Biomechanical Adaptations of Human Gait

Due to External Loads

Minhyung Lee

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State

University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Mechanical Engineering

Michael Roan, Ph.D., Chair

Dennis Hong, Ph.D.

Jamie Carneal, Ph.D.

Martin Johnson, Ph.D.

Thurmon Lockhart, Ph.D.

August 01, 2008

Blacksburg, Virginia

Biomechanical Adaptations of Human Gait Due to External Loads

Minhyung Lee

Abstract

Gait is the method of human locomotion using limbs. Recently, the analysis of human motion, specifically human gait, has received a large amount of research attention. Human gait can contain a wide variety of information that can be used in biometrics, disease diagnosis, injury rehabilitation, and load determination. In this dissertation, the development of a model-based gait analysis technique to classify external loads is presented. Specifically, the effects of external loads on gait are quantified and these effects are then used to classify whether an individual gait pattern is the result of carrying an external load or not.

First of all, the reliability of using continuous relative phase as a metric to determine loading condition is quantified by intra-class correlation coefficients (ICC) and the number of required trials is computed. The ICC(2, 1) values showed moderate reliability and 3 trials are sufficient to determine lower body kinematics under two external load conditions. Then, the work was conducted to provide the baseline separability of load carriage conditions into loaded and unloaded categories using several lower body kinematic parameters. Satisfactory classification of subjects into the correct loading condition was achieved by resorting to linear discriminant analysis (LDA). The baseline performance from 4 subjects who were not included in training data sets shows that the use of LDA provides an 88.9% correct classification over two loaded and unloaded walking conditions. Extra weights, however, can be in the form of an

external load carried by an individual or excessive body weight carried by an overweight individual. The study now attempts to define the differences in lower body gait patterns caused by either external load carriage, excessive body weight, or a combination of both. It was found significant gait differences due to external load carriage and excessive body weight. Principal Component Analysis (PCA) was also used to analyze the lower body gait patterns for four loading conditions: normal weight unloaded, normal weight loaded, overweight unloaded and overweight loaded. PCA has been shown to be a powerful tool for analyzing complex gait data. In this analysis, it is shown that in order to quantify the effects of external loads for both normal weight and overweight subjects, only two principal components (PCs) are needed.

The results in this dissertation suggest that there are gait pattern changes due to external loads, and LDA could be applied successfully to classify the gait patterns with an unknown load condition. Both load carriage and excessive body weight affect lower body kinematics, but it is proved that they are not the same loading conditions. Methods in the current work also give a potential for new medical and clinical ways of investigating gait effects in osteoarthritis patients and/or obese people.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

The research described here was made possible through contributions from my family, committee members, lab mates, and friends.

First of all, I would like to thank my advisor, Dr. Roan, for his support and guidance on this research. His invaluable encouragement and sometimes pushing me hard for publications have been vital in the completion of my Ph.D. degree. Specifically, I would like to thank for his numerous hours of editing papers with me. He showed me how he has been such a successful professor; he keeps working and never takes a break. Again, thank you for challenging me and having confidence in me as well as being an excellent advisor. Special thanks are extended to the committee members, Drs. Carneal, Hong, Johnson, and Lockhart. For all your support and guidance, I will be eternally grateful. Especially, Dr. Hong, your guidance for job searching and Dr. Lockhart, thank you for your advice and encouragement.

I would like to express my gratitude to all members of the Vibration and Acoustics Lab. Especially I would like to thank Ben Smith who has been my best friend at Virginia Tech. He works, talks and discusses with me whenever I needed for this research. Also, I always have a good time when I hang out with him. I will not forget how great the last spring break was with Ben, Kamal, and Tim.

Last but not least, I would like to thank my parents and sisters for their support through this process and throughout my life. You inspired me to go on for higher education.

Chapter 1 - Introduction

1.1. Load effects on gait

Gait is the method of human locomotion using limbs (Kirtley 2006). Normal gait sequences are cyclic and demonstrate almost perfect periodic behavior (Kale, Cuntoor et al. 2003). Recently, the analysis of human motion has received a large amount of research attention. The majority of this research focuses on analysis of human gait. Human gait can contain a wide variety of information that can be used in biometrics (Boulgouris, Hatzinakos et al. 2005), disease diagnosis (Lehmann and DeLateur 1990; Piecha 2008), injury rehabilitation (Mulder, Nienhuis et al. 1998; Hailey and Tomie 2000) and load determination (BenAbdelkader and Davis 2002). In this dissertation, the development of a model-based gait analysis technique to classify external loads is presented. Specifically, the effects of external loads on gait are quantified and these effects are then used to classify whether an individual gait pattern is the result of carrying an external load or not.

Load carriage is a very common daily activity at home and in the workplace. However, it is a common cause of injuries, including those of the knee and lower back (Dalen A, Nilsson J et al. 1978; Knapik, Reynolds et al. 1992). Therefore, it is important to understand the effects of load carriage on human physiology. There are many previous studies that characterize the nature of gait and the effects that external loads have on gait (Kinoshita 1985; Hong and Brueggemann 2000; Chow, Kwok et al. 2005; Chow, Kwok et al. 2006). These studies found that the duration of the swing phase of gait decreases when carrying a load, while the duration of the stance is not affected by loads up to 50% of body weight (Kinoshita 1985; Martin and Nelson 1986).

Additionally it was found that forward inclination of the trunk increases significantly with a backpack loading in order to keep the center of mass (COM) over the feet. Other load adaptations are reduced pelvic rotation and an increase in the foot rotations (Kinoshita 1985; Martin and Nelson 1985; Martin and Nelson 1986).

These previous studies showed that the normal walking pattern was significantly modified by either backpack or double-pack external load conditions. The type of external load carried also increases the energy cost of gait in (Winsmann and Goldman 1976). It was found that the lowest energy cost was achieved when the load was located as close as possible to the center of mass of the body. For this reason, it is generally considered that the double-pack requires less energy than the backpack (Ramanathan, Datta et al. 1972). Backpack loading is a significantly different loading condition than double-pack loading with an evenly distributed load. Few studies provide a method of classification for loaded vs. unloaded gait using kinematic data. The initial goal of the work in this dissertation is to determine if an individual is carrying an evenly distributed load without having a priori knowledge of the individual. As a result, it is necessary to develop a new external load classification method, using gait analysis, which are non-invasive and work at a distance. Further analysis is also done in order to differentiate the gait effects of external loads from those caused by excessive body mass in overweight subjects. By understanding the effects of external loads and excessive body mass on human movements, it would be possible to detect hidden external loads for security purposes as well as improve the understanding of the physical effects of loads on people who carry heavy equipment. Methods in the current work also give potential for new medical and clinical ways of investigating gait effects in osteoarthritis patients and/or obese people.

