'-0.52501'	' 0.017459'
168	'L_arm_sur'	'R_hand_Xrotation1'	'-0.65364'	' 0.0017744'
169	'R_arm_sur'	'R_hand_Xrotation1'	'-0.45625'	' 0.043175'
170	'L_shoulder_vol'	'R_hand_Xrotation1'	'-0.46916'	' 0.036903'
171	'L_shoulder_sur'	'R_hand_Xrotation1'	'-0.70005'	' 0.00058931'
172	'R_shoulder_sur'	'R_hand_Xrotation1'	'-0.44612'	' 0.048651'
173	'L_forearm_sur'	'R_hand_Xrotation1'	'-0.51241'	' 0.020887'
174	'body_vol'	'R_hand_Xrotation1'	'-0.53414'	' 0.015268'
175	'body_sur'	'R_hand_Xrotation1'	'-0.63333'	' 0.0027203'
176	'upper_vol'	'R_hand_Xrotation1'	'-0.49563'	' 0.026265'
177	'upper_sur'	'R_hand_Xrotation1'	'-0.46218'	' 0.0402'
178	'lower_vol'	'R_hand_Xrotation1'	'-0.45948'	' 0.041535'
179	'lower_sur'	'R_hand_Xrotation1'	'-0.50907'	' 0.021882'
180	'left_vol'	'R_hand_Xrotation1'	'-0.52586'	' 0.017245'
181	'left_sur'	'R_hand_Xrotation1'	'-0.50037'	' 0.024646'
182	'right_vol'	'R_hand_Xrotation1'	'-0.44985'	' 0.046579'
183	'hip_vol'	'R_hand_Xrotation1'	' -0.4739'	' 0.034784'
184	'hip_sur'	'R_hand_Xrotation1'	'-0.47461'	' 0.034475'
185	'chest_vol'	'R_hand_Xrotation1'	'-0.52392'	' 0.017737'
186	'noArms_vol'	'R_hand_Xrotation1'	'-0.51211'	' 0.020975'
187	'noArms_sur'	'R_hand_Xrotation1'	'-0.59613'	' 0.0055374'
188	'L_leg_vol'	'R_hand_Yrotation1'	' 0.5278'	' 0.016765'
189	'L_thigh_vol'	'R_hand_Yrotation1'	' 0.48814'	' 0.028991'
190	'R_arm_vol'	'R_hand_Yrotation1'	' 0.51618'	' 0.01981'
191	'R_arm_sur'	'R_hand_Yrotation1'	' 0.45697'	' 0.042809'
192	'hip_vol'	'R_hand_Yrotation1'	' 0.49289'	' 0.027236'
193	'upper_sur'	'Root_Xposition2'	' 0.46077'	' 0.040893'
194	'left_sur'	'Root_Yposition2'	'-0.45514'	' 0.043751'
195	'L_thigh_vol'	'Root_Zposition2'	' 0.48708'	' 0.029393'
196	'L_shin_vol'	'Root_Zposition2'	'-0.52016'	' 0.018721'
197	'L_shin_vol'	'Root_Xrotation2'	' 0.54247'	' 0.013468'

198	'L_shin_vol'	'Root_Zrotation2'	'-0.44587'	' 0.048794'
199	'L_shin_sur'	'Root_Zrotation2'	'-0.48111'	' 0.03175'
200	'chest_sur'	'Root_Zrotation2'	'-0.45824'	' 0.042157'
201	'L_forearm_sur'	'L_thigh_Xrotation2'	' 0.4451'	' 0.049234'
202	'L_arm_vol'	'L_thigh_Yrotation2'	' -0.5015'	' 0.024274'
203	'L_arm_sur'	'L_thigh_Yrotation2'	'-0.64451'	' 0.0021582'
204	'R_arm_sur'	'L_thigh_Yrotation2'	'-0.53616'	' 0.014814'
205	'L_shoulder_sur'	'L_thigh_Yrotation2'	'-0.59856'	' 0.0052995'
206	'R_shoulder_sur'	'L_thigh_Yrotation2'	'-0.47574'	' 0.033989'
207	'L_forearm_vol'	'L_thigh_Yrotation2'	'-0.48198'	' 0.031395'
208	'L_forearm_sur'	'L_thigh_Yrotation2'	'-0.63246'	' 0.0027684'
209	'R_forearm_vol'	'L_thigh_Yrotation2'	'-0.53121'	' 0.015946'
210	'R_forearm_sur'	'L_thigh_Yrotation2'	'-0.56442'	' 0.0095272'
211	'L_leg_vol'	'L_thigh_Zrotation2'	' 0.55196'	' 0.011627'
212	'L_leg_sur'	'L_thigh_Zrotation2'	' 0.5028'	' 0.023849'
213	'R_leg_vol'	'L_thigh_Zrotation2'	' 0.54059'	' 0.013856'
214	'R_leg_sur'	'L_thigh_Zrotation2'	' 0.4466'	' 0.048383'
215	'L_thigh_vol'	'L_thigh_Zrotation2'	' 0.54202'	' 0.013559'
216	'L_thigh_sur'	'L_thigh_Zrotation2'	' 0.5004'	' 0.024637'
217	'R_thigh_vol'	'L_thigh_Zrotation2'	' 0.51927'	' 0.018959'
218	'R_thigh_sur'	'L_thigh_Zrotation2'	' 0.45262'	' 0.045084'
219	'R_shin_vol'	'L_thigh_Zrotation2'	' 0.45227'	' 0.045268'
220	'R_arm_vol'	'L_thigh_Zrotation2'	' 0.49056'	' 0.028088'
221	'R_shoulder_vol'	'L_thigh_Zrotation2'	' 0.54595'	' 0.012768'
222	'R_shoulder_sur'	'L_thigh_Zrotation2'	' 0.49813'	' 0.025402'
223	'L_forearm_sur'	'L_thigh_Zrotation2'	' 0.47847'	' 0.032837'
224	'lower_vol'	'L_thigh_Zrotation2'	' 0.61834'	' 0.0036603'
225	'lower_sur'	'L_thigh_Zrotation2'	' 0.52742'	' 0.016858'
226	'R_leg_vol'	'L_knee_Xrotation2'	'-0.47385'	' 0.034807'
227	'R_thigh_vol'	'L_knee_Xrotation2'	'-0.49787'	' 0.025489'
228	'L_arm_sur'	'L_knee_Xrotation2'	'-0.50054'	' 0.02459'
229	'L_forearm_sur'	'L_knee_Xrotation2'	'-0.44447'	' 0.049591'
230	'left_vol'	'L_knee_Xrotation2'	' -0.5005'	' 0.024602'
231	'left_sur'	'L_knee_Xrotation2'	'-0.61527'	' 0.003883'

232	'right_vol'	'L_knee_Xrotation2'	' -0.4781'	' 0.03299'
233	'right_sur'	'L_knee_Xrotation2'	'-0.61833'	' 0.0036615'
234	'L_leg_vol'	'L_foot_Yrotation2'	'-0.53557'	' 0.014945'
235	'L_leg_sur'	'L_foot_Yrotation2'	'-0.55444'	' 0.011183'
236	'R_leg_vol'	'L_foot_Yrotation2'	' -0.4482'	' 0.047485'
237	'R_leg_sur'	'L_foot_Yrotation2'	'-0.52939'	' 0.016378'
238	'L_thigh_vol'	'L_foot_Yrotation2'	'-0.57112'	' 0.0085321'
239	'L_thigh_sur'	'L_foot_Yrotation2'	'-0.59803'	' 0.0053508'
240	'R_thigh_vol'	'L_foot_Yrotation2'	'-0.48757'	' 0.029208'
241	'R_thigh_sur'	'L_foot_Yrotation2'	' -0.5265'	' 0.017086'
242	'R_shin_vol'	'L_foot_Yrotation2'	'-0.46046'	' 0.041048'
243	'lower_vol'	'L_foot_Yrotation2'	'-0.53507'	' 0.015057'
244	'lower_sur'	'L_foot_Yrotation2'	' -0.5547'	' 0.011137'
245	'L_arm_sur'	'R_thigh_Yrotation2'	'-0.59755'	' 0.0053975'
246	'L_shoulder_sur'	'R_thigh_Yrotation2'	' -0.5659'	' 0.0092997'
247	'L_forearm_vol'	'R_thigh_Yrotation2'	'-0.46407'	' 0.039286'
248	'L_forearm_sur'	'R_thigh_Yrotation2'	'-0.55843'	' 0.010495'
249	'L_leg_vol'	'R_thigh_Zrotation2'	' 0.4949'	' 0.02652'
250	'R_leg_vol'	'R_thigh_Zrotation2'	' 0.46699'	' 0.037902'
251	'R_thigh_vol'	'R_thigh_Zrotation2'	' 0.48856'	' 0.028833'
252	'R_shin_vol'	'R_thigh_Zrotation2'	' 0.46066'	' 0.040949'
253	'torso_vol'	'R_thigh_Zrotation2'	' 0.49773'	' 0.025538'
254	'torso_sur'	'R_thigh_Zrotation2'	' 0.45648'	' 0.043059'
255	'L_arm_vol'	'R_thigh_Zrotation2'	' 0.46719'	' 0.037811'
256	'body_vol'	'R_thigh_Zrotation2'	' 0.51113'	' 0.021264'
257	'body_sur'	'R_thigh_Zrotation2'	' 0.46956'	' 0.036719'
258	'upper_vol'	'R_thigh_Zrotation2'	' 0.51944'	' 0.018914'
259	'upper_sur'	'R_thigh_Zrotation2'	' 0.52785'	' 0.016752'
260	'left_vol'	'R_thigh_Zrotation2'	' 0.45515'	' 0.043749'
261	'right_vol'	'R_thigh_Zrotation2'	' 0.48691'	' 0.02946'
262	'hip_vol'	'R_thigh_Zrotation2'	' 0.62932'	' 0.0029495'
263	'hip_sur'	'R_thigh_Zrotation2'	' 0.52948'	' 0.016355'
264	'chest_vol'	'R_thigh_Zrotation2'	' 0.46601'	' 0.038365'
265	'noArms_vol'	'R_thigh_Zrotation2'	' 0.5062'	' 0.022764'

266	'noArms_sur'	'R_thigh_Zrotation2'	' 0.45967'	' 0.041443'
267	'chest_vol'	'R_knee_Xrotation2'	'-0.49802'	' 0.025439'
268	'chest_sur'	'R_knee_Xrotation2'	'-0.52692'	' 0.016981'
269	'L_arm_vol'	'Spine_0_Xrotation2'	'-0.59384'	' 0.0057688'
270	'L_arm_sur'	'Spine_0_Xrotation2'	'-0.74211'	' 0.00017949'
271	'R_arm_sur'	'Spine_0_Xrotation2'	'-0.50152'	' 0.024266'
272	'L_shoulder_vol'	'Spine_0_Xrotation2'	'-0.45261'	' 0.045088'
273	'L_shoulder_sur'	'Spine_0_Xrotation2'	'-0.70683'	' 0.00049321'
274	'L_forearm_vol'	'Spine_0_Xrotation2'	' -0.5766'	' 0.0077831'
275	'L_forearm_sur'	'Spine_0_Xrotation2'	' -0.6697'	' 0.0012377'
276	'R_forearm_vol'	'Spine_0_Xrotation2'	'-0.47602'	' 0.03387'
277	'R_forearm_sur'	'Spine_0_Xrotation2'	'-0.47129'	' 0.035941'
278	'body_vol'	'Spine_0_Xrotation2'	'-0.47116'	' 0.035997'
279	'body_sur'	'Spine_0_Xrotation2'	'-0.55313'	' 0.011417'
280	'upper_vol'	'Spine_0_Xrotation2'	'-0.44389'	' 0.049925'
281	'left_vol'	'Spine_0_Xrotation2'	'-0.50685'	' 0.022562'
282	'left_sur'	'Spine_0_Xrotation2'	'-0.51256'	' 0.020845'
283	'hip_sur'	'Spine_0_Xrotation2'	'-0.44888'	' 0.047111'
284	'noArms_sur'	'Spine_0_Xrotation2'	'-0.47987'	' 0.032256'
285	'L_arm_sur'	'Spine_1_Yrotation2'	'-0.60978'	' 0.0043088'
286	'L_shoulder_sur'	'Spine_1_Yrotation2'	'-0.56693'	' 0.0091441'
287	'L_forearm_vol'	'Spine_1_Yrotation2'	'-0.49914'	' 0.025057'
288	'L_forearm_sur'	'Spine_1_Yrotation2'	'-0.57097'	' 0.0085543'
289	'L_arm_vol'	'Spine_1_Zrotation2'	'-0.46505'	' 0.038817'
290	'L_forearm_sur'	'Spine_1_Zrotation2'	'-0.48221'	' 0.031306'
291	'R_forearm_vol'	'Spine_1_Zrotation2'	'-0.47326'	' 0.035067'
292	'R_forearm_sur'	'Spine_1_Zrotation2'	'-0.47553'	' 0.034078'
293	'left_sur'	'Spine_1_Zrotation2'	'-0.50197'	' 0.024117'
294	'L_arm_vol'	'neck_Xrotation2'	' 0.56978'	' 0.008725'
295	'L_arm_sur'	'neck_Xrotation2'	' 0.69406'	' 0.00068692'
296	'R_arm_sur'	'neck_Xrotation2'	' 0.46118'	' 0.04069'
297	'L_shoulder_sur'	'neck_Xrotation2'	' 0.67219'	' 0.0011682'
298	'L_forearm_vol'	'neck_Xrotation2'	' 0.50725'	' 0.022439'
299	'L_forearm_sur'	'neck_Xrotation2'	' 0.6207'	' 0.0034964'

300	'R_forearm_vol'	'neck_Xrotation2'	' 0.44811'	' 0.047539'
301	'R_forearm_sur'	'neck_Xrotation2'	' 0.44549'	' 0.049012'
302	'body_sur'	'neck_Xrotation2'	' 0.49778'	' 0.025519'
303	'torso_sur'	'neck_Zrotation2'	' 0.44401'	' 0.049855'
304	'L_arm_vol'	'neck_Zrotation2'	' 0.55847'	' 0.010488'
305	'L_arm_sur'	'neck_Zrotation2'	' 0.70713'	' 0.00048927'
306	'R_arm_sur'	'neck_Zrotation2'	' 0.52131'	' 0.018416'
307	'L_shoulder_sur'	'neck_Zrotation2'	' 0.66693'	' 0.001319'
308	'L_forearm_vol'	'neck_Zrotation2'	' 0.50564'	' 0.022939'
309	'L_forearm_sur'	'neck_Zrotation2'	' 0.6572'	' 0.0016411'
310	'R_forearm_vol'	'neck_Zrotation2'	' 0.49685'	' 0.025841'
311	'R_forearm_sur'	'neck_Zrotation2'	' 0.47335'	' 0.035025'
312	'body_vol'	'neck_Zrotation2'	' 0.45515'	' 0.04375'
313	'body_sur'	'neck_Zrotation2'	' 0.55188'	' 0.011641'
314	'upper_sur'	'neck_Zrotation2'	' 0.4454'	' 0.049062'
315	'left_vol'	'neck_Zrotation2'	' 0.47321'	' 0.035086'
316	'left_sur'	'neck_Zrotation2'	' 0.46639'	' 0.038186'
317	'hip_sur'	'neck_Zrotation2'	' 0.44822'	' 0.047476'
318	'noArms_sur'	'neck_Zrotation2'	' 0.47899'	' 0.032619'
319	'L_arm_vol'	'head_Xrotation2'	'-0.55371'	' 0.011312'
320	'L_arm_sur'	'head_Xrotation2'	'-0.68064'	' 0.00095656'
321	'R_arm_sur'	'head_Xrotation2'	'-0.44792'	' 0.047641'
322	'L_shoulder_sur'	'head_Xrotation2'	'-0.64983'	' 0.0019267'
323	'L_forearm_vol'	'head_Xrotation2'	'-0.51976'	' 0.018828'
324	'L_forearm_sur'	'head_Xrotation2'	'-0.62199'	' 0.00341'
325	'body_sur'	'head_Xrotation2'	'-0.48262'	' 0.031139'
326	'L_arm_vol'	'head_Yrotation2'	' 0.60152'	' 0.005022'
327	'L_arm_sur'	'head_Yrotation2'	' 0.69427'	' 0.00068336'
328	'R_arm_sur'	'head_Yrotation2'	' 0.48823'	' 0.028959'
329	'L_shoulder_vol'	'head_Yrotation2'	' 0.46962'	' 0.036692'
330	'L_shoulder_sur'	'head_Yrotation2'	' 0.67947'	' 0.00098357'
331	'L_forearm_vol'	'head_Yrotation2'	' 0.50081'	' 0.0245'
332	'L_forearm_sur'	'head_Yrotation2'	' 0.61132'	' 0.0041854'
333	'R_forearm_vol'	'head_Yrotation2'	' 0.47147'	' 0.035859'