1.2. Objective

Objective:

This study aims to quantify the gait pattern differences between unloaded and loaded walking and classify these differences using simple analytical models.

Specific aims are:

(1) To evaluate the reliability of lower body kinematics with two external load conditions

(2) To develop a model to classify external loading conditions for treadmill walking

(3) To differentiate the effects of external loads with excessive body mass in gait

(4) To characterize different walking patterns with principal component analysis

Chapter 2 – Background

2.1. *Gait theory*

Normal human gait can be defined by the manner of walking whose normal speed is about 2.5 to 3 mph (Whittle 2002). It is a sequence movement of the two legs containing two distinct phases. A single stance phase (swing phase), in which one foot is in contact with the ground and a double stance phase (ground phase) in which both feet are in contact with the ground. In order for a movement to be classified as normal gait, each of these two phases must be present in the motion. The following terms are used to categorize major events during the gait cycle (Figure 2.1):

1. Initial (right) heel contact (a)

2. Opposite (left) toe off and heel rise (b)

3. Opposite (left) initial contact (c)

4. Toe (right) off (d)

5. Go back to (right) initial contact (e)

	(a)	(b)	(c)	(d)	(e)

| Double Stance | Swing (Left) / Stance (Right) | Double Stance | Stance (Left) / Swing (Right) | Double Stance |
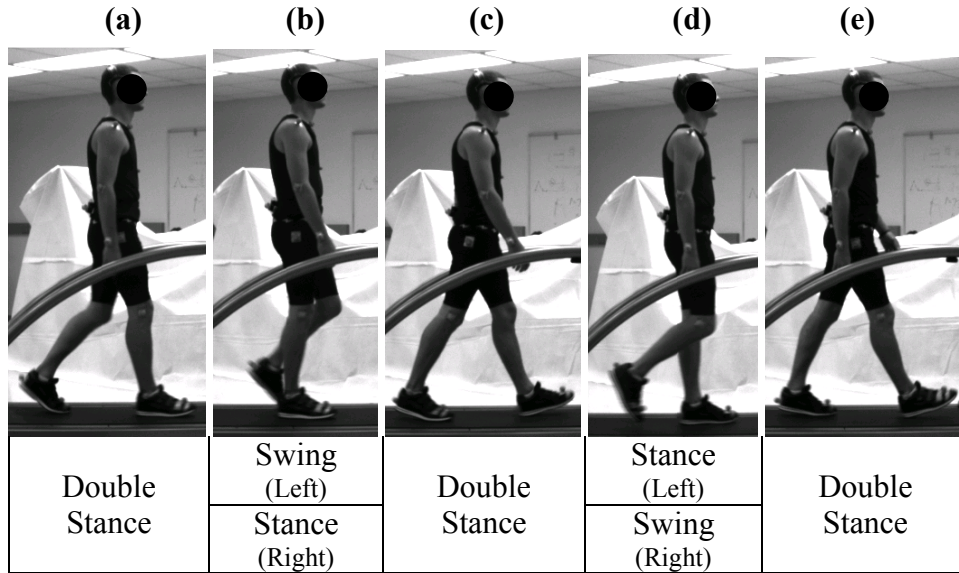
Figure 2. 1. One gait cycle with major events labeled.

Table 2.1 shows the percentage of floor contact for each phase during one gait cycle. Contact periods for the single stance phase are 4 times longer than ones for the double stance.

Table 2. 1. Normal Floor Contact Periods (%)(Perry 1992).

Phase	Contact Period (%)
Double Stance	20
Single Stance	40
Swing	40

There are two types of energy transfer while walking, (1) an exchange of potential and kinetic energy and (2) the energy transfer between one limb segment and another (Whittle 2002). For example, the most obvious exchange of potential and kinetic energy is the trunk movement. In the middle of stance phase, the trunk is the highest vertical position (i.e. maximum potential energy). This potential energy is converted into kinetic energy causing an increase of forward

trunk speed. Generally the energy expended during walking can be categorized by three main components, the muscles, breathing and basal metabolism. Therefore, the energy expenditure should be varied between loaded and unloaded walking and will result in different gait patterns eventually.

There are six major mechanisms used to minimize the excursions(?) of the center of gravity, these are called the determinants of gait and are given below (Saunders, Inman et al. 1953).

1. Pelvic rotation in transversal plane (related to stride length)

2. Pelvic obliquity in frontal plane (reduce the total vertical excursion of the trunk)

3. Knee flexion in stance phase (for the ground clearance)

4. Ankle mechanism (foot loading response)

5. Foot mechanism (toe off)

6. Lateral displacement of body (side to side movement, reduction in lateral leads to less muscular energy.)

Analyses for this dissertation will be based on these parameters in order to effectively investigate the different gait patterns generated by loaded and unloaded conditions.

2.2. *Analysis using phase portraits*

A phase portrait, which is a function of a state vector, is a method to show the trajectories of a dynamic system in the phase plane (Stergiou 2004). The plot consists of the displacement on the x-axis and the velocity on the y-axis. It helps describe the behavior of the dynamic system by

showing the current state of the system versus its rate of change. For human movements, especially gait, it provides insight of the neuromuscular system as well as the control mechanisms (Stergiou 2004).

The x-axis intersections, for instance, are related to transitions of movement patterns. The angular velocity at these points is zero. This happens when there are sudden interruptions in the system; therefore, they are a local minimum or maximum in the angular displacement. A higher number of these points suggests a greater number of dynamic changes in the system (Winstein and Garfinkel 1989). Specifically, it is a good initial indicator of neuromuscular control between normal and abnormal gait patterns.

Variability of the trajectory can be also used to quantify the stability of the neuromuscular system if many gait cycles are plotted (Clark and Phillips 1993). Usually the neuromuscular response to perturbations during the gait cycle are shown as slight variations of the trajectory (Stergiou 2004). These variations help in maintaining a stable movement pattern. On the other hand, instabilities of the neuromuscular system are shown as excessive variability. In this case, it may indicate a disorder in the neuromuscular system (Herman, Giladi et al. 2005). The phase portrait can be used as a way of quantifying the lower body movements during a gait cycle. The phase angle, for example, quantifies the behavior of a lower extremity. In order to calculate the phase angle, the phase portrait is transformed from (x, $\dot{x}$) positions to polar coordinates (r, θ), as shown in Figure 2.2. The angle from the horizontal axis is the phase angle of the trajectory as shown in Equation 2.1.

7

$$\theta = \tan^{-1}\left(\frac{\dot{x}_i}{x_i}\right)$$

Equation 2.1

Where $\dot{x}$ is the angular velocity and x is the angular displacement at ith point of the trajectory. The phase angle is defined between the x-axis and the vector r. In this work, quantification of the phase portrait is done by the path length of the trajectory as well as the phase angle.
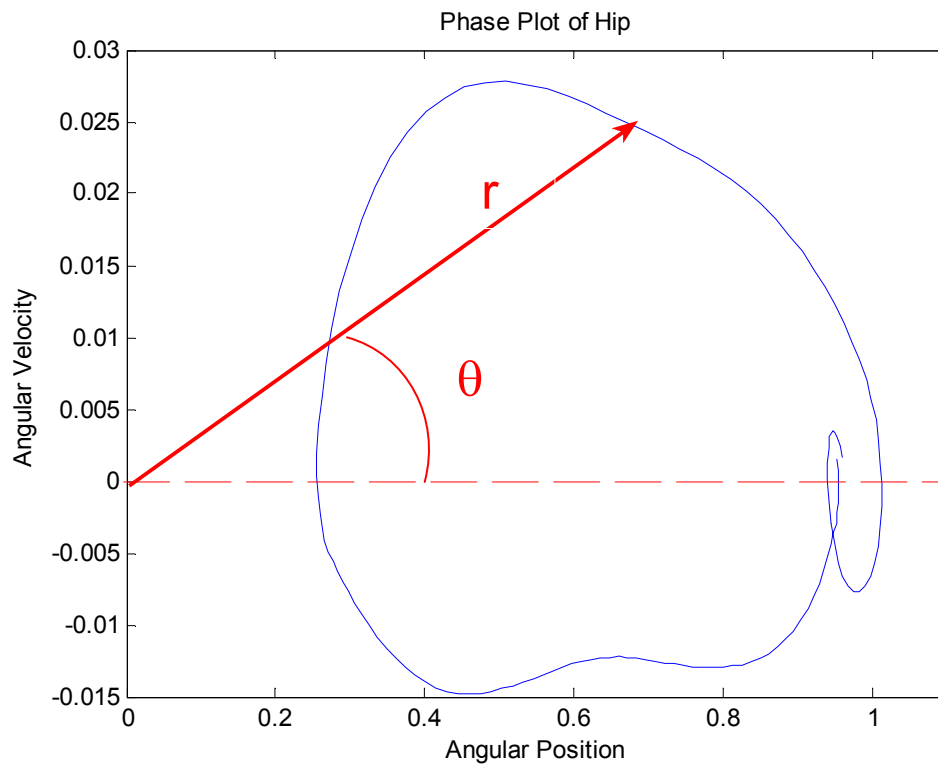
Figure 2. 2. A definition of the phase angle.

2.3. *Fundamentals of reliability using ICC*

There are variations between data sets when repeated measurements are performed. The intraclass correlation coefficient (ICC) is often used as an index for consistency between data sets. It is also used to determine the sample size required to test a hypothesis (McGraw and Wong 1996). ICC values are varied from zero (no reliability) to one (strong reliability). Higher ICC values indicate that reliability of data sets measured is good. Because the ICC is an average correlation across measurements, low ICC values are caused when measurements have different trends (Figure 2.3).

(A)
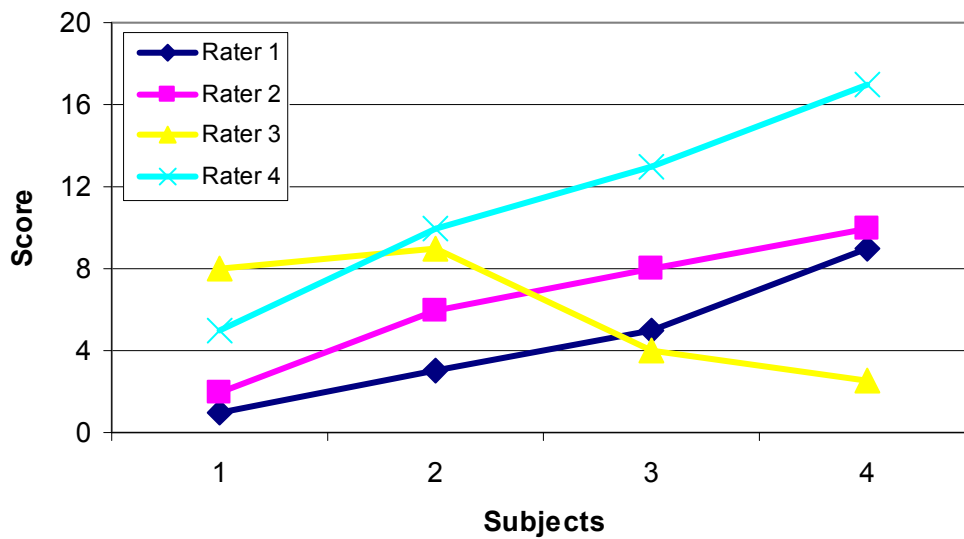
(B)
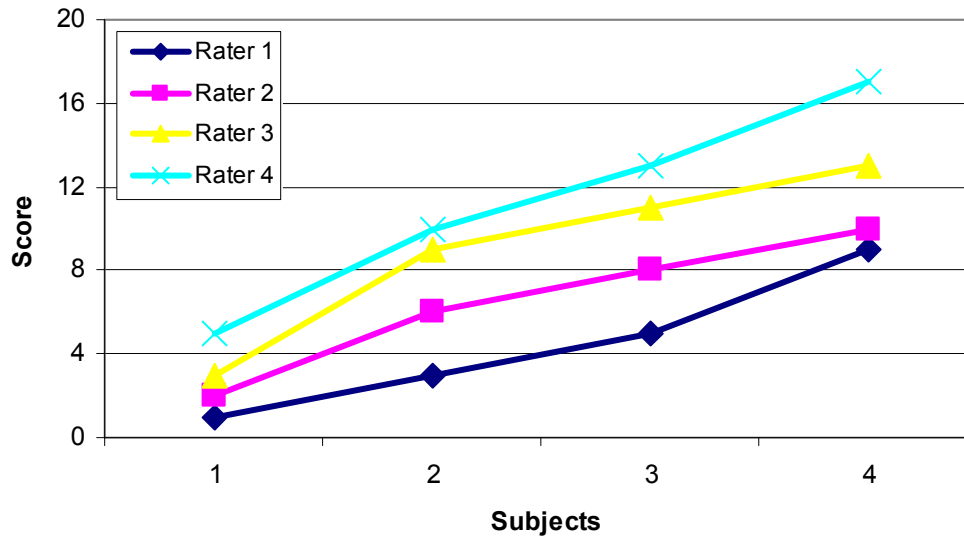
Figure 2. 3. An example of (A) a low ICC value (= 0.425) because Rater 3 demonstrates inconsistent responses and (B) a high ICC value (= 0.982) because all raters show consistent responses.