334	'R_forearm_sur'	'head_Yrotation2'	' 0.44449'	' 0.049583'
335	'body_sur'	'head_Yrotation2'	' 0.51151'	' 0.021151'
336	'L_arm_vol'	'head_Zrotation2'	' 0.59038'	' 0.0061344'
337	'L_arm_sur'	'head_Zrotation2'	' 0.71179'	' 0.00043172'
338	'L_shoulder_vol'	'head_Zrotation2'	' 0.47343'	' 0.03499'
339	'L_shoulder_sur'	'head_Zrotation2'	' 0.69897'	' 0.00060598'
340	'L_forearm_vol'	'head_Zrotation2'	' 0.51492'	' 0.020166'
341	'L_forearm_sur'	'head_Zrotation2'	' 0.61412'	' 0.0039694'
342	'body_sur'	'head_Zrotation2'	' 0.48375'	' 0.030689'
343	'L_thigh_vol'	'L_shoulder_Xrotation2'	' -0.5086'	' 0.022023'
344	'L_shoulder_vol'	'L_shoulder_Xrotation2'	' 0.47933'	' 0.032479'
345	'chest_vol'	'L_shoulder_Xrotation2'	' 0.503'	' 0.023783'
346	'L_arm_vol'	'L_shoulder_Zrotation2'	'-0.48214'	' 0.031334'
347	'L_arm_sur'	'L_shoulder_Zrotation2'	'-0.64097'	' 0.0023242'
348	'L_shoulder_sur'	'L_shoulder_Zrotation2'	'-0.64536'	' 0.0021198'
349	'L_forearm_vol'	'L_shoulder_Zrotation2'	'-0.48563'	' 0.029954'
350	'L_forearm_sur'	'L_shoulder_Zrotation2'	'-0.54963'	' 0.012059'
351	'body_sur'	'L_shoulder_Zrotation2'	'-0.46692'	' 0.037937'
352	'torso_vol'	'L_elbow_Xrotation2'	'-0.49846'	' 0.025287'
353	'torso_sur'	'L_elbow_Xrotation2'	'-0.58482'	' 0.006761'
354	'upper_vol'	'L_elbow_Xrotation2'	'-0.45209'	' 0.045367'
355	'right_vol'	'L_elbow_Xrotation2'	'-0.47307'	' 0.03515'
356	'hip_vol'	'L_elbow_Xrotation2'	'-0.44966'	' 0.046682'
357	'hip_sur'	'L_elbow_Xrotation2'	'-0.51987'	' 0.018798'
358	'chest_sur'	'L_elbow_Xrotation2'	'-0.47114'	' 0.036009'
359	'noArms_vol'	'L_elbow_Xrotation2'	' -0.4886'	' 0.028818'
360	'noArms_sur'	'L_elbow_Xrotation2'	' -0.5106'	' 0.021423'
361	'L_leg_vol'	'L_elbow_Zrotation2'	'-0.64486'	' 0.0021422'
362	'L_leg_sur'	'L_elbow_Zrotation2'	'-0.50309'	' 0.023755'
363	'R_leg_vol'	'L_elbow_Zrotation2'	'-0.45979'	' 0.041382'
364	'L_thigh_vol'	'L_elbow_Zrotation2'	'-0.54074'	' 0.013825'
365	'L_thigh_sur'	'L_elbow_Zrotation2'	'-0.55109'	' 0.011787'
366	'R_thigh_vol'	'L_elbow_Zrotation2'	'-0.47495'	' 0.034329'
367	'R_shin_vol'	'L_elbow_Zrotation2'	'-0.44507'	' 0.049248'

368	'torso_vol'	'L_elbow_Zrotation2'	'-0.45827'	' 0.042147'
369	'body_vol'	'L_elbow_Zrotation2'	'-0.50047'	' 0.024612'
370	'lower_vol'	'L_elbow_Zrotation2'	'-0.56775'	' 0.0090227'
371	'lower_sur'	'L_elbow_Zrotation2'	'-0.45955'	' 0.0415'
372	'left_vol'	'L_elbow_Zrotation2'	' -0.4726'	' 0.035357'
373	'hip_vol'	'L_elbow_Zrotation2'	'-0.46822'	' 0.037335'
374	'chest_vol'	'L_elbow_Zrotation2'	'-0.45938'	' 0.041583'
375	'noArms_vol'	'L_elbow_Zrotation2'	'-0.49712'	' 0.025748'
376	'noArms_sur'	'L_elbow_Zrotation2'	'-0.45058'	' 0.046178'
377	'R_arm_vol'	'L_hand_Xrotation2'	'-0.45093'	' 0.045992'
378	'R_arm_sur'	'L_hand_Xrotation2'	'-0.53308'	' 0.015509'
379	'R_shoulder_sur'	'L_hand_Xrotation2'	'-0.49947'	' 0.024947'
380	'L_shoulder_sur'	'L_hand_Zrotation2'	' 0.46503'	' 0.038828'
381	'torso_vol'	'R_shoulder_Yrotation2'	'-0.55358'	' 0.011336'
382	'torso_sur'	'R_shoulder_Yrotation2'	'-0.67658'	' 0.0010537'
383	'L_arm_vol'	'R_shoulder_Yrotation2'	'-0.55058'	' 0.011882'
384	'L_arm_sur'	'R_shoulder_Yrotation2'	'-0.51973'	' 0.018837'
385	'L_shoulder_vol'	'R_shoulder_Yrotation2'	'-0.59282'	' 0.0058746'
386	'L_shoulder_sur'	'R_shoulder_Yrotation2'	'-0.50988'	' 0.021639'
387	'body_vol'	'R_shoulder_Yrotation2'	'-0.54509'	' 0.012938'
388	'body_sur'	'R_shoulder_Yrotation2'	'-0.59055'	' 0.0061159'
389	'upper_vol'	'R_shoulder_Yrotation2'	' -0.5641'	' 0.0095777'
390	'upper_sur'	'R_shoulder_Yrotation2'	'-0.57937'	' 0.0074257'
391	'left_vol'	'R_shoulder_Yrotation2'	'-0.54107'	' 0.013757'
392	'left_sur'	'R_shoulder_Yrotation2'	'-0.56063'	' 0.01013'
393	'right_vol'	'R_shoulder_Yrotation2'	'-0.57365'	' 0.0081797'
394	'right_sur'	'R_shoulder_Yrotation2'	'-0.54451'	' 0.013053'
395	'hip_vol'	'R_shoulder_Yrotation2'	'-0.52045'	' 0.018642'
396	'hip_sur'	'R_shoulder_Yrotation2'	'-0.65026'	' 0.0019091'
397	'chest_vol'	'R_shoulder_Yrotation2'	'-0.54701'	' 0.01256'
398	'noArms_vol'	'R_shoulder_Yrotation2'	'-0.53797'	' 0.014418'
399	'noArms_sur'	'R_shoulder_Yrotation2'	' -0.5526'	' 0.011512'
400	'L_shoulder_vol'	'R_shoulder_Zrotation2'	' 0.53511'	' 0.015048'
401	'L_leg_vol'	'R_elbow_Xrotation2'	' 0.47303'	' 0.035169'

402	'R_leg_sur'	'R_elbow_Xrotation2'	' 0.4506'	' 0.046171'
403	'L_thigh_vol'	'R_elbow_Xrotation2'	' 0.54213'	' 0.013537'
404	'L_thigh_sur'	'R_elbow_Xrotation2'	' 0.4715'	' 0.035845'
405	'R_thigh_vol'	'R_elbow_Xrotation2'	' 0.48358'	' 0.030757'
406	'R_thigh_sur'	'R_elbow_Xrotation2'	' 0.4967'	' 0.025892'
407	'lower_vol'	'R_elbow_Xrotation2'	' 0.49251'	' 0.027375'
408	'lower_sur'	'R_elbow_Xrotation2'	' 0.4678'	' 0.037526'
409	'right_sur'	'R_elbow_Yrotation2'	'-0.44901'	' 0.047037'
410	'R_leg_vol'	'R_forearm_Xrotation2'	' 0.45359'	' 0.044564'
411	'R_thigh_vol'	'R_forearm_Xrotation2'	' 0.47304'	' 0.035161'
412	'R_thigh_sur'	'R_forearm_Xrotation2'	' 0.45717'	' 0.042707'
413	'torso_sur'	'R_forearm_Xrotation2'	' 0.47285'	' 0.035246'
414	'noArms_sur'	'R_forearm_Xrotation2'	' 0.45608'	' 0.043267'
415	'R_thigh_sur'	'R_forearm_Yrotation2'	' 0.45974'	' 0.041404'
416	'torso_vol'	'R_hand_Xrotation2'	'-0.49048'	' 0.028118'
417	'torso_sur'	'R_hand_Xrotation2'	'-0.46001'	' 0.041268'
418	'L_arm_vol'	'R_hand_Xrotation2'	'-0.53705'	' 0.014618'
419	'L_arm_sur'	'R_hand_Xrotation2'	'-0.60186'	' 0.0049905'
420	'L_shoulder_vol'	'R_hand_Xrotation2'	'-0.48557'	' 0.029976'
421	'L_shoulder_sur'	'R_hand_Xrotation2'	'-0.60981'	' 0.0043061'
422	'L_forearm_sur'	'R_hand_Xrotation2'	'-0.54555'	' 0.012845'
423	'body_vol'	'R_hand_Xrotation2'	'-0.51667'	' 0.019674'
424	'body_sur'	'R_hand_Xrotation2'	'-0.54753'	' 0.01246'
425	'upper_vol'	'R_hand_Xrotation2'	'-0.48936'	' 0.028533'
426	'left_vol'	'R_hand_Xrotation2'	'-0.54317'	' 0.013323'
427	'left_sur'	'R_hand_Xrotation2'	'-0.46556'	' 0.038576'
428	'hip_vol'	'R_hand_Xrotation2'	'-0.44934'	' 0.046856'
429	'chest_vol'	'R_hand_Xrotation2'	'-0.53975'	' 0.014035'
430	'noArms_vol'	'R_hand_Xrotation2'	'-0.50022'	' 0.024695'
431	'noArms_sur'	'R_hand_Xrotation2'	'-0.50607'	' 0.022807'
432	'chest_sur'	'R_hand_Yrotation2'	' 0.50953'	' 0.021744'
433	'torso_sur'	'Root_Xposition3'	' 0.53804'	' 0.014401'
434	'upper_vol'	'Root_Xposition3'	' 0.45971'	' 0.041423'
435	'upper_sur'	'Root_Xposition3'	' 0.54693'	' 0.012576'

436	'hip_sur'	'Root_Xposition3'	' 0.45973'	' 0.041411'
437	'chest_vol'	'Root_Xposition3'	' 0.49663'	' 0.025915'
438	'R_shin_vol'	'Root_Yrotation3'	'-0.45159'	' 0.045631'
439	'chest_sur'	'Root_Zrotation3'	'-0.74868'	' 0.00014612'
440	'L_arm_sur'	'L_thigh_Xrotation3'	' 0.56158'	' 0.0099767'
441	'L_shoulder_sur'	'L_thigh_Xrotation3'	' 0.58555'	' 0.0066761'
442	'L_arm_vol'	'L_thigh_Yrotation3'	'-0.58989'	' 0.0061882'
443	'L_arm_sur'	'L_thigh_Yrotation3'	'-0.61659'	' 0.0037863'
444	'R_arm_sur'	'L_thigh_Yrotation3'	'-0.44847'	' 0.047338'
445	'L_shoulder_vol'	'L_thigh_Yrotation3'	'-0.54906'	' 0.012167'
446	'L_shoulder_sur'	'L_thigh_Yrotation3'	' -0.6331'	' 0.0027326'
447	'L_forearm_sur'	'L_thigh_Yrotation3'	' -0.5454'	' 0.012876'
448	'R_forearm_vol'	'L_thigh_Yrotation3'	'-0.49194'	' 0.027582'
449	'R_forearm_sur'	'L_thigh_Yrotation3'	'-0.52296'	' 0.017983'
450	'L_leg_sur'	'L_thigh_Zrotation3'	' 0.50967'	' 0.0217'
451	'R_leg_vol'	'L_thigh_Zrotation3'	' 0.44522'	' 0.049164'
452	'L_shin_sur'	'L_thigh_Zrotation3'	' 0.53287'	' 0.015559'
453	'R_arm_vol'	'L_thigh_Zrotation3'	' 0.44598'	' 0.048734'
454	'R_arm_sur'	'L_thigh_Zrotation3'	' 0.48669'	' 0.029545'
455	'R_shoulder_vol'	'L_thigh_Zrotation3'	' 0.51067'	' 0.0214'
456	'R_shoulder_sur'	'L_thigh_Zrotation3'	' 0.50617'	' 0.022774'
457	'lower_vol'	'L_thigh_Zrotation3'	' 0.48539'	' 0.030048'
458	'lower_sur'	'L_thigh_Zrotation3'	' 0.50934'	' 0.0218'
459	'torso_vol'	'L_knee_Xrotation3'	'-0.59884'	' 0.005273'
460	'torso_sur'	'L_knee_Xrotation3'	' -0.5369'	' 0.014651'
461	'L_forearm_vol'	'L_knee_Xrotation3'	'-0.45564'	' 0.043493'
462	'body_vol'	'L_knee_Xrotation3'	'-0.54426'	' 0.013102'
463	'upper_vol'	'L_knee_Xrotation3'	'-0.59852'	' 0.0053038'
464	'upper_sur'	'L_knee_Xrotation3'	'-0.49779'	' 0.025517'
465	'left_vol'	'L_knee_Xrotation3'	'-0.48721'	' 0.029345'
466	'right_vol'	'L_knee_Xrotation3'	'-0.52524'	' 0.017399'
467	'hip_vol'	'L_knee_Xrotation3'	'-0.66562'	' 0.001359'
468	'hip_sur'	'L_knee_Xrotation3'	'-0.60338'	' 0.0048531'
469	'chest_vol'	'L_knee_Xrotation3'	'-0.53543'	' 0.014976'

470	'noArms_vol'	'L_knee_Xrotation3'	'-0.54731'	' 0.012501'
471	'torso_vol'	'L_foot_Yrotation3'	' 0.46287'	' 0.039866'
472	'torso_sur'	'L_foot_Yrotation3'	' 0.45951'	' 0.041519'
473	'L_arm_sur'	'L_foot_Yrotation3'	' 0.45891'	' 0.041823'
474	'body_vol'	'L_foot_Yrotation3'	' 0.46351'	' 0.039557'
475	'upper_vol'	'L_foot_Yrotation3'	' 0.47963'	' 0.032355'
476	'right_vol'	'L_foot_Yrotation3'	' 0.45478'	' 0.04394'
477	'hip_vol'	'L_foot_Yrotation3'	' 0.48812'	' 0.029001'
478	'hip_sur'	'L_foot_Yrotation3'	' 0.45726'	' 0.04266'
479	'noArms_vol'	'L_foot_Yrotation3'	' 0.45752'	' 0.042525'
480	'R_leg_sur'	'R_thigh_Yrotation3'	' 0.44819'	' 0.047494'
481	'torso_vol'	'R_thigh_Zrotation3'	' 0.47278'	' 0.035278'
482	'torso_sur'	'R_thigh_Zrotation3'	' 0.44602'	' 0.048709'
483	'L_arm_vol'	'R_thigh_Zrotation3'	' 0.56531'	' 0.00939'
484	'L_arm_sur'	'R_thigh_Zrotation3'	' 0.65414'	' 0.0017551'
485	'L_shoulder_vol'	'R_thigh_Zrotation3'	' 0.57073'	' 0.0085883'
486	'L_shoulder_sur'	'R_thigh_Zrotation3'	' 0.58948'	' 0.0062323'
487	'L_forearm_vol'	'R_thigh_Zrotation3'	' 0.59065'	' 0.0061049'
488	'L_forearm_sur'	'R_thigh_Zrotation3'	' 0.62621'	' 0.0031377'
489	'body_vol'	'R_thigh_Zrotation3'	' 0.49566'	' 0.026255'
490	'body_sur'	'R_thigh_Zrotation3'	' 0.48156'	' 0.031566'
491	'upper_vol'	'R_thigh_Zrotation3'	' 0.49362'	' 0.026977'
492	'upper_sur'	'R_thigh_Zrotation3'	' 0.45753'	' 0.042521'
493	'left_vol'	'R_thigh_Zrotation3'	' 0.48407'	' 0.030566'
494	'left_sur'	'R_thigh_Zrotation3'	' 0.44511'	' 0.049226'
495	'right_vol'	'R_thigh_Zrotation3'	' 0.46646'	' 0.038153'
496	'hip_vol'	'R_thigh_Zrotation3'	' 0.5143'	' 0.020341'
497	'hip_sur'	'R_thigh_Zrotation3'	' 0.46585'	' 0.038438'
498	'chest_vol'	'R_thigh_Zrotation3'	' 0.4551'	' 0.043772'
499	'noArms_vol'	'R_thigh_Zrotation3'	' 0.4719'	' 0.035667'
500	'L_leg_vol'	'R_foot_Xrotation3'	'-0.47799'	' 0.033036'
501	'lower_vol'	'R_foot_Xrotation3'	'-0.46198'	' 0.0403'
502	'L_shin_sur'	'R_foot_Zrotation3'	' 0.4507'	' 0.046117'
503	'L_leg_vol'	'R_toe_Xrotation3'	' 0.46217'	' 0.040205'

504	'R_leg_vol'	'R_toe_Xrotation3'	' 0.46583'	' 0.038448'
505	'L_thigh_vol'	'R_toe_Xrotation3'	' 0.54438'	' 0.013078'
506	'R_thigh_vol'	'R_toe_Xrotation3'	' 0.4645'	' 0.039082'
507	'R_arm_vol'	'R_toe_Xrotation3'	' 0.56116'	' 0.010044'
508	'R_arm_sur'	'R_toe_Xrotation3'	' 0.57717'	' 0.0077094'
509	'R_shoulder_vol'	'R_toe_Xrotation3'	' 0.4846'	' 0.030357'
510	'R_shoulder_sur'	'R_toe_Xrotation3'	' 0.55814'	' 0.010544'
511	'lower_vol'	'R_toe_Xrotation3'	' 0.46152'	' 0.040526'
512	'L_thigh_vol'	'Spine_0_Zrotation3'	'-0.44594'	' 0.048752'
513	'R_thigh_vol'	'Spine_0_Zrotation3'	'-0.50159'	' 0.024243'
514	'L_arm_sur'	'Spine_0_Zrotation3'	'-0.51779'	' 0.019363'
515	'L_shoulder_sur'	'Spine_0_Zrotation3'	'-0.44658'	' 0.048394'
516	'L_forearm_sur'	'Spine_0_Zrotation3'	'-0.51855'	' 0.019156'
517	'L_arm_vol'	'Spine_1_Xrotation3'	' 0.46663'	' 0.038071'
518	'upper_sur'	'Spine_1_Xrotation3'	' 0.45189'	' 0.045474'
519	'L_arm_sur'	'Spine_1_Yrotation3'	'-0.53399'	' 0.015301'
520	'L_shoulder_sur'	'Spine_1_Yrotation3'	'-0.50989'	' 0.021633'
521	'L_forearm_sur'	'Spine_1_Yrotation3'	'-0.46523'	' 0.038733'
522	'L_arm_vol'	'Spine_1_Zrotation3'	'-0.45341'	' 0.044664'
523	'R_forearm_vol'	'Spine_1_Zrotation3'	' -0.511'	' 0.021304'
524	'R_forearm_sur'	'Spine_1_Zrotation3'	'-0.46529'	' 0.038705'
525	'left_sur'	'Spine_1_Zrotation3'	'-0.46119'	' 0.040683'
526	'L_arm_vol'	'neck_Xrotation3'	' 0.56723'	' 0.0090999'
527	'L_arm_sur'	'neck_Xrotation3'	' 0.69835'	' 0.00061577'
528	'R_arm_sur'	'neck_Xrotation3'	' 0.4757'	' 0.034009'
529	'L_shoulder_sur'	'neck_Xrotation3'	' 0.67288'	' 0.0011495'
530	'L_forearm_vol'	'neck_Xrotation3'	' 0.5106'	' 0.021421'
531	'L_forearm_sur'	'neck_Xrotation3'	' 0.63113'	' 0.0028441'
532	'R_forearm_vol'	'neck_Xrotation3'	' 0.4525'	' 0.045145'
533	'R_forearm_sur'	'neck_Xrotation3'	' 0.44597'	' 0.048736'
534	'body_sur'	'neck_Xrotation3'	' 0.50055'	' 0.024587'
535	'L_arm_sur'	'neck_Yrotation3'	' 0.58554'	' 0.0066778'
536	'L_shoulder_sur'	'neck_Yrotation3'	' 0.57251'	' 0.0083377'
537	'L_forearm_sur'	'neck_Yrotation3'	' 0.53147'	' 0.015885'

538	'L_arm_vol'	'neck_Zrotation3'	' 0.56254'	' 0.0098225'
539	'L_arm_sur'	'neck_Zrotation3'	' 0.69601'	' 0.00065371'
540	'R_arm_sur'	'neck_Zrotation3'	' 0.49287'	' 0.027244'
541	'L_shoulder_sur'	'neck_Zrotation3'	' 0.65824'	' 0.0016037'
542	'L_forearm_vol'	'neck_Zrotation3'	' 0.51065'	' 0.021408'
543	'L_forearm_sur'	'neck_Zrotation3'	' 0.64386'	' 0.002188'
544	'R_forearm_vol'	'neck_Zrotation3'	' 0.46753'	' 0.037655'
545	'R_forearm_sur'	'neck_Zrotation3'	' 0.44989'	' 0.046556'
546	'body_sur'	'neck_Zrotation3'	' 0.50837'	' 0.022096'
547	'L_arm_vol'	'head_Xrotation3'	'-0.45779'	' 0.04239'
548	'L_arm_sur'	'head_Xrotation3'	'-0.59907'	' 0.005251'
549	'R_arm_sur'	'head_Xrotation3'	'-0.49833'	' 0.025332'
550	'L_shoulder_sur'	'head_Xrotation3'	'-0.54533'	' 0.01289'
551	'L_forearm_vol'	'head_Xrotation3'	'-0.50633'	' 0.022724'
552	'L_forearm_sur'	'head_Xrotation3'	'-0.58726'	' 0.00648'
553	'R_forearm_vol'	'head_Xrotation3'	'-0.52623'	' 0.017152'
554	'R_forearm_sur'	'head_Xrotation3'	' -0.5175'	' 0.019443'
555	'body_sur'	'head_Xrotation3'	'-0.46513'	' 0.038781'
556	'L_arm_vol'	'head_Yrotation3'	' 0.57168'	' 0.0084538'
557	'L_arm_sur'	'head_Yrotation3'	' 0.69702'	' 0.00063708'
558	'R_arm_sur'	'head_Yrotation3'	' 0.48163'	' 0.031537'
559	'L_shoulder_sur'	'head_Yrotation3'	' 0.66854'	' 0.0012711'
560	'L_forearm_vol'	'head_Yrotation3'	' 0.51348'	' 0.020578'
561	'L_forearm_sur'	'head_Yrotation3'	' 0.63116'	' 0.0028423'
562	'R_forearm_vol'	'head_Yrotation3'	' 0.46294'	' 0.039832'
563	'R_forearm_sur'	'head_Yrotation3'	' 0.45785'	' 0.042356'
564	'body_sur'	'head_Yrotation3'	' 0.49753'	' 0.025606'
565	'L_arm_vol'	'head_Zrotation3'	' 0.5735'	' 0.0082009'
566	'L_arm_sur'	'head_Zrotation3'	' 0.70313'	' 0.00054387'
567	'R_arm_sur'	'head_Zrotation3'	' 0.47778'	' 0.033126'
568	'L_shoulder_sur'	'head_Zrotation3'	' 0.67815'	' 0.0010151'
569	'L_forearm_vol'	'head_Zrotation3'	' 0.50765'	' 0.022315'
570	'L_forearm_sur'	'head_Zrotation3'	' 0.63354'	' 0.0027086'
571	'R_forearm_vol'	'head_Zrotation3'	' 0.45141'	' 0.04573'

572	'body_sur'	'head_Zrotation3'	' 0.50036'	' 0.02465'
573	'torso_vol'	'L_shoulder_Xrotation3'	' 0.46803'	' 0.037421'
574	'torso_sur'	'L_shoulder_Xrotation3'	' 0.49754'	' 0.025604'
575	'hip_vol'	'L_shoulder_Xrotation3'	' 0.4738'	' 0.034831'
576	'hip_sur'	'L_shoulder_Xrotation3'	' 0.47325'	' 0.035069'
577	'noArms_vol'	'L_shoulder_Xrotation3'	' 0.45411'	' 0.044294'
578	'L_arm_sur'	'L_shoulder_Zrotation3'	'-0.61172'	' 0.0041538'
579	'L_shoulder_sur'	'L_shoulder_Zrotation3'	'-0.60299'	' 0.0048878'
580	'L_forearm_vol'	'L_shoulder_Zrotation3'	'-0.52872'	' 0.01654'
581	'L_forearm_sur'	'L_shoulder_Zrotation3'	' -0.5148'	' 0.0202'
582	'R_thigh_sur'	'L_elbow_Xrotation3'	'-0.45488'	' 0.043891'
583	'torso_sur'	'L_elbow_Xrotation3'	' -0.5029'	' 0.023816'
584	'L_forearm_vol'	'L_elbow_Xrotation3'	'-0.53658'	' 0.014722'
585	'R_forearm_sur'	'L_elbow_Xrotation3'	'-0.45198'	' 0.045422'
586	'body_sur'	'L_elbow_Xrotation3'	'-0.48566'	' 0.029944'
587	'hip_vol'	'L_elbow_Xrotation3'	'-0.44935'	' 0.046853'
588	'hip_sur'	'L_elbow_Xrotation3'	'-0.51061'	' 0.021418'
589	'noArms_sur'	'L_elbow_Xrotation3'	'-0.48728'	' 0.029319'
590	'L_shoulder_sur'	'L_elbow_Yrotation3'	'-0.53744'	' 0.014532'
591	'R_shoulder_vol'	'L_forearm_Yrotation3'	' 0.4773'	' 0.033328'
592	'L_arm_sur'	'L_hand_Yrotation3'	'-0.55594'	' 0.010919'
593	'L_shoulder_sur'	'L_hand_Yrotation3'	'-0.51687'	' 0.019617'
594	'L_forearm_sur'	'L_hand_Yrotation3'	'-0.54767'	' 0.012432'
595	'body_sur'	'L_hand_Yrotation3'	'-0.46387'	' 0.039384'
596	'L_arm_vol'	'L_hand_Zrotation3'	' 0.51386'	' 0.020468'
597	'L_shoulder_vol'	'L_hand_Zrotation3'	' 0.48381'	' 0.030667'
598	'left_sur'	'L_hand_Zrotation3'	' 0.4828'	' 0.031069'
599	'right_sur'	'L_hand_Zrotation3'	' 0.49404'	' 0.026825'
600	'torso_vol'	'R_shoulder_Xrotation3'	'-0.50319'	' 0.023721'
601	'torso_sur'	'R_shoulder_Xrotation3'	'-0.53616'	' 0.014814'
602	'body_vol'	'R_shoulder_Xrotation3'	' -0.5001'	' 0.024737'
603	'body_sur'	'R_shoulder_Xrotation3'	'-0.47596'	' 0.033896'
604	'upper_vol'	'R_shoulder_Xrotation3'	'-0.47836'	' 0.032881'
605	'left_vol'	'R_shoulder_Xrotation3'	'-0.49638'	' 0.026005'

606	'right_vol'	'R_shoulder_Xrotation3'	'-0.46413'	' 0.039256'
607	'hip_vol'	'R_shoulder_Xrotation3'	'-0.53335'	' 0.015447'
608	'hip_sur'	'R_shoulder_Xrotation3'	'-0.51738'	' 0.019477'
609	'noArms_vol'	'R_shoulder_Xrotation3'	'-0.53311'	' 0.015504'
610	'noArms_sur'	'R_shoulder_Xrotation3'	'-0.54387'	' 0.013181'
611	'torso_sur'	'R_shoulder_Yrotation3'	' -0.4795'	' 0.032409'
612	'L_arm_vol'	'R_shoulder_Yrotation3'	'-0.51338'	' 0.020606'
613	'L_shoulder_vol'	'R_shoulder_Yrotation3'	'-0.60155'	' 0.0050192'
614	'left_sur'	'R_shoulder_Yrotation3'	'-0.47233'	' 0.035475'
615	'right_vol'	'R_shoulder_Yrotation3'	'-0.46351'	' 0.039555'
616	'right_sur'	'R_shoulder_Yrotation3'	'-0.47997'	' 0.032213'
617	'hip_sur'	'R_shoulder_Yrotation3'	'-0.46918'	' 0.036893'
618	'chest_vol'	'R_shoulder_Yrotation3'	'-0.46211'	' 0.040233'
619	'chest_sur'	'R_shoulder_Zrotation3'	' 0.54199'	' 0.013565'
620	'L_leg_sur'	'R_elbow_Xrotation3'	' 0.59176'	' 0.0059865'
621	'R_leg_vol'	'R_elbow_Xrotation3'	' 0.52798'	' 0.016719'
622	'R_leg_sur'	'R_elbow_Xrotation3'	' 0.56892'	' 0.008849'
623	'L_thigh_sur'	'R_elbow_Xrotation3'	' 0.54788'	' 0.012391'
624	'R_thigh_vol'	'R_elbow_Xrotation3'	' 0.55354'	' 0.011343'
625	'R_thigh_sur'	'R_elbow_Xrotation3'	' 0.55512'	' 0.011063'
626	'L_shin_sur'	'R_elbow_Xrotation3'	' 0.57309'	' 0.0082567'
627	'R_shin_vol'	'R_elbow_Xrotation3'	' 0.51952'	' 0.018893'
628	'R_shin_sur'	'R_elbow_Xrotation3'	' 0.48145'	' 0.03161'
629	'L_arm_sur'	'R_elbow_Xrotation3'	' 0.49375'	' 0.026928'
630	'R_arm_vol'	'R_elbow_Xrotation3'	' 0.46385'	' 0.039391'
631	'R_arm_sur'	'R_elbow_Xrotation3'	' 0.53623'	' 0.014797'
632	'L_shoulder_sur'	'R_elbow_Xrotation3'	' 0.44533'	' 0.049101'
633	'R_shoulder_vol'	'R_elbow_Xrotation3'	' 0.48386'	' 0.030647'
634	'R_shoulder_sur'	'R_elbow_Xrotation3'	' 0.50923'	' 0.021834'
635	'L_forearm_sur'	'R_elbow_Xrotation3'	' 0.53876'	' 0.014246'
636	'R_forearm_sur'	'R_elbow_Xrotation3'	' 0.4643'	' 0.039174'
637	'body_sur'	'R_elbow_Xrotation3'	' 0.45264'	' 0.045069'
638	'lower_vol'	'R_elbow_Xrotation3'	' 0.55146'	' 0.01172'
639	'lower_sur'	'R_elbow_Xrotation3'	' 0.60351'	' 0.0048415'