The ICC is calculated based on an analysis of variance (ANOVA) (Shrout and Fleiss 1979). There are several statistical advantages to using ICC over other reliability methods. The reliability for two or more trials is easily measured and there are three major models for ICC. The ICC models vary depending on types of trials (judges) and targets (subjects). These considerations make six (=3 models x 2 types) forms of intraclass correlation (Shrout and Fleiss 1979; Portney and Watkins 2000). A brief description of the ICC types is introduced below. More information about ICC models and sample size requirements can be found in (Shrout and Fleiss 1979; Donner and Eliasziw 1987; Walter, Eliasziw et al. 1998; Portney and Watkins 2000; Bonett 2002).

Model 1 (one-way random effects model):

This model is good for a design where subjects are evaluated by raters. In this model, "subjects" are treated as the independent variables. In other words, the ICC is interpreted as the proportion of subject variance associated with differences among the scores of the subjects. This model can be computed by Equation 2.3.

$$ICC(1,\,k) = \frac{BMS - WMS}{BMS}$$

Equation. 2.3

Where k is the number of ratings for each subject, BMS is the between-subjects mean square from the analysis of variance, and WMS is the within-groups (error) mean square.

Model 2 (Two-way random effects model):

This is the most often used model for inter-rater reliability studies where all n subjects are measured by k raters. It is based on a repeated measures analysis of variance as shown in Equation 2.4. The ICC is interpreted as the proportion of subject plus rater variance that is associated with differences among the scores of the subjects. This model is also used for the current work to determine the reliability of gait variables.

$$ICC(2,k) = \frac{BMS - EMS}{BMS + \dfrac{(RMS - EMS)}{n}}$$

Equation 2.4

Where EMS is the error mean square, RMS is the between-raters mean square, k is the number of raters, and n is the number of subjects tested.

Model 3 (Two-way mixed model):

This model is also based on a repeated measures analysis of variance (Equation 2.5). This model is appropriate for testing intra-rater reliability with multiple scores from the same rater, as it is not reasonable to generalize one rater's scores to a larger population of raters. The ICC is interpreted as not being generalizable beyond the given judges.

$$ICC(3,k) = \frac{BMS - EMS}{BMS}$$ Equation 2.5

For this dissertation, Model 2 is used to calculate the reliability of gait variables since it is a repeated measures method. In addition, the sample size requirements are computed based on the ICC values. Detailed results will be introduced in Chapter 4.

2.4.   Linear Discriminant Analysis (LDA)

LDA is a statistical method used to find the linear relationship that can classify two or more classes of data (McLachlan 2004). It is basically used to express one dependent variable as a linear combination of other measurements in order to model the difference between the classes (Johnson and Wichern 1998). There are many methods for classification of data. Principal Component Analysis (PCA) and LDA are two common methods used to classify data as well as reduce dimensionality (McLachlan 2004). In PCA, the location and shape of the original data sets change after transformation to a different space. However, LDA does not change the

location, rather it provides more class separability. Detailed information for PCA is introduced in the next section.

The dependent variable for LDA is the group and the independent variables are the characteristics of the group. In this study, the dependent variables are unloaded and loaded walking while the independent variables are related to the lower body movements such as joint angles and phase angles. If data has a normal distribution and the same covariance matrix, the means and a covariance matrix from the variables of the training data set are calculated. Then, the discriminant function, f, is computed by following (Johnson and Wichern 1998):

$$f_i = \mu_i C^{-1} x_k^T - \frac{1}{2} \mu_i C^{-1} x_i^T + \ln(p_i) \qquad \text{Equation 2.6}$$

Where μ is a mean, C is a covariance matrix, x is independent variables, p is a probability vector, k is an object, and i is a group. In order to test, the testing data are converted into the f1-f2 coordinates. Figure 2.4 shows the example of classification results.
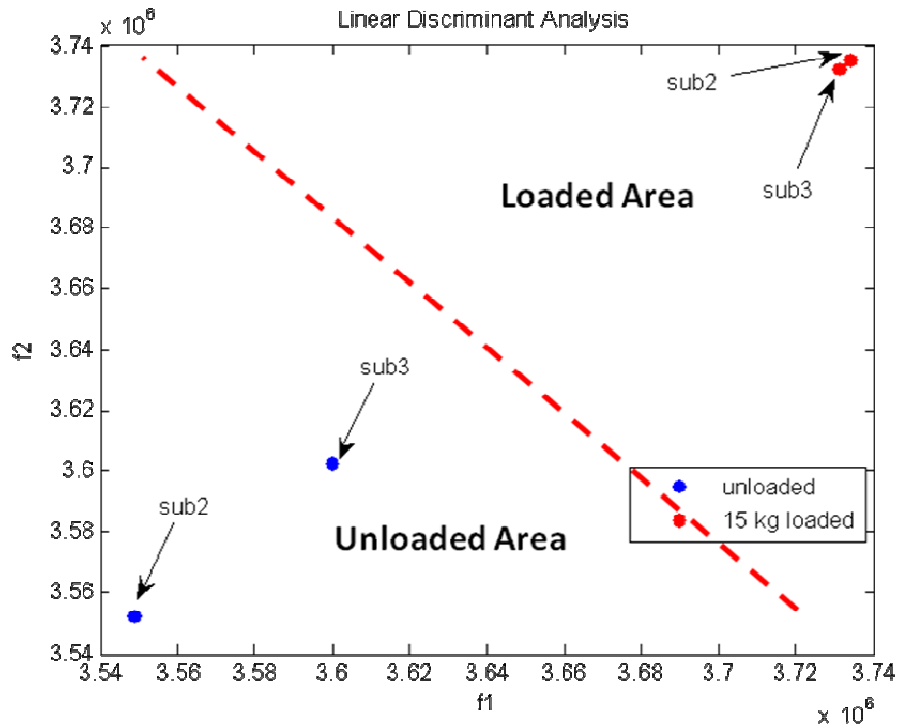
Figure 2. 4. An example of linear discriminant analysis with 4 subjects data showing two separate classes of data.