640	'L_thigh_sur'	'R_elbow_Zrotation3'	' 0.44487'	' 0.049364'
641	'L_arm_vol'	'R_forearm_Xrotation3'	' 0.51272'	' 0.020799'
642	'L_shoulder_vol'	'R_forearm_Xrotation3'	' 0.53196'	' 0.01577'
643	'right_vol'	'R_forearm_Xrotation3'	' 0.53921'	' 0.01415'
644	'right_sur'	'R_forearm_Xrotation3'	' 0.45675'	' 0.042921'
645	'chest_vol'	'R_forearm_Xrotation3'	' 0.45182'	' 0.04551'
646	'L_forearm_vol'	'R_forearm_Zrotation3'	' 0.50202'	' 0.024102'
647	'torso_vol'	'R_hand_Xrotation3'	'-0.47216'	' 0.035552'
648	'torso_sur'	'R_hand_Xrotation3'	' -0.5044'	' 0.023332'
649	'L_arm_vol'	'R_hand_Xrotation3'	'-0.53649'	' 0.014741'
650	'L_arm_sur'	'R_hand_Xrotation3'	'-0.69504'	' 0.00067011'
651	'R_arm_sur'	'R_hand_Xrotation3'	'-0.44879'	' 0.047158'
652	'L_shoulder_vol'	'R_hand_Xrotation3'	'-0.45014'	' 0.046417'
653	'L_shoulder_sur'	'R_hand_Xrotation3'	'-0.68142'	' 0.00093865'
654	'L_forearm_vol'	'R_hand_Xrotation3'	'-0.48298'	' 0.030995'
655	'L_forearm_sur'	'R_hand_Xrotation3'	' -0.6405'	' 0.0023472'
656	'body_vol'	'R_hand_Xrotation3'	'-0.50106'	' 0.024417'
657	'body_sur'	'R_hand_Xrotation3'	'-0.58238'	' 0.0070526'
658	'upper_vol'	'R_hand_Xrotation3'	'-0.48275'	' 0.03109'
659	'upper_sur'	'R_hand_Xrotation3'	'-0.48105'	' 0.031773'
660	'left_vol'	'R_hand_Xrotation3'	'-0.51321'	' 0.020657'
661	'left_sur'	'R_hand_Xrotation3'	'-0.49202'	' 0.027552'
662	'hip_vol'	'R_hand_Xrotation3'	'-0.46077'	' 0.040895'
663	'hip_sur'	'R_hand_Xrotation3'	'-0.48523'	' 0.030107'
664	'chest_vol'	'R_hand_Xrotation3'	'-0.50003'	' 0.02476'
665	'noArms_vol'	'R_hand_Xrotation3'	'-0.47987'	' 0.032258'
666	'noArms_sur'	'R_hand_Xrotation3'	' -0.5287'	' 0.016544'
667	'L_leg_sur'	'R_hand_Yrotation3'	' 0.46866'	' 0.037132'
668	'R_leg_sur'	'R_hand_Yrotation3'	' 0.46781'	' 0.037522'
669	'L_thigh_sur'	'R_hand_Yrotation3'	' 0.5717'	' 0.0084502'
670	'R_thigh_sur'	'R_hand_Yrotation3'	' 0.49088'	' 0.027969'
671	'L_shin_vol'	'R_hand_Yrotation3'	' 0.51315'	' 0.020672'
672	'R_shin_vol'	'R_hand_Yrotation3'	' 0.45087'	' 0.04602'
673	'R_shin_sur'	'R_hand_Yrotation3'	' 0.4943'	' 0.026733'

674	'torso_vol'	'R_hand_Yrotation3'	' 0.75562'	' 0.00011678'
675	'torso_sur'	'R_hand_Yrotation3'	' 0.67909'	' 0.00099263'
676	'L_arm_vol'	'R_hand_Yrotation3'	' 0.66688'	' 0.0013205'
677	'L_shoulder_vol'	'R_hand_Yrotation3'	' 0.71575'	' 0.00038732'
678	'body_vol'	'R_hand_Yrotation3'	' 0.74251'	' 0.0001773'
679	'body_sur'	'R_hand_Yrotation3'	' 0.65942'	' 0.0015624'
680	'upper_vol'	'R_hand_Yrotation3'	' 0.73475'	' 0.00022445'
681	'upper_sur'	'R_hand_Yrotation3'	' 0.56'	' 0.010234'
682	'lower_sur'	'R_hand_Yrotation3'	' 0.4586'	' 0.041979'
683	'left_vol'	'R_hand_Yrotation3'	' 0.69436'	' 0.00068182'
684	'left_sur'	'R_hand_Yrotation3'	' 0.56137'	' 0.010011'
685	'right_vol'	'R_hand_Yrotation3'	' 0.72702'	' 0.00028177'
686	'right_sur'	'R_hand_Yrotation3'	' 0.53427'	' 0.015239'
687	'hip_vol'	'R_hand_Yrotation3'	' 0.73281'	' 0.0002378'
688	'hip_sur'	'R_hand_Yrotation3'	' 0.61594'	' 0.0038336'
689	'chest_vol'	'R_hand_Yrotation3'	' 0.76969'	'7.2442e-005'
690	'chest_sur'	'R_hand_Yrotation3'	' 0.46613'	' 0.038309'
691	'noArms_vol'	'R_hand_Yrotation3'	' 0.74917'	' 0.00014384'
692	'noArms_sur'	'R_hand_Yrotation3'	' 0.68518'	' 0.00085681'
693	'L_shin_vol'	'R_hand_Zrotation3'	'-0.58251'	' 0.0070371'
694	'L_shin_sur'	'R_hand_Zrotation3'	'-0.46601'	' 0.038361'
695	'R_shin_sur'	'R_hand_Zrotation3'	'-0.45072'	' 0.046103'
696	'torso_sur'	'Root_Xposition4'	' 0.45385'	' 0.044432'
697	'upper_sur'	'Root_Xposition4'	' 0.47987'	' 0.032254'
698	'L_thigh_vol'	'Root_Zposition4'	' 0.51963'	' 0.018863'
699	'L_shin_vol'	'Root_Zposition4'	'-0.54659'	' 0.012642'
700	'L_arm_vol'	'Root_Yrotation4'	'-0.45013'	' 0.046425'
701	'L_arm_sur'	'Root_Yrotation4'	'-0.48252'	' 0.03118'
702	'R_arm_vol'	'Root_Yrotation4'	'-0.44931'	' 0.046875'
703	'R_arm_sur'	'Root_Yrotation4'	'-0.52239'	' 0.018132'
704	'R_shoulder_vol'	'Root_Yrotation4'	'-0.46981'	' 0.036608'
705	'R_shoulder_sur'	'Root_Yrotation4'	'-0.46929'	' 0.036845'
706	'L_forearm_sur'	'Root_Yrotation4'	'-0.53246'	' 0.015653'
707	'R_forearm_vol'	'Root_Yrotation4'	'-0.45132'	' 0.045777'

708	'chest_sur'	'Root_Zrotation4'	'-0.71245'	' 0.00042403'
709	'L_arm_sur'	'L_thigh_Xrotation4'	' 0.49525'	' 0.026398'
710	'L_forearm_sur'	'L_thigh_Xrotation4'	' 0.50054'	' 0.024588'
711	'L_arm_vol'	'L_thigh_Yrotation4'	'-0.60377'	' 0.0048184'
712	'L_arm_sur'	'L_thigh_Yrotation4'	'-0.67719'	' 0.0010386'
713	'R_arm_sur'	'L_thigh_Yrotation4'	'-0.46367'	' 0.039477'
714	'L_shoulder_vol'	'L_thigh_Yrotation4'	'-0.51918'	' 0.018985'
715	'L_shoulder_sur'	'L_thigh_Yrotation4'	'-0.64965'	' 0.0019343'
716	'L_forearm_vol'	'L_thigh_Yrotation4'	'-0.46149'	' 0.040539'
717	'L_forearm_sur'	'L_thigh_Yrotation4'	'-0.61848'	' 0.0036509'
718	'R_forearm_vol'	'L_thigh_Yrotation4'	' -0.4736'	' 0.034918'
719	'R_forearm_sur'	'L_thigh_Yrotation4'	'-0.45094'	' 0.045986'
720	'body_sur'	'L_thigh_Yrotation4'	'-0.48449'	' 0.030399'
721	'L_leg_sur'	'L_thigh_Zrotation4'	' 0.46103'	' 0.040764'
722	'R_leg_vol'	'L_thigh_Zrotation4'	' 0.55601'	' 0.010907'
723	'R_leg_sur'	'L_thigh_Zrotation4'	' 0.52335'	' 0.017882'
724	'L_thigh_vol'	'L_thigh_Zrotation4'	' 0.47998'	' 0.032209'
725	'L_thigh_sur'	'L_thigh_Zrotation4'	' 0.54583'	' 0.01279'
726	'R_thigh_vol'	'L_thigh_Zrotation4'	' 0.57762'	' 0.00765'
727	'R_thigh_sur'	'L_thigh_Zrotation4'	' 0.55938'	' 0.010336'
728	'R_shin_vol'	'L_thigh_Zrotation4'	' 0.53154'	' 0.015868'
729	'L_arm_sur'	'L_thigh_Zrotation4'	' 0.67409'	' 0.0011174'
730	'R_arm_vol'	'L_thigh_Zrotation4'	' 0.54109'	' 0.013752'
731	'R_arm_sur'	'L_thigh_Zrotation4'	' 0.56362'	' 0.0096518'
732	'L_shoulder_sur'	'L_thigh_Zrotation4'	' 0.60225'	' 0.0049547'
733	'R_shoulder_vol'	'L_thigh_Zrotation4'	' 0.52081'	' 0.018548'
734	'R_shoulder_sur'	'L_thigh_Zrotation4'	' 0.50856'	' 0.022036'
735	'L_forearm_vol'	'L_thigh_Zrotation4'	' 0.54105'	' 0.013762'
736	'L_forearm_sur'	'L_thigh_Zrotation4'	' 0.6946'	' 0.00067759'
737	'body_vol'	'L_thigh_Zrotation4'	' 0.44425'	' 0.049717'
738	'body_sur'	'L_thigh_Zrotation4'	' 0.54975'	' 0.012037'
739	'lower_vol'	'L_thigh_Zrotation4'	' 0.51999'	' 0.018767'
740	'lower_sur'	'L_thigh_Zrotation4'	' 0.52076'	' 0.018561'
741	'left_vol'	'L_thigh_Zrotation4'	' 0.44858'	' 0.047279'

742	'noArms_sur'	'L_thigh_Zrotation4'	' 0.47611'	' 0.03383'
743	'torso_vol'	'L_knee_Xrotation4'	'-0.50599'	' 0.02283'
744	'torso_sur'	'L_knee_Xrotation4'	'-0.44701'	' 0.04815'
745	'L_arm_vol'	'L_knee_Xrotation4'	'-0.49674'	' 0.025877'
746	'L_shoulder_vol'	'L_knee_Xrotation4'	'-0.45865'	' 0.041951'
747	'body_vol'	'L_knee_Xrotation4'	'-0.47719'	' 0.033373'
748	'upper_vol'	'L_knee_Xrotation4'	'-0.53565'	' 0.014928'
749	'upper_sur'	'L_knee_Xrotation4'	'-0.56485'	' 0.0094606'
750	'left_vol'	'L_knee_Xrotation4'	'-0.50591'	' 0.022856'
751	'left_sur'	'L_knee_Xrotation4'	'-0.44768'	' 0.047774'
752	'right_vol'	'L_knee_Xrotation4'	'-0.57969'	' 0.0073853'
753	'right_sur'	'L_knee_Xrotation4'	'-0.50586'	' 0.022871'
754	'hip_vol'	'L_knee_Xrotation4'	'-0.46362'	' 0.039504'
755	'hip_sur'	'L_knee_Xrotation4'	'-0.47244'	' 0.035425'
756	'chest_vol'	'L_knee_Xrotation4'	'-0.49354'	' 0.027003'
757	'noArms_vol'	'L_knee_Xrotation4'	'-0.47656'	' 0.033642'
758	'torso_sur'	'L_foot_Yrotation4'	' 0.49676'	' 0.025871'
759	'body_vol'	'L_foot_Yrotation4'	' 0.44607'	' 0.048681'
760	'body_sur'	'L_foot_Yrotation4'	' 0.46927'	' 0.036854'
761	'hip_vol'	'L_foot_Yrotation4'	' 0.44941'	' 0.046817'
762	'hip_sur'	'L_foot_Yrotation4'	' 0.47798'	' 0.03304'
763	'noArms_vol'	'L_foot_Yrotation4'	' 0.45206'	' 0.045384'
764	'noArms_sur'	'L_foot_Yrotation4'	' 0.44794'	' 0.047631'
765	'L_shin_vol'	'L_foot_Zrotation4'	'-0.51547'	' 0.02001'
766	'L_shin_sur'	'L_foot_Zrotation4'	'-0.49654'	' 0.025946'
767	'R_forearm_vol'	'L_foot_Zrotation4'	'-0.55374'	' 0.011307'
768	'R_forearm_sur'	'L_foot_Zrotation4'	'-0.49291'	' 0.027229'
769	'L_leg_sur'	'R_thigh_Zrotation4'	' 0.44694'	' 0.048192'
770	'R_leg_vol'	'R_thigh_Zrotation4'	' 0.50446'	' 0.023315'
771	'L_thigh_sur'	'R_thigh_Zrotation4'	' 0.50249'	' 0.023947'
772	'R_thigh_vol'	'R_thigh_Zrotation4'	' 0.50794'	' 0.022227'
773	'R_shin_vol'	'R_thigh_Zrotation4'	' 0.50913'	' 0.021864'
774	'torso_vol'	'R_thigh_Zrotation4'	' 0.58522'	' 0.006715'
775	'torso_sur'	'R_thigh_Zrotation4'	' 0.55331'	' 0.011384'

776	'L_arm_vol'	'R_thigh_Zrotation4'	' 0.65765'	' 0.0016246'
777	'L_arm_sur'	'R_thigh_Zrotation4'	' 0.62634'	' 0.0031296'
778	'R_arm_sur'	'R_thigh_Zrotation4'	' 0.50436'	' 0.023346'
779	'L_shoulder_vol'	'R_thigh_Zrotation4'	' 0.55035'	' 0.011924'
780	'L_shoulder_sur'	'R_thigh_Zrotation4'	' 0.52969'	' 0.016305'
781	'L_forearm_vol'	'R_thigh_Zrotation4'	' 0.6182'	' 0.0036703'
782	'L_forearm_sur'	'R_thigh_Zrotation4'	' 0.68081'	' 0.00095264'
783	'R_forearm_vol'	'R_thigh_Zrotation4'	' 0.50135'	' 0.024323'
784	'body_vol'	'R_thigh_Zrotation4'	' 0.63293'	' 0.0027421'
785	'body_sur'	'R_thigh_Zrotation4'	' 0.62486'	' 0.0032228'
786	'upper_vol'	'R_thigh_Zrotation4'	' 0.61064'	' 0.0042398'
787	'upper_sur'	'R_thigh_Zrotation4'	' 0.60421'	' 0.0047797'
788	'lower_vol'	'R_thigh_Zrotation4'	' 0.45536'	' 0.04364'
789	'left_vol'	'R_thigh_Zrotation4'	' 0.59732'	' 0.0054194'
790	'left_sur'	'R_thigh_Zrotation4'	' 0.508'	' 0.022208'
791	'right_vol'	'R_thigh_Zrotation4'	' 0.59694'	' 0.0054574'
792	'right_sur'	'R_thigh_Zrotation4'	' 0.46905'	' 0.036954'
793	'hip_vol'	'R_thigh_Zrotation4'	' 0.6468'	' 0.0020559'
794	'hip_sur'	'R_thigh_Zrotation4'	' 0.59095'	' 0.0060735'
795	'chest_vol'	'R_thigh_Zrotation4'	' 0.5433'	' 0.013296'
796	'noArms_vol'	'R_thigh_Zrotation4'	' 0.60977'	' 0.0043094'
797	'noArms_sur'	'R_thigh_Zrotation4'	' 0.57603'	' 0.0078596'
798	'L_leg_vol'	'R_foot_Xrotation4'	'-0.49612'	' 0.026094'
799	'lower_vol'	'R_foot_Xrotation4'	'-0.46885'	' 0.037042'
800	'L_thigh_vol'	'R_toe_Xrotation4'	' 0.51786'	' 0.019344'
801	'L_shoulder_vol'	'Spine_0_Xrotation4'	' 0.45379'	' 0.044461'
802	'L_arm_vol'	'Spine_0_Zrotation4'	'-0.54266'	' 0.013427'
803	'L_arm_sur'	'Spine_0_Zrotation4'	'-0.67638'	' 0.0010588'
804	'R_arm_vol'	'Spine_0_Zrotation4'	'-0.46346'	' 0.039581'
805	'R_arm_sur'	'Spine_0_Zrotation4'	'-0.54825'	' 0.01232'
806	'L_shoulder_sur'	'Spine_0_Zrotation4'	'-0.59343'	' 0.0058118'
807	'L_forearm_vol'	'Spine_0_Zrotation4'	'-0.54371'	' 0.013214'
808	'L_forearm_sur'	'Spine_0_Zrotation4'	'-0.70183'	' 0.00056266'
809	'R_forearm_vol'	'Spine_0_Zrotation4'	'-0.59068'	' 0.0061019'

810	'R_forearm_sur'	'Spine_0_Zrotation4'	'-0.54929'	' 0.012123'
811	'body_sur'	'Spine_0_Zrotation4'	'-0.52121'	' 0.018442'
812	'left_vol'	'Spine_0_Zrotation4'	'-0.47434'	' 0.034593'
813	'left_sur'	'Spine_0_Zrotation4'	' -0.538'	' 0.014411'
814	'right_sur'	'Spine_0_Zrotation4'	'-0.46027'	' 0.041142'
815	'hip_sur'	'Spine_0_Zrotation4'	'-0.48008'	' 0.032171'
816	'L_arm_vol'	'Spine_1_Xrotation4'	' 0.64773'	' 0.0020155'
817	'L_arm_sur'	'Spine_1_Xrotation4'	' 0.46465'	' 0.03901'
818	'L_shoulder_vol'	'Spine_1_Xrotation4'	' 0.48231'	' 0.031266'
819	'L_forearm_vol'	'Spine_1_Xrotation4'	' 0.45591'	' 0.043351'
820	'L_forearm_sur'	'Spine_1_Xrotation4'	' 0.45996'	' 0.041297'
821	'upper_sur'	'Spine_1_Xrotation4'	' 0.44682'	' 0.048257'
822	'chest_vol'	'Spine_1_Xrotation4'	' 0.44388'	' 0.049934'
823	'L_arm_sur'	'Spine_1_Yrotation4'	' -0.6158'	' 0.0038442'
824	'L_shoulder_sur'	'Spine_1_Yrotation4'	'-0.58919'	' 0.0062642'
825	'L_forearm_vol'	'Spine_1_Yrotation4'	'-0.47798'	' 0.033041'
826	'L_forearm_sur'	'Spine_1_Yrotation4'	'-0.56015'	' 0.010209'
827	'L_arm_vol'	'neck_Xrotation4'	' 0.56429'	' 0.0095483'
828	'L_arm_sur'	'neck_Xrotation4'	' 0.69614'	' 0.00065162'
829	'R_arm_sur'	'neck_Xrotation4'	' 0.4732'	' 0.035092'
830	'L_shoulder_sur'	'neck_Xrotation4'	' 0.6696'	' 0.0012405'
831	'L_forearm_vol'	'neck_Xrotation4'	' 0.50557'	' 0.022962'
832	'L_forearm_sur'	'neck_Xrotation4'	' 0.62989'	' 0.0029155'
833	'R_forearm_vol'	'neck_Xrotation4'	' 0.45015'	' 0.046415'
834	'body_sur'	'neck_Xrotation4'	' 0.49938'	' 0.024976'
835	'L_arm_vol'	'neck_Yrotation4'	' 0.46707'	' 0.037869'
836	'L_arm_sur'	'neck_Yrotation4'	' 0.61396'	' 0.0039811'
837	'L_shoulder_sur'	'neck_Yrotation4'	' 0.58333'	' 0.0069384'
838	'L_forearm_vol'	'neck_Yrotation4'	' 0.44525'	' 0.049147'
839	'L_forearm_sur'	'neck_Yrotation4'	' 0.5746'	' 0.0080503'
840	'L_arm_sur'	'neck_Zrotation4'	' 0.4655'	' 0.038604'
841	'L_forearm_sur'	'neck_Zrotation4'	' 0.58724'	' 0.006482'
842	'R_forearm_vol'	'neck_Zrotation4'	' 0.44564'	' 0.048923'
843	'left_sur'	'neck_Zrotation4'	' 0.46107'	' 0.040746'

844	'L_arm_sur'	'head_Xrotation4'	'-0.53703'	' 0.014623'
845	'R_arm_sur'	'head_Xrotation4'	'-0.46461'	' 0.039028'
846	'L_shoulder_sur'	'head_Xrotation4'	'-0.48037'	' 0.032052'
847	'L_forearm_vol'	'head_Xrotation4'	'-0.46226'	' 0.040162'
848	'L_forearm_sur'	'head_Xrotation4'	'-0.56295'	' 0.0097574'
849	'R_forearm_vol'	'head_Xrotation4'	'-0.46602'	' 0.038357'
850	'R_forearm_sur'	'head_Xrotation4'	'-0.46998'	' 0.036529'
851	'L_arm_vol'	'head_Yrotation4'	' 0.5941'	' 0.0057423'
852	'L_arm_sur'	'head_Yrotation4'	' 0.68819'	' 0.00079563'
853	'R_arm_sur'	'head_Yrotation4'	' 0.48622'	' 0.029724'
854	'L_shoulder_sur'	'head_Yrotation4'	' 0.66815'	' 0.0012825'
855	'L_forearm_vol'	'head_Yrotation4'	' 0.48679'	' 0.029506'
856	'L_forearm_sur'	'head_Yrotation4'	' 0.61088'	' 0.0042202'
857	'R_forearm_vol'	'head_Yrotation4'	' 0.46808'	' 0.037398'
858	'R_forearm_sur'	'head_Yrotation4'	' 0.45326'	' 0.044743'
859	'body_sur'	'head_Yrotation4'	' 0.49394'	' 0.026861'
860	'L_arm_vol'	'head_Zrotation4'	' 0.57027'	' 0.008654'
861	'L_arm_sur'	'head_Zrotation4'	' 0.6992'	' 0.00060245'
862	'R_arm_sur'	'head_Zrotation4'	' 0.47341'	' 0.035002'
863	'L_shoulder_sur'	'head_Zrotation4'	' 0.67215'	' 0.0011691'
864	'L_forearm_vol'	'head_Zrotation4'	' 0.50966'	' 0.021705'
865	'L_forearm_sur'	'head_Zrotation4'	' 0.63251'	' 0.0027655'
866	'R_forearm_vol'	'head_Zrotation4'	' 0.44417'	' 0.049765'
867	'body_sur'	'head_Zrotation4'	' 0.49348'	' 0.027024'
868	'R_shoulder_vol'	'L_shoulder_Xrotation4'	'-0.44578'	' 0.048847'
869	'R_shoulder_sur'	'L_shoulder_Xrotation4'	' -0.4531'	' 0.044828'
870	'R_leg_sur'	'L_elbow_Xrotation4'	' -0.4929'	' 0.027235'
871	'R_thigh_vol'	'L_elbow_Xrotation4'	'-0.45497'	' 0.043841'
872	'R_thigh_sur'	'L_elbow_Xrotation4'	'-0.50091'	' 0.024469'
873	'torso_vol'	'L_elbow_Xrotation4'	'-0.47541'	' 0.03413'
874	'torso_sur'	'L_elbow_Xrotation4'	'-0.50342'	' 0.023648'
875	'L_forearm_vol'	'L_elbow_Xrotation4'	'-0.64244'	' 0.0022541'
876	'L_forearm_sur'	'L_elbow_Xrotation4'	' -0.506'	' 0.022828'
877	'body_vol'	'L_elbow_Xrotation4'	'-0.50199'	' 0.024111'

878	'body_sur'	'L_elbow_Xrotation4'	'-0.52198'	' 0.01824'
879	'upper_vol'	'L_elbow_Xrotation4'	'-0.47655'	' 0.033643'
880	'left_vol'	'L_elbow_Xrotation4'	' -0.5335'	' 0.015413'
881	'left_sur'	'L_elbow_Xrotation4'	'-0.59844'	' 0.0053111'
882	'right_vol'	'L_elbow_Xrotation4'	'-0.60166'	' 0.0050086'
883	'right_sur'	'L_elbow_Xrotation4'	'-0.61824'	' 0.0036679'
884	'hip_vol'	'L_elbow_Xrotation4'	'-0.48278'	' 0.031076'
885	'hip_sur'	'L_elbow_Xrotation4'	'-0.52516'	' 0.017422'
886	'noArms_vol'	'L_elbow_Xrotation4'	'-0.49228'	' 0.027456'
887	'noArms_sur'	'L_elbow_Xrotation4'	'-0.51604'	' 0.019849'
888	'L_shoulder_sur'	'L_elbow_Yrotation4'	'-0.48266'	' 0.031124'
889	'torso_vol'	'R_shoulder_Xrotation4'	'-0.50823'	' 0.022137'
890	'torso_sur'	'R_shoulder_Xrotation4'	'-0.53807'	' 0.014396'
891	'body_vol'	'R_shoulder_Xrotation4'	'-0.50392'	' 0.023486'
892	'body_sur'	'R_shoulder_Xrotation4'	'-0.47579'	' 0.03397'
893	'upper_vol'	'R_shoulder_Xrotation4'	'-0.48339'	' 0.030834'
894	'left_vol'	'R_shoulder_Xrotation4'	'-0.50037'	' 0.024646'
895	'right_vol'	'R_shoulder_Xrotation4'	'-0.46716'	' 0.037826'
896	'hip_vol'	'R_shoulder_Xrotation4'	'-0.53953'	' 0.014082'
897	'hip_sur'	'R_shoulder_Xrotation4'	'-0.52242'	' 0.018124'
898	'noArms_vol'	'R_shoulder_Xrotation4'	' -0.5365'	' 0.014738'
899	'noArms_sur'	'R_shoulder_Xrotation4'	'-0.54253'	' 0.013454'
900	'R_shin_sur'	'R_shoulder_Yrotation4'	'-0.47516'	' 0.034238'
901	'L_leg_vol'	'R_elbow_Xrotation4'	' 0.57636'	' 0.0078148'
902	'L_leg_sur'	'R_elbow_Xrotation4'	' 0.52313'	' 0.017939'
903	'R_leg_vol'	'R_elbow_Xrotation4'	' 0.45335'	' 0.044695'
904	'L_thigh_vol'	'R_elbow_Xrotation4'	' 0.52127'	' 0.018427'
905	'L_thigh_sur'	'R_elbow_Xrotation4'	' 0.50405'	' 0.023445'
906	'L_shin_sur'	'R_elbow_Xrotation4'	' 0.49824'	' 0.025363'
907	'R_shin_vol'	'R_elbow_Xrotation4'	' 0.49351'	' 0.027015'
908	'R_arm_vol'	'R_elbow_Xrotation4'	' 0.51609'	' 0.019837'
909	'R_arm_sur'	'R_elbow_Xrotation4'	' 0.48702'	' 0.029419'
910	'R_shoulder_vol'	'R_elbow_Xrotation4'	' 0.4957'	' 0.026239'
911	'R_shoulder_sur'	'R_elbow_Xrotation4'	' 0.48653'	' 0.029606'

912	'lower_vol'	'R_elbow_Xrotation4'	' 0.57057'	' 0.0086105'
913	'lower_sur'	'R_elbow_Xrotation4'	' 0.49246'	' 0.027392'
914	'L_thigh_sur'	'R_elbow_Zrotation4'	' 0.45941'	' 0.04157'
915	'L_forearm_vol'	'R_forearm_Zrotation4'	' 0.44968'	' 0.046671'
916	'torso_vol'	'R_hand_Xrotation4'	'-0.44628'	' 0.048565'
917	'torso_sur'	'R_hand_Xrotation4'	'-0.49576'	' 0.026218'
918	'L_arm_vol'	'R_hand_Xrotation4'	'-0.55731'	' 0.010684'
919	'L_arm_sur'	'R_hand_Xrotation4'	'-0.73723'	' 0.00020833'
920	'R_arm_sur'	'R_hand_Xrotation4'	'-0.47235'	' 0.035466'
921	'L_shoulder_vol'	'R_hand_Xrotation4'	'-0.45933'	' 0.041612'
922	'L_shoulder_sur'	'R_hand_Xrotation4'	'-0.72705'	' 0.00028147'
923	'L_forearm_vol'	'R_hand_Xrotation4'	'-0.50273'	' 0.02387'
924	'L_forearm_sur'	'R_hand_Xrotation4'	' -0.653'	' 0.0017993'
925	'body_vol'	'R_hand_Xrotation4'	'-0.48726'	' 0.029328'
926	'body_sur'	'R_hand_Xrotation4'	'-0.59413'	' 0.0057395'
927	'upper_vol'	'R_hand_Xrotation4'	'-0.46347'	' 0.039575'
928	'upper_sur'	'R_hand_Xrotation4'	'-0.47903'	' 0.032604'
929	'left_vol'	'R_hand_Xrotation4'	'-0.50272'	' 0.023872'
930	'left_sur'	'R_hand_Xrotation4'	'-0.50969'	' 0.021695'
931	'hip_sur'	'R_hand_Xrotation4'	'-0.47645'	' 0.033687'
932	'chest_vol'	'R_hand_Xrotation4'	'-0.47324'	' 0.035075'
933	'noArms_vol'	'R_hand_Xrotation4'	' -0.4612'	' 0.040679'
934	'noArms_sur'	'R_hand_Xrotation4'	'-0.53437'	' 0.015215'
935	'torso_vol'	'R_hand_Yrotation4'	' 0.6701'	' 0.0012263'
936	'torso_sur'	'R_hand_Yrotation4'	' 0.55991'	' 0.010249'
937	'L_arm_vol'	'R_hand_Yrotation4'	' 0.5765'	' 0.0077971'
938	'L_shoulder_vol'	'R_hand_Yrotation4'	' 0.65014'	' 0.0019141'
939	'body_vol'	'R_hand_Yrotation4'	' 0.64503'	' 0.0021345'
940	'body_sur'	'R_hand_Yrotation4'	' 0.52268'	' 0.018057'
941	'upper_vol'	'R_hand_Yrotation4'	' 0.65787'	' 0.001617'
942	'upper_sur'	'R_hand_Yrotation4'	' 0.47478'	' 0.034402'
943	'left_vol'	'R_hand_Yrotation4'	' 0.59668'	' 0.005483'
944	'left_sur'	'R_hand_Yrotation4'	' 0.46124'	' 0.040662'
945	'right_vol'	'R_hand_Yrotation4'	' 0.65442'	' 0.0017442'