2.5. *An artificial neural network*

An artificial neural network (ANN) is an interconnected group of artificial neurons that use a mathematical or computational model to minimize the desired error measure (Mehrotra, Mohan et al. 1996). Generally, ANNs are an adaptive system that change its structure based on external or internal information throughout the network. In more practical terms, ANNs are a parallel information-processing system that has certain characteristics that mimic brain function. For that reason, ANNs are able to model complex relationships between inputs and outputs or to find/classify patterns in data. Briefly, the characteristics of ANNs are 1) learning from experience, 2) generalization from previous cases to new data and 3) abstraction from insufficient data or distorted data.

There are two major learning types: supervised learning and unsupervised learning. In supervised learning, there is a given set of example pairs (teacher or training) and the aim is to find a function that matches the examples. In fact, it is accomplished by presenting a sequence of training vectors to the network with corresponding known target vectors. A commonly used cost function is the mean-squared error which tries to minimize the average error between the network's output and the target (desired) value over all the example pairs. Thus, supervised learning is considered to be useful for pattern recognition, classification and regression. On the other hand, in unsupervised learning, the cost function to be minimized can be any function of the data and the network's output. In other words, there are no such training or target vectors required and similar input vectors are assigned to the same output cluster. Therefore, unsupervised learning is practical for general estimation problems including clustering, the estimation of statistical distributions, compression and filtering.

The simplest neural network model is a single-layer perceptron network which consists of an input vector, a set of synaptic weights (w), an activation (transfer) function in a hidden layer and an output vector (Figure 2.5).
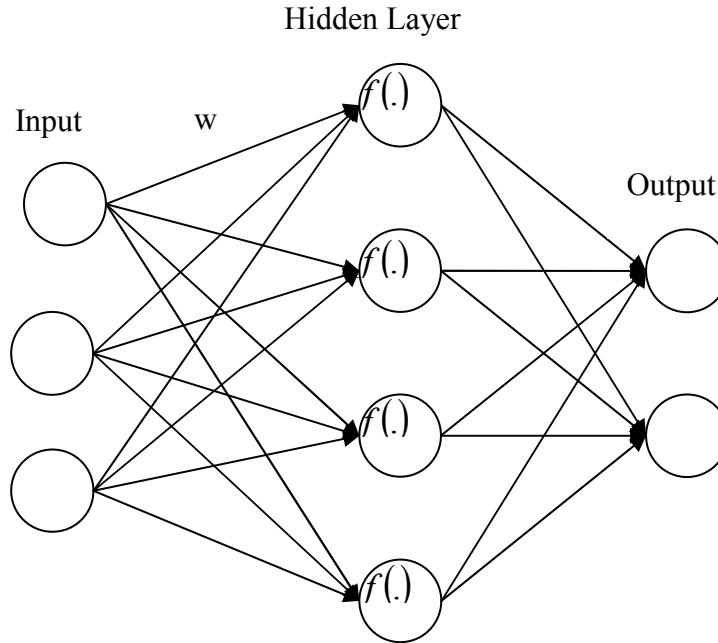
Figure 2. 5. A feed-forward single layer perceptron network.

The 4 most commonly used activation (transfer) functions are : 1) a Heaviside, 2) a piecewise

linear, 3) a sigmoid and 4) a low-gain saturation function (Lynch 2004).

1) $f(v)=\begin{cases}1, & v\geq 0,\\-1, & v<0;\end{cases}$
2) $f(v)=\begin{cases}1, & v\geq 0.5,\\v, & -0.5<v<0.5,\\-1, & v\leq 0;\end{cases}$

3) $f(v)=\tanh(a\cdot v);$
4) $f(v)=\dfrac{1}{2a}\log\dfrac{\cosh(a(v+1))}{\cosh(a(v-1))}$

    Perceptrons can be trained by a simple learning algorithm that is usually called the delta

rule or least mean square rule which calculates the errors between current calculated output and

target value, and uses these errors to adjust the weights (Figure 2.6), thus implementing a form of

gradient descent. In this study, this kind of simple neural network will be used to classify unloaded and loaded walking with several lower body kinematic variables as an input vector.
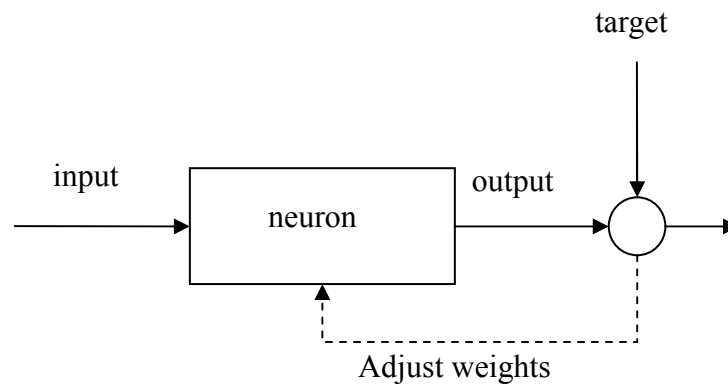
Figure 2. 6. A simple learning algorithm for perceptron.

A multi-layer perceptron, however, consists of multiple layers of computational units in interconnected hidden layers. Although multi-layer networks use a variety of learning techniques, the most popular one is back-propagation, which means that the output values are compared with the correct answer by some predefined error-function. Then, the algorithm adjusts the weights of each connection using the results from this error fuction.

2.6.   Principal Component Analysis (PCA)

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordination by principal components (Daffertshofer, Lamoth et al. 2004). PCA has found application in fields such as face recognition (Oravec and Pavlovicova 2004) and image compression (Meyer-Baese 2000), and is a common technique for finding patterns in data of high dimension (Daffertshofer, Lamoth et al. 2004). In other words, it is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and

17

differences. Another main advantage of PCA is that once we have found these patterns in the data, and we can compress the data (reducing the number of dimensions) without much loss of information (Sadeghi, Allard et al. 2002). PCA is to compute the most meaningful basis to re-express a noisy data set. This new basis will filter out the noise and reveal hidden structure.

PCA can be also used for dimensionality reduction in a data set by retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data (Daffertshofer, Lamoth et al. 2004). The results of a PCA are usually discussed in terms of component scores and loading vectors.

Mathematical Background

Covariance is useful to find out how much the dimensions vary from the mean with respect to each other (Figure 2.7). Covariance is always measured between 2 dimensions unlike 1-dimensional standard deviation and variance. It can be calculated by Equation 2.7.

$$\text{cov}(X, Y) = \frac{\sum_{i=1}^{n}(X_i - \overline{X}) \cdot (Y_i - \overline{Y})}{n-1}$$

Equation 2.7
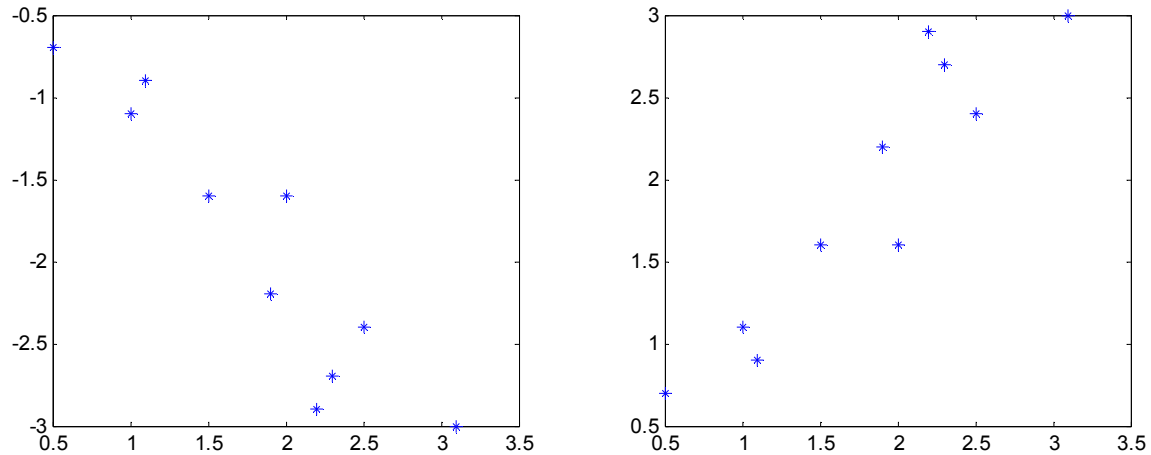
Figure 2. 7. Examples of Negative Covariance (left) and Positive Covariance (right).

Properties of the covariance are:

1. If the value is positive, both dimensions increase together.

2. If the value is negative, then as one dimension increases, the other decreases.

3. If the covariance is zero, it indicates that the two dimensions are independent of each other.

In PCA, Eigenvectors of a covariance matrix indicate the directions of the matrix. All the eigenvectors of a matrix are perpendicular (orthogonal) no matter how many dimensions are (Johnson and Wichern 1998). Also, Eigenvalues indicate the lengths of the corresponding direction (eigenvector).

Here are brief steps to do PCA. First, subtract the mean from original data (Figure 2.8). This is to make a data set whose mean is zero.

19
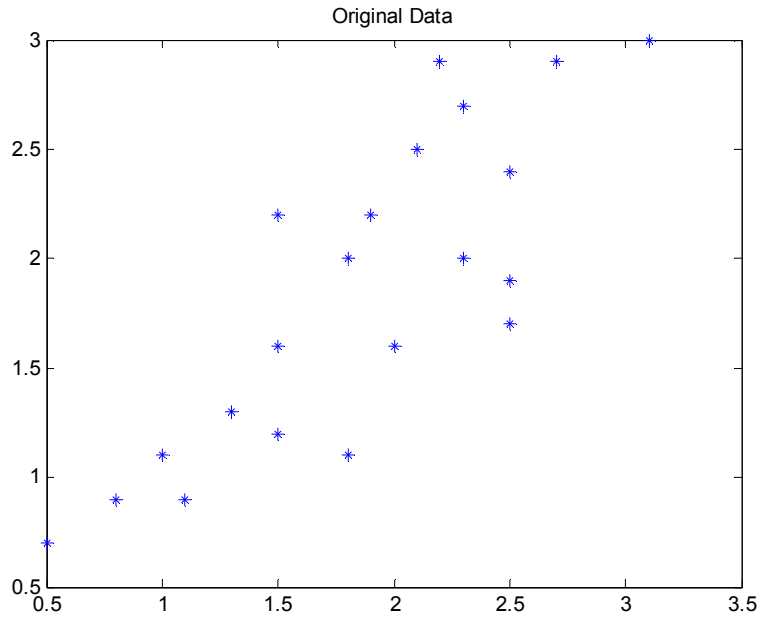
Figure 2. 8. An example of original data for PCA.

Then the covariance matrix, and its eigenvectors and eigenvalues are calculated. First

eigenvector, u1, (corresponding to largest eigenvalues) shows how data sets are related along

that line. In other words, it accounts for the largest proportion of the data variance (Daffertshofer,

Lamoth et al. 2004). The second eigenvector, u2, gives us the other, less important, pattern in the

data (Figure 2.9). However, it must also be uncorrelated (orthogonal) with the first. In fact,

singular value decomposition (SVD) is widely used for the diagonalisation of eigenvalues

because of its numerical stability (Jolliffe 2002). Principal components are chosen to reduce

dimensionality of data. The eigenvector with the largest eignevalue is the principle component of

the data set (n), which is the most significant relationship between the data dimensions.

Therefore, we should order eigenvectors by eigenvalue, largest to smallest. This gives the

components in order of significance. Then, the components (k) of lesser significance can be

ignored. This is how the dimension reduction works with a minimum loss of information (Jolliffe 2002). In order to choose k, Equation 2.8 can be used:

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} > Threshold \ (0.9 \ or \ 0.95), \quad where \ \lambda_i \ is \ eigenvalue \qquad \text{Equation 2.8}$$
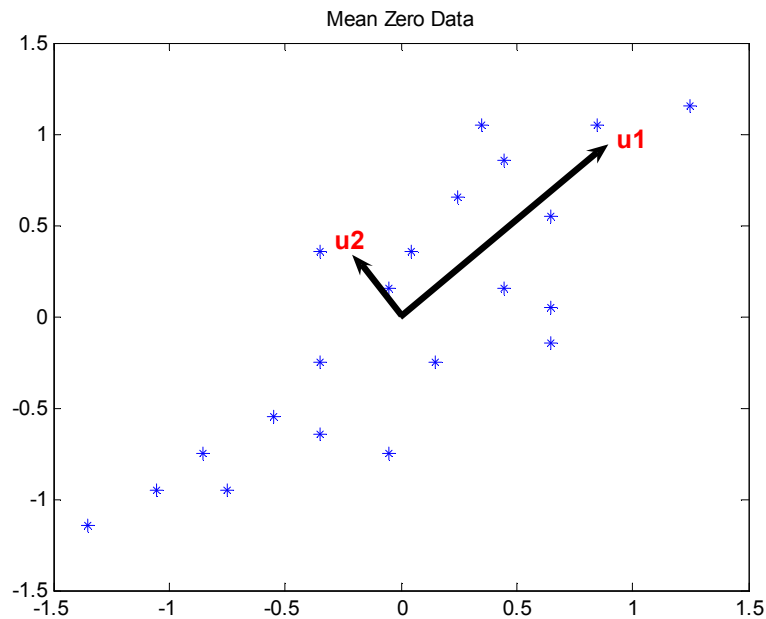
Figure 2. 9. The first (u1) and second (u2) principal components after PCA.