946	'hip_vol'	'R_hand_Yrotation4'	' 0.68417'	' 0.00087805'
947	'hip_sur'	'R_hand_Yrotation4'	' 0.56326'	' 0.0097092'
948	'chest_vol'	'R_hand_Yrotation4'	' 0.65327'	' 0.0017886'
949	'noArms_vol'	'R_hand_Yrotation4'	' 0.64366'	' 0.0021968'
950	'noArms_sur'	'R_hand_Yrotation4'	' 0.5257'	' 0.017285'
951	'L_shin_vol'	'R_hand_Zrotation4'	'-0.49858'	' 0.025249'
952	'L_shin_sur'	'R_hand_Zrotation4'	' -0.4616'	' 0.040485'
953	'torso_sur'	'Root_Xposition5'	' 0.47494'	' 0.034333'
954	'upper_sur'	'Root_Xposition5'	' 0.49971'	' 0.024866'
955	'L_arm_sur'	'Root_Yrotation5'	' -0.447'	' 0.048156'
956	'R_arm_sur'	'Root_Yrotation5'	' -0.546'	' 0.012757'
957	'R_shoulder_vol'	'Root_Yrotation5'	'-0.46297'	' 0.039818'
958	'R_shoulder_sur'	'Root_Yrotation5'	'-0.45592'	' 0.04335'
959	'L_forearm_sur'	'Root_Yrotation5'	' -0.5049'	' 0.023175'
960	'R_forearm_vol'	'Root_Yrotation5'	'-0.51093'	' 0.021324'
961	'R_forearm_sur'	'Root_Yrotation5'	'-0.47479'	' 0.0344'
962	'chest_sur'	'Root_Zrotation5'	'-0.75999'	' 0.00010102'
963	'L_arm_sur'	'L_thigh_Xrotation5'	' 0.53675'	' 0.014684'
964	'L_shoulder_sur'	'L_thigh_Xrotation5'	' 0.48353'	' 0.030777'
965	'L_forearm_sur'	'L_thigh_Xrotation5'	' 0.52058'	' 0.018609'
966	'L_leg_sur'	'L_thigh_Yrotation5'	'-0.44993'	' 0.046535'
967	'L_shin_sur'	'L_thigh_Yrotation5'	'-0.45525'	' 0.043698'
968	'L_arm_vol'	'L_thigh_Yrotation5'	'-0.60076'	' 0.0050921'
969	'L_arm_sur'	'L_thigh_Yrotation5'	'-0.72168'	' 0.0003282'
970	'R_arm_vol'	'L_thigh_Yrotation5'	'-0.55864'	' 0.010459'
971	'R_arm_sur'	'L_thigh_Yrotation5'	'-0.64222'	' 0.0022644'
972	'L_shoulder_vol'	'L_thigh_Yrotation5'	' -0.4811'	' 0.031751'
973	'L_shoulder_sur'	'L_thigh_Yrotation5'	'-0.68707'	' 0.00081788'
974	'R_shoulder_vol'	'L_thigh_Yrotation5'	'-0.56345'	' 0.0096797'
975	'R_shoulder_sur'	'L_thigh_Yrotation5'	'-0.61019'	' 0.0042755'
976	'L_forearm_vol'	'L_thigh_Yrotation5'	'-0.52904'	' 0.016463'
977	'L_forearm_sur'	'L_thigh_Yrotation5'	'-0.70516'	' 0.00051557'
978	'R_forearm_vol'	'L_thigh_Yrotation5'	'-0.57211'	' 0.0083936'
979	'R_forearm_sur'	'L_thigh_Yrotation5'	'-0.57969'	' 0.0073851'

980	'body_sur'	'L_thigh_Yrotation5'	'-0.53959'	' 0.014068'
981	'lower_sur'	'L_thigh_Yrotation5'	'-0.45275'	' 0.045014'
982	'left_vol'	'L_thigh_Yrotation5'	'-0.45329'	' 0.044728'
983	'left_sur'	'L_thigh_Yrotation5'	'-0.49219'	' 0.027491'
984	'L_leg_sur'	'L_thigh_Zrotation5'	' 0.46645'	' 0.038157'
985	'R_leg_sur'	'L_thigh_Zrotation5'	' 0.48373'	' 0.030699'
986	'L_shin_sur'	'L_thigh_Zrotation5'	' 0.61806'	' 0.0036804'
987	'R_shin_vol'	'L_thigh_Zrotation5'	' 0.54721'	' 0.012521'
988	'R_shin_sur'	'L_thigh_Zrotation5'	' 0.56603'	' 0.00928'
989	'lower_sur'	'L_thigh_Zrotation5'	' 0.51483'	' 0.02019'
990	'R_arm_vol'	'L_foot_Zrotation5'	'-0.48734'	' 0.029296'
991	'R_forearm_vol'	'L_foot_Zrotation5'	'-0.60701'	' 0.0045378'
992	'R_forearm_sur'	'L_foot_Zrotation5'	'-0.56994'	' 0.008702'
993	'upper_sur'	'R_thigh_Xrotation5'	' -0.5611'	' 0.010055'
994	'torso_vol'	'R_thigh_Zrotation5'	' 0.4719'	' 0.035668'
995	'L_arm_vol'	'R_thigh_Zrotation5'	' 0.46775'	' 0.037553'
996	'L_shoulder_vol'	'R_thigh_Zrotation5'	' 0.55134'	' 0.011742'
997	'body_vol'	'R_thigh_Zrotation5'	' 0.45002'	' 0.046484'
998	'upper_vol'	'R_thigh_Zrotation5'	' 0.45836'	' 0.042098'
999	'right_vol'	'R_thigh_Zrotation5'	' 0.47544'	' 0.034119'
1000	'hip_vol'	'R_thigh_Zrotation5'	' 0.4493'	' 0.046882'
1001	'chest_vol'	'R_thigh_Zrotation5'	' 0.52061'	' 0.018602'
1002	'chest_sur'	'R_thigh_Zrotation5'	' 0.4451'	' 0.049234'
1003	'noArms_vol'	'R_thigh_Zrotation5'	' 0.46496'	' 0.038859'
1004	'L_leg_vol'	'R_knee_Xrotation5'	'-0.47855'	' 0.032804'
1005	'L_leg_sur'	'R_knee_Xrotation5'	'-0.44907'	' 0.047006'
1006	'chest_sur'	'R_foot_Yrotation5'	'-0.60936'	' 0.0043433'
1007	'chest_sur'	'R_toe_Xrotation5'	'-0.47754'	' 0.033226'
1008	'chest_sur'	'Spine_0_Xrotation5'	' 0.46924'	' 0.036868'
1009	'L_arm_vol'	'Spine_0_Yrotation5'	' 0.47607'	' 0.03385'
1010	'L_arm_sur'	'Spine_0_Yrotation5'	' 0.44929'	' 0.046888'
1011	'L_shoulder_vol'	'Spine_0_Yrotation5'	' 0.52264'	' 0.018067'
1012	'L_arm_vol'	'Spine_0_Zrotation5'	'-0.50435'	' 0.023349'
1013	'L_arm_sur'	'Spine_0_Zrotation5'	'-0.64774'	' 0.0020149'

1014	'R_arm_sur'	'Spine_0_Zrotation5'	'-0.51088'	' 0.021339'
1015	'L_shoulder_sur'	'Spine_0_Zrotation5'	' -0.6091'	' 0.0043641'
1016	'L_forearm_vol'	'Spine_0_Zrotation5'	' -0.4568'	' 0.042895'
1017	'L_forearm_sur'	'Spine_0_Zrotation5'	'-0.61901'	' 0.0036137'
1018	'R_forearm_vol'	'Spine_0_Zrotation5'	'-0.53812'	' 0.014383'
1019	'R_forearm_sur'	'Spine_0_Zrotation5'	'-0.51901'	' 0.019031'
1020	'body_sur'	'Spine_0_Zrotation5'	'-0.48053'	' 0.031986'
1021	'L_arm_vol'	'Spine_1_Xrotation5'	' 0.53254'	' 0.015636'
1022	'L_shoulder_vol'	'Spine_1_Xrotation5'	' 0.45658'	' 0.043009'
1023	'L_arm_sur'	'Spine_1_Yrotation5'	'-0.53218'	' 0.015717'
1024	'L_shoulder_sur'	'Spine_1_Yrotation5'	'-0.50246'	' 0.023957'
1025	'L_forearm_sur'	'Spine_1_Yrotation5'	'-0.47501'	' 0.034304'
1026	'R_forearm_vol'	'Spine_1_Zrotation5'	'-0.57166'	' 0.0084571'
1027	'R_forearm_sur'	'Spine_1_Zrotation5'	'-0.44516'	' 0.049199'
1028	'left_sur'	'Spine_1_Zrotation5'	'-0.48934'	' 0.02854'
1029	'right_sur'	'Spine_1_Zrotation5'	'-0.53323'	' 0.015475'
1030	'L_arm_vol'	'neck_Xrotation5'	' 0.5643'	' 0.0095462'
1031	'L_arm_sur'	'neck_Xrotation5'	' 0.69544'	' 0.00066328'
1032	'R_arm_sur'	'neck_Xrotation5'	' 0.47218'	' 0.035544'
1033	'L_shoulder_sur'	'neck_Xrotation5'	' 0.66991'	' 0.0012315'
1034	'L_forearm_vol'	'neck_Xrotation5'	' 0.50356'	' 0.023602'
1035	'L_forearm_sur'	'neck_Xrotation5'	' 0.62867'	' 0.0029882'
1036	'R_forearm_vol'	'neck_Xrotation5'	' 0.45004'	' 0.046474'
1037	'body_sur'	'neck_Xrotation5'	' 0.50291'	' 0.023811'
1038	'L_arm_vol'	'neck_Yrotation5'	' 0.50582'	' 0.022884'
1039	'L_arm_sur'	'neck_Yrotation5'	' 0.65565'	' 0.001698'
1040	'R_arm_sur'	'neck_Yrotation5'	' 0.46384'	' 0.039398'
1041	'L_shoulder_sur'	'neck_Yrotation5'	' 0.62772'	' 0.0030449'
1042	'L_forearm_vol'	'neck_Yrotation5'	' 0.51481'	' 0.020197'
1043	'L_forearm_sur'	'neck_Yrotation5'	' 0.62707'	' 0.003085'
1044	'body_sur'	'neck_Yrotation5'	' 0.48103'	' 0.031782'
1045	'L_arm_vol'	'neck_Zrotation5'	' 0.58675'	' 0.0065387'
1046	'L_arm_sur'	'neck_Zrotation5'	' 0.72593'	' 0.00029077'
1047	'R_arm_sur'	'neck_Zrotation5'	' 0.48967'	' 0.028418'

1048	'L_shoulder_vol'	'neck_Zrotation5'	' 0.44514'	' 0.049209'
1049	'L_shoulder_sur'	'neck_Zrotation5'	' 0.68711'	' 0.00081701'
1050	'L_forearm_vol'	'neck_Zrotation5'	' 0.54097'	' 0.013777'
1051	'L_forearm_sur'	'neck_Zrotation5'	' 0.6608'	' 0.0015149'
1052	'R_forearm_vol'	'neck_Zrotation5'	' 0.44601'	' 0.048716'
1053	'body_sur'	'neck_Zrotation5'	' 0.51841'	' 0.019194'
1054	'upper_sur'	'neck_Zrotation5'	' 0.44715'	' 0.048073'
1055	'left_sur'	'neck_Zrotation5'	' 0.4484'	' 0.047378'
1056	'L_leg_sur'	'head_Xrotation5'	'-0.49599'	' 0.026139'
1057	'L_thigh_sur'	'head_Xrotation5'	'-0.49394'	' 0.026861'
1058	'L_arm_vol'	'head_Xrotation5'	'-0.48651'	' 0.029615'
1059	'L_arm_sur'	'head_Xrotation5'	'-0.56359'	' 0.0096565'
1060	'L_shoulder_sur'	'head_Xrotation5'	' -0.5693'	' 0.0087946'
1061	'L_forearm_sur'	'head_Xrotation5'	'-0.48118'	' 0.031721'
1062	'L_arm_vol'	'head_Yrotation5'	' 0.59186'	' 0.0059759'
1063	'L_arm_sur'	'head_Yrotation5'	' 0.68619'	' 0.00083585'
1064	'R_arm_sur'	'head_Yrotation5'	' 0.5029'	' 0.023815'
1065	'L_shoulder_sur'	'head_Yrotation5'	' 0.67017'	' 0.0012243'
1066	'L_forearm_vol'	'head_Yrotation5'	' 0.46693'	' 0.037932'
1067	'L_forearm_sur'	'head_Yrotation5'	' 0.59409'	' 0.005743'
1068	'R_forearm_vol'	'head_Yrotation5'	' 0.47268'	' 0.035321'
1069	'R_forearm_sur'	'head_Yrotation5'	' 0.46062'	' 0.040965'
1070	'body_sur'	'head_Yrotation5'	' 0.50502'	' 0.023135'
1071	'L_arm_vol'	'head_Zrotation5'	' 0.56866'	' 0.008888'
1072	'L_arm_sur'	'head_Zrotation5'	' 0.70284'	' 0.00054804'
1073	'R_arm_sur'	'head_Zrotation5'	' 0.47672'	' 0.033573'
1074	'L_shoulder_sur'	'head_Zrotation5'	' 0.6761'	' 0.0010657'
1075	'L_forearm_vol'	'head_Zrotation5'	' 0.5133'	' 0.020629'
1076	'L_forearm_sur'	'head_Zrotation5'	' 0.63613'	' 0.0025688'
1077	'R_forearm_vol'	'head_Zrotation5'	' 0.44583'	' 0.048815'
1078	'body_sur'	'head_Zrotation5'	' 0.49872'	' 0.025199'
1079	'right_sur'	'L_shoulder_Yrotation5'	'-0.45729'	' 0.042641'
1080	'L_leg_sur'	'L_shoulder_Zrotation5'	' -0.4699'	' 0.036565'
1081	'R_forearm_sur'	'L_shoulder_Zrotation5'	'-0.51703'	' 0.019573'

1082	'chest_sur'	'L_shoulder_Zrotation5'	'-0.49757'	' 0.025591'
1083	'R_leg_sur'	'L_elbow_Xrotation5'	'-0.49563'	' 0.026266'
1084	'R_thigh_sur'	'L_elbow_Xrotation5'	'-0.49714'	' 0.025739'
1085	'R_shin_vol'	'L_elbow_Xrotation5'	'-0.46305'	' 0.039779'
1086	'torso_vol'	'L_elbow_Xrotation5'	'-0.54405'	' 0.013144'
1087	'torso_sur'	'L_elbow_Xrotation5'	'-0.56618'	' 0.0092572'
1088	'L_forearm_vol'	'L_elbow_Xrotation5'	'-0.47664'	' 0.033607'
1089	'R_forearm_vol'	'L_elbow_Xrotation5'	'-0.44424'	' 0.049723'
1090	'R_forearm_sur'	'L_elbow_Xrotation5'	'-0.47951'	' 0.032404'
1091	'body_vol'	'L_elbow_Xrotation5'	'-0.56076'	' 0.010109'
1092	'body_sur'	'L_elbow_Xrotation5'	'-0.56022'	' 0.010198'
1093	'upper_vol'	'L_elbow_Xrotation5'	'-0.53833'	' 0.014338'
1094	'upper_sur'	'L_elbow_Xrotation5'	'-0.47498'	' 0.034318'
1095	'left_vol'	'L_elbow_Xrotation5'	'-0.59901'	' 0.0052569'
1096	'left_sur'	'L_elbow_Xrotation5'	'-0.61551'	' 0.0038652'
1097	'right_vol'	'L_elbow_Xrotation5'	'-0.64065'	' 0.0023398'
1098	'right_sur'	'L_elbow_Xrotation5'	'-0.64883'	' 0.0019684'
1099	'hip_vol'	'L_elbow_Xrotation5'	' -0.5763'	' 0.0078229'
1100	'hip_sur'	'L_elbow_Xrotation5'	'-0.62172'	' 0.003428'
1101	'noArms_vol'	'L_elbow_Xrotation5'	'-0.56146'	' 0.0099961'
1102	'noArms_sur'	'L_elbow_Xrotation5'	'-0.57308'	' 0.0082583'
1103	'L_shoulder_sur'	'L_elbow_Yrotation5'	'-0.50414'	' 0.023415'
1104	'L_forearm_sur'	'L_forearm_Yrotation5'	' 0.46188'	' 0.040347'
1105	'R_forearm_vol'	'L_forearm_Yrotation5'	' 0.472'	' 0.035621'
1106	'hip_vol'	'L_forearm_Yrotation5'	' 0.49227'	' 0.027461'
1107	'hip_sur'	'L_forearm_Yrotation5'	' 0.52623'	' 0.017153'
1108	'R_shoulder_sur'	'L_hand_Xrotation5'	'-0.45255'	' 0.045118'
1109	'L_forearm_sur'	'L_hand_Xrotation5'	'-0.49471'	' 0.026589'
1110	'L_arm_sur'	'L_hand_Yrotation5'	'-0.55734'	' 0.010679'
1111	'L_shoulder_sur'	'L_hand_Yrotation5'	' -0.4943'	' 0.026733'
1112	'L_forearm_vol'	'L_hand_Yrotation5'	'-0.50471'	' 0.023236'
1113	'L_forearm_sur'	'L_hand_Yrotation5'	' -0.5854'	' 0.006694'
1114	'left_sur'	'L_hand_Yrotation5'	'-0.46872'	' 0.037102'
1115	'L_arm_vol'	'L_hand_Zrotation5'	' 0.55277'	' 0.011481'

1116	'L_shoulder_vol'	'L_hand_Zrotation5'	' 0.48592'	' 0.029839'
1117	'torso_vol'	'R_shoulder_Xrotation5'	'-0.50913'	' 0.021865'
1118	'torso_sur'	'R_shoulder_Xrotation5'	' -0.5391'	' 0.014173'
1119	'body_vol'	'R_shoulder_Xrotation5'	'-0.50457'	' 0.023277'
1120	'body_sur'	'R_shoulder_Xrotation5'	' -0.476'	' 0.033877'
1121	'upper_vol'	'R_shoulder_Xrotation5'	'-0.48439'	' 0.030436'
1122	'left_vol'	'R_shoulder_Xrotation5'	'-0.50081'	' 0.0245'
1123	'right_vol'	'R_shoulder_Xrotation5'	'-0.46795'	' 0.03746'
1124	'hip_vol'	'R_shoulder_Xrotation5'	'-0.54122'	' 0.013725'
1125	'hip_sur'	'R_shoulder_Xrotation5'	'-0.52457'	' 0.017571'
1126	'noArms_vol'	'R_shoulder_Xrotation5'	'-0.53704'	' 0.01462'
1127	'noArms_sur'	'R_shoulder_Xrotation5'	'-0.54252'	' 0.013456'
1128	'L_leg_vol'	'R_elbow_Xrotation5'	' 0.65106'	' 0.0018763'
1129	'L_leg_sur'	'R_elbow_Xrotation5'	' 0.6256'	' 0.0031762'
1130	'R_leg_vol'	'R_elbow_Xrotation5'	' 0.54773'	' 0.01242'
1131	'R_leg_sur'	'R_elbow_Xrotation5'	' 0.53814'	' 0.014381'
1132	'L_thigh_vol'	'R_elbow_Xrotation5'	' 0.59754'	' 0.0053989'
1133	'L_thigh_sur'	'R_elbow_Xrotation5'	' 0.62099'	' 0.0034772'
1134	'R_thigh_vol'	'R_elbow_Xrotation5'	' 0.51277'	' 0.020784'
1135	'R_thigh_sur'	'R_elbow_Xrotation5'	' 0.53446'	' 0.015196'
1136	'L_shin_sur'	'R_elbow_Xrotation5'	' 0.53483'	' 0.015111'
1137	'R_shin_vol'	'R_elbow_Xrotation5'	' 0.53344'	' 0.015426'
1138	'R_shin_sur'	'R_elbow_Xrotation5'	' 0.459'	' 0.041775'
1139	'R_arm_vol'	'R_elbow_Xrotation5'	' 0.4922'	' 0.027488'
1140	'R_arm_sur'	'R_elbow_Xrotation5'	' 0.44629'	' 0.048558'
1141	'R_shoulder_vol'	'R_elbow_Xrotation5'	' 0.54492'	' 0.01297'
1142	'R_shoulder_sur'	'R_elbow_Xrotation5'	' 0.50888'	' 0.021938'
1143	'lower_vol'	'R_elbow_Xrotation5'	' 0.67193'	' 0.0011752'
1144	'lower_sur'	'R_elbow_Xrotation5'	' 0.62644'	' 0.0031238'
1145	'L_forearm_vol'	'R_elbow_Yrotation5'	' 0.54082'	' 0.013808'
1146	'L_leg_vol'	'R_elbow_Zrotation5'	' 0.53423'	' 0.015248'
1147	'L_leg_sur'	'R_elbow_Zrotation5'	' 0.51221'	' 0.020946'
1148	'R_leg_vol'	'R_elbow_Zrotation5'	' 0.47791'	' 0.03307'
1149	'L_thigh_vol'	'R_elbow_Zrotation5'	' 0.46607'	' 0.038335'

1150	'L_thigh_sur'	'R_elbow_Zrotation5'	' 0.57086'	' 0.0085692'
1151	'R_thigh_sur'	'R_elbow_Zrotation5'	' 0.45711'	' 0.042733'
1152	'R_shin_vol'	'R_elbow_Zrotation5'	' 0.46205'	' 0.040262'
1153	'lower_vol'	'R_elbow_Zrotation5'	' 0.55287'	' 0.011462'
1154	'lower_sur'	'R_elbow_Zrotation5'	' 0.51882'	' 0.019081'
1155	'R_leg_vol'	'R_forearm_Xrotation5'	' 0.54233'	' 0.013495'
1156	'R_leg_sur'	'R_forearm_Xrotation5'	' 0.55297'	' 0.011445'
1157	'R_thigh_vol'	'R_forearm_Xrotation5'	' 0.54762'	' 0.012441'
1158	'R_thigh_sur'	'R_forearm_Xrotation5'	' 0.60931'	' 0.0043471'
1159	'R_shin_vol'	'R_forearm_Xrotation5'	' 0.56637'	' 0.0092288'
1160	'R_shin_sur'	'R_forearm_Xrotation5'	' 0.51151'	' 0.021153'
1161	'torso_vol'	'R_forearm_Xrotation5'	' 0.4888'	' 0.028742'
1162	'torso_sur'	'R_forearm_Xrotation5'	' 0.6058'	' 0.0046414'
1163	'L_arm_vol'	'R_forearm_Xrotation5'	' 0.45906'	' 0.041746'
1164	'body_vol'	'R_forearm_Xrotation5'	' 0.50526'	' 0.02306'
1165	'body_sur'	'R_forearm_Xrotation5'	' 0.57366'	' 0.0081789'
1166	'upper_vol'	'R_forearm_Xrotation5'	' 0.47924'	' 0.032518'
1167	'upper_sur'	'R_forearm_Xrotation5'	' 0.48546'	' 0.03002'
1168	'lower_sur'	'R_forearm_Xrotation5'	' 0.44729'	' 0.047996'
1169	'left_sur'	'R_forearm_Xrotation5'	' 0.456'	' 0.043308'
1170	'right_vol'	'R_forearm_Xrotation5'	' 0.53718'	' 0.01459'
1171	'right_sur'	'R_forearm_Xrotation5'	' 0.4843'	' 0.030474'
1172	'hip_vol'	'R_forearm_Xrotation5'	' 0.46647'	' 0.038148'
1173	'hip_sur'	'R_forearm_Xrotation5'	' 0.49899'	' 0.02511'
1174	'chest_vol'	'R_forearm_Xrotation5'	' 0.53927'	' 0.014137'
1175	'noArms_vol'	'R_forearm_Xrotation5'	' 0.5128'	' 0.020776'
1176	'noArms_sur'	'R_forearm_Xrotation5'	' 0.58265'	' 0.0070197'
1177	'L_shin_vol'	'R_forearm_Yrotation5'	'-0.48634'	' 0.029678'
1178	'L_arm_sur'	'R_hand_Xrotation5'	'-0.56712'	' 0.0091165'
1179	'L_shoulder_sur'	'R_hand_Xrotation5'	'-0.53464'	' 0.015155'
1180	'L_forearm_sur'	'R_hand_Xrotation5'	'-0.49188'	' 0.027605'
1181	'L_thigh_sur'	'R_hand_Yrotation5'	' 0.47094'	' 0.036097'
1182	'L_shin_vol'	'R_hand_Yrotation5'	' 0.53161'	' 0.015851'
1183	'torso_vol'	'R_hand_Yrotation5'	' 0.6014'	' 0.0050324'

1184	'torso_sur'	'R_hand_Yrotation5'	' 0.51417'	' 0.02038'
1185	'L_arm_vol'	'R_hand_Yrotation5'	' 0.63564'	' 0.0025948'
1186	'L_shoulder_vol'	'R_hand_Yrotation5'	' 0.64907'	' 0.0019583'
1187	'body_vol'	'R_hand_Yrotation5'	' 0.59765'	' 0.0053876'
1188	'body_sur'	'R_hand_Yrotation5'	' 0.51438'	' 0.02032'
1189	'upper_vol'	'R_hand_Yrotation5'	' 0.58483'	' 0.0067601'
1190	'left_vol'	'R_hand_Yrotation5'	' 0.54793'	' 0.012382'
1191	'right_vol'	'R_hand_Yrotation5'	' 0.59987'	' 0.0051756'
1192	'hip_vol'	'R_hand_Yrotation5'	' 0.58814'	' 0.0063813'
1193	'hip_sur'	'R_hand_Yrotation5'	' 0.46352'	' 0.039552'
1194	'chest_vol'	'R_hand_Yrotation5'	' 0.61728'	' 0.0037363'
1195	'noArms_vol'	'R_hand_Yrotation5'	' 0.59337'	' 0.0058175'
1196	'noArms_sur'	'R_hand_Yrotation5'	' 0.51214'	' 0.020968'

Appendix 5.2

Table 55: A list of all significantly correlated 3D lower limb static and lower limb dynamic features.

Dynamic feature	Static feature	Correlation coefficient	P-value
'R_thigh_Zrotation2'	'L_leg_vol'	' 0.4949'	' 0.02652'
'R_foot_Xrotation3'	'L_leg_vol'	'-0.47799'	' 0.033036'
'R_toe_Xrotation3'	'L_leg_vol'	' 0.46217'	' 0.040205'
'R_foot_Xrotation4'	'L_leg_vol'	'-0.49612'	' 0.026094'
'R_knee_Xrotation5'	'L_leg_vol'	'-0.47855'	' 0.032804'
'L_thigh_Zrotation1'	'L_leg_sur'	' 0.53255'	' 0.015632'
'L_thigh_Zrotation2'	'L_leg_sur'	' 0.5028'	' 0.023849'
'L_foot_Yrotation2'	'L_leg_sur'	'-0.55444'	' 0.011183'
'L_thigh_Zrotation3'	'L_leg_sur'	' 0.50967'	' 0.0217'
'L_thigh_Zrotation4'	'L_leg_sur'	' 0.46103'	' 0.040764'
'R_thigh_Zrotation4'	'L_leg_sur'	' 0.44694'	' 0.048192'
'L_thigh_Yrotation5'	'L_leg_sur'	'-0.44993'	' 0.046535'
'L_thigh_Zrotation5'	'L_leg_sur'	' 0.46645'	' 0.038157'
'R_knee_Xrotation5'	'L_leg_sur'	'-0.44907'	' 0.047006'
'Root_Zposition1'	'R_leg_vol'	' 0.46975'	' 0.036634'
'L_thigh_Zrotation1'	'R_leg_vol'	' 0.62524'	' 0.0031988'
'L_thigh_Zrotation2'	'R_leg_vol'	' 0.54059'	' 0.013856'
'L_knee_Xrotation2'	'R_leg_vol'	'-0.47385'	' 0.034807'
'L_foot_Yrotation2'	'R_leg_vol'	' -0.4482'	' 0.047485'
'R_thigh_Zrotation2'	'R_leg_vol'	' 0.46699'	' 0.037902'
'L_thigh_Zrotation3'	'R_leg_vol'	' 0.44522'	' 0.049164'
'R_toe_Xrotation3'	'R_leg_vol'	' 0.46583'	' 0.038448'
'L_thigh_Zrotation4'	'R_leg_vol'	' 0.55601'	' 0.010907'
'R_thigh_Zrotation4'	'R_leg_vol'	' 0.50446'	' 0.023315'
'L_thigh_Zrotation1'	'R_leg_sur'	' 0.47872'	' 0.032733'
'L_thigh_Zrotation2'	'R_leg_sur'	' 0.4466'	' 0.048383'
'L_foot_Yrotation2'	'R_leg_sur'	'-0.52939'	' 0.016378'
'R_thigh_Yrotation3'	'R_leg_sur'	' 0.44819'	' 0.047494'
'L_thigh_Zrotation4'	'R_leg_sur'	' 0.52335'	' 0.017882'

'L_thigh_Zrotation5'	'R_leg_sur'	' 0.48373'	' 0.030699'
'Root_Zposition1'	'L_thigh_vol'	' 0.7219'	'0.00032615'
'L_thigh_Zrotation1'	'L_thigh_vol'	' 0.64315'	' 0.0022207'
'R_foot_Zrotation1'	'L_thigh_vol'	'-0.45046'	' 0.046244'
'R_toe_Xrotation1'	'L_thigh_vol'	'-0.57457'	' 0.008054'
'Root_Zposition2'	'L_thigh_vol'	' 0.48708'	' 0.029393'
'L_thigh_Zrotation2'	'L_thigh_vol'	' 0.54202'	' 0.013559'
'L_foot_Yrotation2'	'L_thigh_vol'	'-0.57112'	' 0.0085321'
'R_toe_Xrotation3'	'L_thigh_vol'	' 0.54438'	' 0.013078'
'Root_Zposition4'	'L_thigh_vol'	' 0.51963'	' 0.018863'
'L_thigh_Zrotation4'	'L_thigh_vol'	' 0.47998'	' 0.032209'
'R_toe_Xrotation4'	'L_thigh_vol'	' 0.51786'	' 0.019344'
'L_thigh_Zrotation1'	'L_thigh_sur'	' 0.54915'	' 0.012149'
'L_thigh_Zrotation2'	'L_thigh_sur'	' 0.5004'	' 0.024637'
'L_foot_Yrotation2'	'L_thigh_sur'	'-0.59803'	' 0.0053508'
'L_thigh_Zrotation4'	'L_thigh_sur'	' 0.54583'	' 0.01279'
'R_thigh_Zrotation4'	'L_thigh_sur'	' 0.50249'	' 0.023947'
'Root_Zposition1'	'R_thigh_vol'	' 0.56926'	' 0.0088004'
'L_thigh_Zrotation1'	'R_thigh_vol'	' 0.6004'	' 0.0051255'
'L_thigh_Zrotation2'	'R_thigh_vol'	' 0.51927'	' 0.018959'
'L_knee_Xrotation2'	'R_thigh_vol'	'-0.49787'	' 0.025489'
'L_foot_Yrotation2'	'R_thigh_vol'	'-0.48757'	' 0.029208'
'R_thigh_Zrotation2'	'R_thigh_vol'	' 0.48856'	' 0.028833'
'R_toe_Xrotation3'	'R_thigh_vol'	' 0.4645'	' 0.039082'
'L_thigh_Zrotation4'	'R_thigh_vol'	' 0.57762'	' 0.00765'
'R_thigh_Zrotation4'	'R_thigh_vol'	' 0.50794'	' 0.022227'
'L_thigh_Zrotation1'	'R_thigh_sur'	' 0.48822'	' 0.028961'
'L_thigh_Zrotation2'	'R_thigh_sur'	' 0.45262'	' 0.045084'
'L_foot_Yrotation2'	'R_thigh_sur'	' -0.5265'	' 0.017086'
'L_thigh_Zrotation4'	'R_thigh_sur'	' 0.55938'	' 0.010336'
'Root_Zrotation1'	'L_shin_vol'	'-0.44528'	' 0.049129'
'L_foot_Zrotation1'	'L_shin_vol'	'-0.46406'	' 0.03929'
'R_toe_Xrotation1'	'L_shin_vol'	' 0.44404'	' 0.049841'
'Root_Zposition2'	'L_shin_vol'	'-0.52016'	' 0.018721'

'Root_Xrotation2'	'L_shin_vol'	' 0.54247'	' 0.013468'
'Root_Zrotation2'	'L_shin_vol'	'-0.44587'	' 0.048794'
'Root_Zposition4'	'L_shin_vol'	'-0.54659'	' 0.012642'
'L_foot_Zrotation4'	'L_shin_vol'	'-0.51547'	' 0.02001'
'R_foot_Zrotation1'	'L_shin_sur'	' 0.46914'	' 0.036911'
'Root_Zrotation2'	'L_shin_sur'	'-0.48111'	' 0.03175'
'L_thigh_Zrotation3'	'L_shin_sur'	' 0.53287'	' 0.015559'
'R_foot_Zrotation3'	'L_shin_sur'	' 0.4507'	' 0.046117'
'L_foot_Zrotation4'	'L_shin_sur'	'-0.49654'	' 0.025946'
'L_thigh_Yrotation5'	'L_shin_sur'	'-0.45525'	' 0.043698'
'L_thigh_Zrotation5'	'L_shin_sur'	' 0.61806'	' 0.0036804'
'L_thigh_Zrotation1'	'R_shin_vol'	' 0.52853'	' 0.016586'
'L_thigh_Zrotation2'	'R_shin_vol'	' 0.45227'	' 0.045268'
'L_foot_Yrotation2'	'R_shin_vol'	'-0.46046'	' 0.041048'
'R_thigh_Zrotation2'	'R_shin_vol'	' 0.46066'	' 0.040949'
'Root_Yrotation3'	'R_shin_vol'	'-0.45159'	' 0.045631'
'L_thigh_Zrotation4'	'R_shin_vol'	' 0.53154'	' 0.015868'
'R_thigh_Zrotation4'	'R_shin_vol'	' 0.50913'	' 0.021864'
'L_thigh_Zrotation5'	'R_shin_vol'	' 0.54721'	' 0.012521'
'L_thigh_Zrotation5'	'R_shin_sur'	' 0.56603'	' 0.00928'
'R_thigh_Zrotation2'	'L_leg_vol'	' 0.4949'	' 0.02652'
'R_foot_Xrotation3'	'L_leg_vol'	'-0.47799'	' 0.033036'
'R_toe_Xrotation3'	'L_leg_vol'	' 0.46217'	' 0.040205'
'R_foot_Xrotation4'	'L_leg_vol'	'-0.49612'	' 0.026094'

Appendix 5.3

Table 56: A list of all significantly correlated 3D upper body static and lower limb dynamic features.