Transformation into a new coordination is performed to represent the original data solely in terms of the components selected above (Figure 2.10). It is one of PCA advantages because it makes the selected components are always perpendicular to each other.
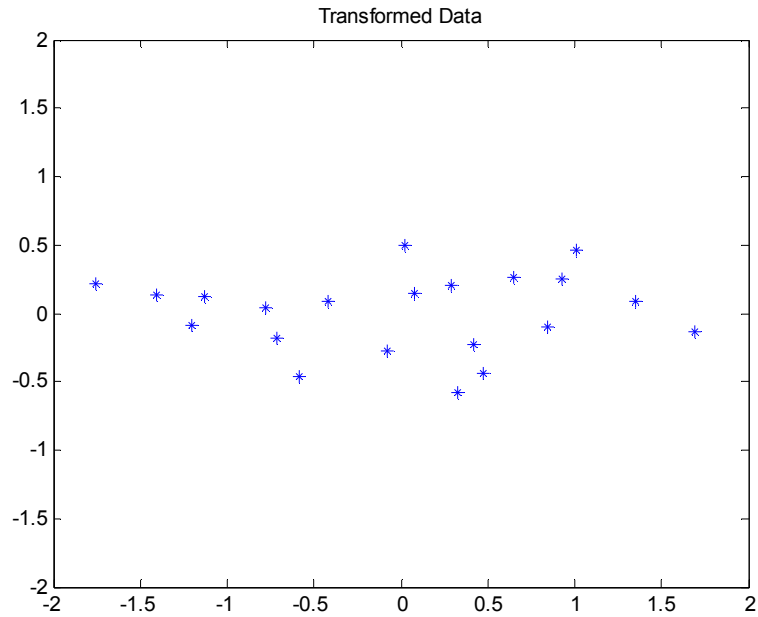
Figure 2. 10. Transformed data after PCA.

In short, PCA is the formation of new variables that are linear combinations of the original variables. Basically, it projects the data along the directions where the data varies the most. These directions are determined by the eigenvectors of the covariance matrix corresponding to the largest eigenvalues. For gait analysis, PCA can be done for comparison of PCs between normal weight subjects and overweight subjects or between unloaded and loaded walking in this study.

Chapter 3 - Preliminary Results

3.1.   *Front loading classification using LDA*

We have used linear discriminant analysis (LDA) to classify unloaded and loaded walking for 51 indoor, even terrain walking in 4 healthy volunteers with various external load conditions. Subjects walked while holding a box of 5, 10 and 15 kg (loaded walking) and without any external load (unloaded walking). There are two more psychological loading conditions: 1) to pretend carrying a loaded box when it was actually empty and 2) to pretend carrying an empty box when it was actually loaded with 15 kg load. 19 reflective markers were placed on the subjects' anatomical landmarks and 2 markers on the carried box. Measurements were repeated up to 4 times in each load condition to reduce the random errors. Linear discriminant analysis (LDA) was used to find the linear combination of features that best separate the two or more classes of motion, unloaded and loaded walking. LDA attempts to express one dependent variable as a linear combination of other features of measurements. Based on LDA, detection of two different walking patterns was performed with 4 variables, cross-correlations from continuous relative phase (CRP) between right and left legs ($XCorr_{Hip\text{-}Knee}$, $XCorr_{Knee\text{-}Ankle}$) and path lengths from phase portraits (PL_{Hip} and PL_{Knee}). Detailed information on these variables is shown in Chapter 4. As shown in Table 3.1, a 90.2% detection rate (46 out of 51) is determined and the false alarm rate, which is the rate that detects unloaded walking as a loaded one, is 13.3% (2 out of 15).

Table 3. 1. Detection Rate based on the linear discriminant analysis.

Load condition	# of false	Detection rate (%)
NB	1/8	87.5
0 kg	1/7	85.7
5 kg	1/5	80.0
10 kg	0/8	100.0
15 kg	0/8	100.0
15 kg → 0 kg	0/8	100.0
0 kg → 15 kg	2/7	71.4
Total	**5/51**	**90.2**

NB indicates no box held. "15 kg → 0 kg" indicates that we asked subjects to pretend carrying a loaded box when it was actually empty. "0 kg → 15 kg" indicates that we asked subjects to pretend carrying an empty box when it was actually loaded with 15 kg load.

Cross-correlations of CRP and path lengths are reliable metrics for the detection of external loads. There are decreasing XCorr values with external loads. This indicates inter-limb CRPs are less similar in loaded walking than unloaded walking, which suggests more asymmetry and/or longer delay in lower body relative movements between left and right leg due to external loads. In addition, the results for hip path length show that external loads cause rapid changes in hip motion and more changes in the vertical direction. This implies a shorter single phase duration. This agrees with previous studies that show increased double stance but decreased single stance duration when carrying loads. Slower changes of knee motions may help absorb a sudden shock due to additional loads. A lower detection rate in the "*0 kg → 15 kg*" loading condition (Table 3.1) implies that it is easier to pretend that a box is heavy than vice versa.

3.2.   *Double-pack classification using ANNs*

We have also tested for 101 indoor treadmill data sets with two external load conditions, unloaded and loaded, for 19 subjects (Figure 3.1).

Figure 3. 1. Subject with reflective markers (A) unloaded walking and (B) loaded walking.

Artificial neural networks (ANNs) classification achieved an 86.1% detection rate (87 out of 101), which mean that 86.1% of the unknown load conditions were assigned into the right category (Figure 3.2). The false alarm rate, which is the rate that detects unloaded walking as loaded one, is 16.7% (8 out of 48).