Dynamic feature	Static feature	Correlation coefficient	P-value
'L_thigh_Yrotation1'	'L_arm_vol'	'-0.53389'	' 0.015325'
'L_foot_Yrotation1'	'L_arm_vol'	' 0.49477'	' 0.026568'
'L_thigh_Yrotation2'	'L_arm_vol'	' -0.5015'	' 0.024274'
'R_thigh_Zrotation2'	'L_arm_vol'	' 0.46719'	' 0.037811'
'L_thigh_Yrotation3'	'L_arm_vol'	'-0.58989'	' 0.0061882'
'R_thigh_Zrotation3'	'L_arm_vol'	' 0.56531'	' 0.00939'
'Root_Yrotation4'	'L_arm_vol'	'-0.45013'	' 0.046425'
'L_thigh_Yrotation4'	'L_arm_vol'	'-0.60377'	' 0.0048184'
'L_knee_Xrotation4'	'L_arm_vol'	'-0.49674'	' 0.025877'
'R_thigh_Zrotation4'	'L_arm_vol'	' 0.65765'	' 0.0016246'
'L_thigh_Yrotation5'	'L_arm_vol'	'-0.60076'	' 0.0050921'
'R_thigh_Zrotation5'	'L_arm_vol'	' 0.46775'	' 0.037553'
'L_thigh_Yrotation1'	'L_arm_sur'	'-0.63148'	' 0.0028238'
'L_thigh_Yrotation2'	'L_arm_sur'	'-0.64451'	' 0.0021582'
'L_knee_Xrotation2'	'L_arm_sur'	'-0.50054'	' 0.02459'
'R_thigh_Yrotation2'	'L_arm_sur'	'-0.59755'	' 0.0053975'
'L_thigh_Xrotation3'	'L_arm_sur'	' 0.56158'	' 0.0099767'
'L_thigh_Yrotation3'	'L_arm_sur'	'-0.61659'	' 0.0037863'
'L_foot_Yrotation3'	'L_arm_sur'	' 0.45891'	' 0.041823'
'R_thigh_Zrotation3'	'L_arm_sur'	' 0.65414'	' 0.0017551'
'Root_Yrotation4'	'L_arm_sur'	'-0.48252'	' 0.03118'
'L_thigh_Xrotation4'	'L_arm_sur'	' 0.49525'	' 0.026398'
'L_thigh_Yrotation4'	'L_arm_sur'	'-0.67719'	' 0.0010386'
'L_thigh_Zrotation4'	'L_arm_sur'	' 0.67409'	' 0.0011174'
'R_thigh_Zrotation4'	'L_arm_sur'	' 0.62634'	' 0.0031296'
'Root_Yrotation5'	'L_arm_sur'	' -0.447'	' 0.048156'
'L_thigh_Xrotation5'	'L_arm_sur'	' 0.53675'	' 0.014684'

'L_thigh_Yrotation5'	'L_arm_sur'	'-0.72168'	' 0.0003282'
'L_thigh_Zrotation1'	'R_arm_vol'	' 0.54276'	' 0.013407'
'L_thigh_Zrotation2'	'R_arm_vol'	' 0.49056'	' 0.028088'
'L_thigh_Zrotation3'	'R_arm_vol'	' 0.44598'	' 0.048734'
'R_toe_Xrotation3'	'R_arm_vol'	' 0.56116'	' 0.010044'
'Root_Yrotation4'	'R_arm_vol'	'-0.44931'	' 0.046875'
'L_thigh_Zrotation4'	'R_arm_vol'	' 0.54109'	' 0.013752'
'L_thigh_Yrotation5'	'R_arm_vol'	'-0.55864'	' 0.010459'
'L_foot_Zrotation5'	'R_arm_vol'	'-0.48734'	' 0.029296'
'L_thigh_Zrotation1'	'R_arm_sur'	' 0.5066'	' 0.022641'
'L_thigh_Yrotation2'	'R_arm_sur'	'-0.53616'	' 0.014814'
'L_thigh_Yrotation3'	'R_arm_sur'	'-0.44847'	' 0.047338'
'L_thigh_Zrotation3'	'R_arm_sur'	' 0.48669'	' 0.029545'
'R_toe_Xrotation3'	'R_arm_sur'	' 0.57717'	' 0.0077094'
'Root_Yrotation4'	'R_arm_sur'	'-0.52239'	' 0.018132'
'L_thigh_Yrotation4'	'R_arm_sur'	'-0.46367'	' 0.039477'
'L_thigh_Zrotation4'	'R_arm_sur'	' 0.56362'	' 0.0096518'
'R_thigh_Zrotation4'	'R_arm_sur'	' 0.50436'	' 0.023346'
'Root_Yrotation5'	'R_arm_sur'	' -0.546'	' 0.012757'
'L_thigh_Yrotation5'	'R_arm_sur'	'-0.64222'	' 0.0022644'
'L_thigh_Yrotation3'	'L_shoulder_vol'	'-0.54906'	' 0.012167'
'R_thigh_Zrotation3'	'L_shoulder_vol'	' 0.57073'	' 0.0085883'
'L_thigh_Yrotation4'	'L_shoulder_vol'	'-0.51918'	' 0.018985'
'L_knee_Xrotation4'	'L_shoulder_vol'	'-0.45865'	' 0.041951'
'R_thigh_Zrotation4'	'L_shoulder_vol'	' 0.55035'	' 0.011924'
'L_thigh_Yrotation5'	'L_shoulder_vol'	' -0.4811'	' 0.031751'
'R_thigh_Zrotation5'	'L_shoulder_vol'	' 0.55134'	' 0.011742'
'L_thigh_Yrotation1'	'L_shoulder_sur'	'-0.61853'	' 0.0036472'
'L_thigh_Yrotation2'	'L_shoulder_sur'	'-0.59856'	' 0.0052995'
'R_thigh_Yrotation2'	'L_shoulder_sur'	' -0.5659'	' 0.0092997'
'L_thigh_Xrotation3'	'L_shoulder_sur'	' 0.58555'	' 0.0066761'

'L_thigh_Yrotation3'	'L_shoulder_sur'	' -0.6331'	' 0.0027326'
'R_thigh_Zrotation3'	'L_shoulder_sur'	' 0.58948'	' 0.0062323'
'L_thigh_Yrotation4'	'L_shoulder_sur'	'-0.64965'	' 0.0019343'
'L_thigh_Zrotation4'	'L_shoulder_sur'	' 0.60225'	' 0.0049547'
'R_thigh_Zrotation4'	'L_shoulder_sur'	' 0.52969'	' 0.016305'
'L_thigh_Xrotation5'	'L_shoulder_sur'	' 0.48353'	' 0.030777'
'L_thigh_Yrotation5'	'L_shoulder_sur'	'-0.68707'	'0.00081788'
'L_thigh_Zrotation1'	'R_shoulder_vol'	' 0.62092'	' 0.0034815'
'L_thigh_Zrotation2'	'R_shoulder_vol'	' 0.54595'	' 0.012768'
'L_thigh_Zrotation3'	'R_shoulder_vol'	' 0.51067'	' 0.0214'
'R_toe_Xrotation3'	'R_shoulder_vol'	' 0.4846'	' 0.030357'
'Root_Yrotation4'	'R_shoulder_vol'	'-0.46981'	' 0.036608'
'L_thigh_Zrotation4'	'R_shoulder_vol'	' 0.52081'	' 0.018548'
'Root_Yrotation5'	'R_shoulder_vol'	'-0.46297'	' 0.039818'
'L_thigh_Yrotation5'	'R_shoulder_vol'	'-0.56345'	' 0.0096797'
'L_thigh_Zrotation1'	'R_shoulder_sur'	' 0.57975'	' 0.0073783'
'L_thigh_Yrotation2'	'R_shoulder_sur'	'-0.47574'	' 0.033989'
'L_thigh_Zrotation2'	'R_shoulder_sur'	' 0.49813'	' 0.025402'
'L_thigh_Zrotation3'	'R_shoulder_sur'	' 0.50617'	' 0.022774'
'R_toe_Xrotation3'	'R_shoulder_sur'	' 0.55814'	' 0.010544'
'Root_Yrotation4'	'R_shoulder_sur'	'-0.46929'	' 0.036845'
'L_thigh_Zrotation4'	'R_shoulder_sur'	' 0.50856'	' 0.022036'
'Root_Yrotation5'	'R_shoulder_sur'	'-0.45592'	' 0.04335'
'L_thigh_Yrotation5'	'R_shoulder_sur'	'-0.61019'	' 0.0042755'
'L_thigh_Yrotation1'	'L_forearm_vol'	'-0.48672'	' 0.029531'
'L_thigh_Yrotation2'	'L_forearm_vol'	'-0.48198'	' 0.031395'
'R_thigh_Yrotation2'	'L_forearm_vol'	'-0.46407'	' 0.039286'
'L_knee_Xrotation3'	'L_forearm_vol'	'-0.45564'	' 0.043493'
'R_thigh_Zrotation3'	'L_forearm_vol'	' 0.59065'	' 0.0061049'
'L_thigh_Yrotation4'	'L_forearm_vol'	'-0.46149'	' 0.040539'
'L_thigh_Zrotation4'	'L_forearm_vol'	' 0.54105'	' 0.013762'

'R_thigh_Zrotation4'	'L_forearm_vol'	' 0.6182'	' 0.0036703'
'L_thigh_Yrotation5'	'L_forearm_vol'	'-0.52904'	' 0.016463'
'L_thigh_Xrotation1'	'L_forearm_sur'	'-0.45788'	' 0.042343'
'L_thigh_Yrotation1'	'L_forearm_sur'	'-0.56044'	' 0.010162'
'L_thigh_Zrotation1'	'L_forearm_sur'	' 0.47919'	' 0.032535'
'L_thigh_Xrotation2'	'L_forearm_sur'	' 0.4451'	' 0.049234'
'L_thigh_Yrotation2'	'L_forearm_sur'	'-0.63246'	' 0.0027684'
'L_thigh_Zrotation2'	'L_forearm_sur'	' 0.47847'	' 0.032837'
'L_knee_Xrotation2'	'L_forearm_sur'	'-0.44447'	' 0.049591'
'R_thigh_Yrotation2'	'L_forearm_sur'	'-0.55843'	' 0.010495'
'L_thigh_Yrotation3'	'L_forearm_sur'	' -0.5454'	' 0.012876'
'R_thigh_Zrotation3'	'L_forearm_sur'	' 0.62621'	' 0.0031377'
'Root_Yrotation4'	'L_forearm_sur'	'-0.53246'	' 0.015653'
'L_thigh_Xrotation4'	'L_forearm_sur'	' 0.50054'	' 0.024588'
'L_thigh_Yrotation4'	'L_forearm_sur'	'-0.61848'	' 0.0036509'
'L_thigh_Zrotation4'	'L_forearm_sur'	' 0.6946'	'0.00067759'
'R_thigh_Zrotation4'	'L_forearm_sur'	' 0.68081'	'0.00095264'
'Root_Yrotation5'	'L_forearm_sur'	' -0.5049'	' 0.023175'
'L_thigh_Xrotation5'	'L_forearm_sur'	' 0.52058'	' 0.018609'
'L_thigh_Yrotation5'	'L_forearm_sur'	'-0.70516'	'0.00051557'
'L_thigh_Yrotation2'	'R_forearm_vol'	'-0.53121'	' 0.015946'
'L_thigh_Yrotation3'	'R_forearm_vol'	'-0.49194'	' 0.027582'
'Root_Yrotation4'	'R_forearm_vol'	'-0.45132'	' 0.045777'
'L_thigh_Yrotation4'	'R_forearm_vol'	' -0.4736'	' 0.034918'
'L_foot_Zrotation4'	'R_forearm_vol'	'-0.55374'	' 0.011307'
'R_thigh_Zrotation4'	'R_forearm_vol'	' 0.50135'	' 0.024323'
'Root_Yrotation5'	'R_forearm_vol'	'-0.51093'	' 0.021324'
'L_thigh_Yrotation5'	'R_forearm_vol'	'-0.57211'	' 0.0083936'
'L_foot_Zrotation5'	'R_forearm_vol'	'-0.60701'	' 0.0045378'
'R_foot_Xrotation1'	'R_forearm_sur'	' 0.53883'	' 0.014232'
'R_foot_Yrotation1'	'R_forearm_sur'	' 0.47581'	' 0.033962'

'R_foot_Zrotation1'	'R_forearm_sur'	' 0.49431'	' 0.026729'
'R_toe_Xrotation1'	'R_forearm_sur'	' 0.47186'	' 0.035683'
'L_thigh_Yrotation2'	'R_forearm_sur'	'-0.56442'	' 0.0095272'
'L_thigh_Yrotation3'	'R_forearm_sur'	'-0.52296'	' 0.017983'
'L_thigh_Yrotation4'	'R_forearm_sur'	'-0.45094'	' 0.045986'
'L_foot_Zrotation4'	'R_forearm_sur'	'-0.49291'	' 0.027229'
'Root_Yrotation5'	'R_forearm_sur'	'-0.47479'	' 0.0344'
'L_thigh_Yrotation5'	'R_forearm_sur'	'-0.57969'	' 0.0073851'
'L_foot_Zrotation5'	'R_forearm_sur'	'-0.56994'	' 0.008702'

Appendix 6: Publications

"The relationship between 2D static features and 2D dynamic features used in gait recognition"

Authors: Hamad M Alawar, Hassan Ugail, Mumtaz Kamala, David Connah

Publication Date: 31st May, 2013

Proceedings from the Biometric and Surveillance: Technology for Human and Activity Identification Conference (SPIE 8712)

Abstract
In most gait recognition techniques, both static and dynamic features are used to define a subject's gait signature. In this study, the existence of a relationship between static and dynamic features was investigated. The correlation coefficient was used to analyse the relationship between the features extracted from the "University of Bradford Multi-Modal Gait Database". This study includes two dimensional dynamic and static features from 19 subjects. The dynamic features were compromised of Phase-Weighted Magnitudes driven by a Fourier Transform of the temporal rotational data of a subject's joints (knee, thigh, shoulder, and elbow). The results concluded that there are eleven pairs of features that are considered significantly correlated with ($p<0.05$). This result indicates the existence of a statistical relationship between static and dynamics features, which challenges the results of several similar studies. These results bare great potential for further research into the area, and would potentially contribute to the creation of a gait signature using latent data.

"THE BRADFORD MULTI-MODAL GAIT DATA-BASE: Gateway to using static measurements to create a dynamic gait signature"

Authors: Hamad M Alawar, Hassan Ugail, Mumtaz Kamala, David Connah

Publication status: Accepted, pending revision.

Journal name: British Journal of Applied Science & Technology

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