(A)
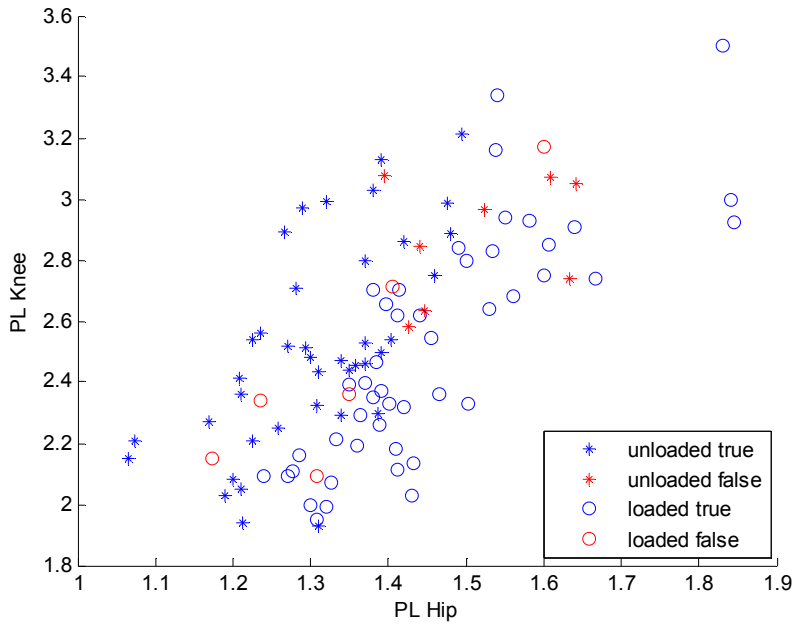
(A)
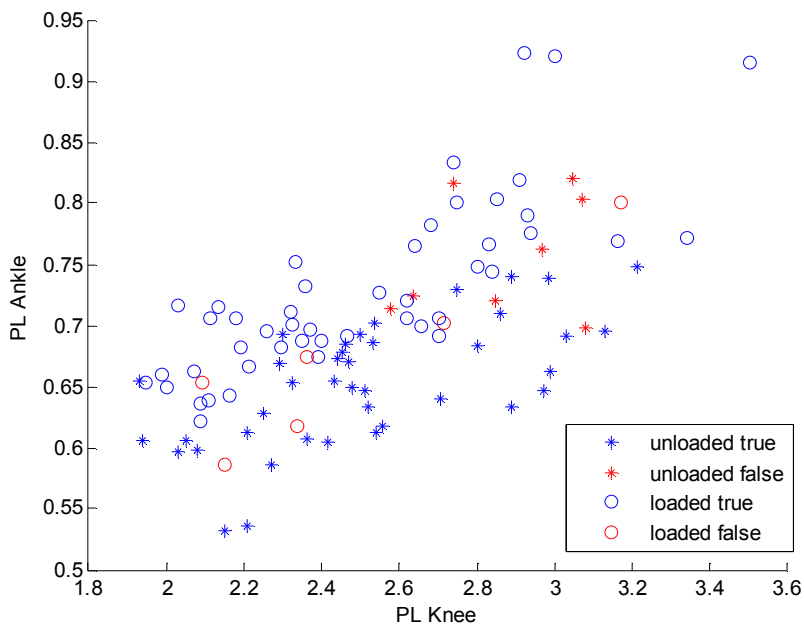
Figure 3. 2. Scatter plots of load classification after artificial neural network. (A) hip path length vs. knee path length and (B) hip path length vs. knee path length for each trial. *True* is the correct decision and *false* is the incorrect decision after artificial neural network classification. It indicates that any linear classifier or statistical methods are difficult or unable to classify loaded and unloaded working with the high probability of detection.

Table 3. 2. ANOVA table for 5 measurements between loaded and unloaded walking.

Var	Unloaded	Loaded	p-value
$XCorr_{Hip-Knee}$	590554 ± 28733	572603 ± 42128	0.134
$XCorr_{Knee-Ankle}$	590499 ± 28669	572601 ± 42111	0.134
PL_{Hip}	1.377 ± 0.147	1.456 ± 0.101	0.061
PL_{Knee}	2.583 ± 0.292	2.570 ± 0.261	0.886
PL_{Ankle}	0.689 ± 0.073	0.728 ± 0.050	0.061

Our results confirm that external loads on a person can be classified by analysis of gait kinematics using ANNs. The method presented in this study combines the benefits of both quantitative analyses and advanced classifiers. Various points of the body were tracked using a 3-D motion capture system, then this data was used to quantify the lower body kinematics and ANNs were utilized to yield an accurate detection of the external load carriage.

The path length shows that it is difficult to linearly separate the two load conditions. The observed differences between load conditions are found to be smaller than the standard deviation of each condition. This suggests that it is difficult to detect evenly-distributed load carriage as compared to one-sided (only front or back) loading conditions. Therefore, the use of ANNs is necessary to provide acceptable classification results.

The analysis of lower body joints is significant because their movement patterns are closely related to gait efficiency and smoothness of locomotion (Stokes, Andersson et al. 1989). A previous study (Wittman, Ward et al. 2005) reported the knee movement is one of the most significant variables in the analysis of load carriage. In this study, knee path length during one stride tends to decrease in loaded walking (Table 3.2). Also, we found XCorr tends to decrease in loaded walking. This decreased XCorr indicates CRPs between inter-legs may be less similar in loaded walking than unloaded walking. A possible reason for this is that there is more

asymmetry and/or longer delay in lower body relative movements between left and right leg due to external loads. As presented in (Sadeghi, Allard et al. 2000; Chow, Kwok et al. 2005), this asymmetry is related to the contribution of each limb to propulsion and control tasks rather than abnormality.

In this work, we cannot find any statistically significant difference between measurements on unloaded and loaded walking (Table 3.2). One possible reason is that we used the same treadmill speed, set as the normal walking, for both load conditions. Thus we can ensure that cases we have are as hard to detect as possible, since both walking with each condition is close to identical in terms of spatio-temporal measurements, i.e. nearly constant stride frequency and leg swing time at a given speed. Further study would be necessary to find the statistical significance of walking speed by having each subject walking at a normal walking speed for each load condition or on the over ground. However, if we have a sufficient number of training set data, then we would be able to apply this method to the detection of any unknown person carrying a hidden external load. Also, whole joint trajectories rather than computed values can be used as inputs for ANNs similar to pattern or sequence recognition, or it is possible to use unsupervised ANNs, so learning is accomplished by the input data itself unlike the supervised ANNs in this study. In other words, with unsupervised ANNs, there is no need for training data sets (Begg and Palaniswami 2006).

3.3.   *A mathematical gait model*

A linear inverted double pendulum model has been used to describe the biped locomotion. This model can walk down an inclined plane with a steady gait (Mochon and McMahon 1980).

McGeer experimentally studied a simple unpowered walking machine which is well known as *passive dynamic walking (McGeer 1990)*. After MaGeer's work, Goswami (Goswami, Espiau et al. 1996) considered its limit cycles and stability in a passive bipedal gait. This passive walker generated its steady walking pattern without control forces, so the gait was energy-effective. On the other hand, this model did not have a knee joint which makes the motion dissimilar to human walking. In this section, a simple mathematical model for a passive walking with knee is developed to 1) compare its joint angles with experimental data and 2) investigate the load effects.
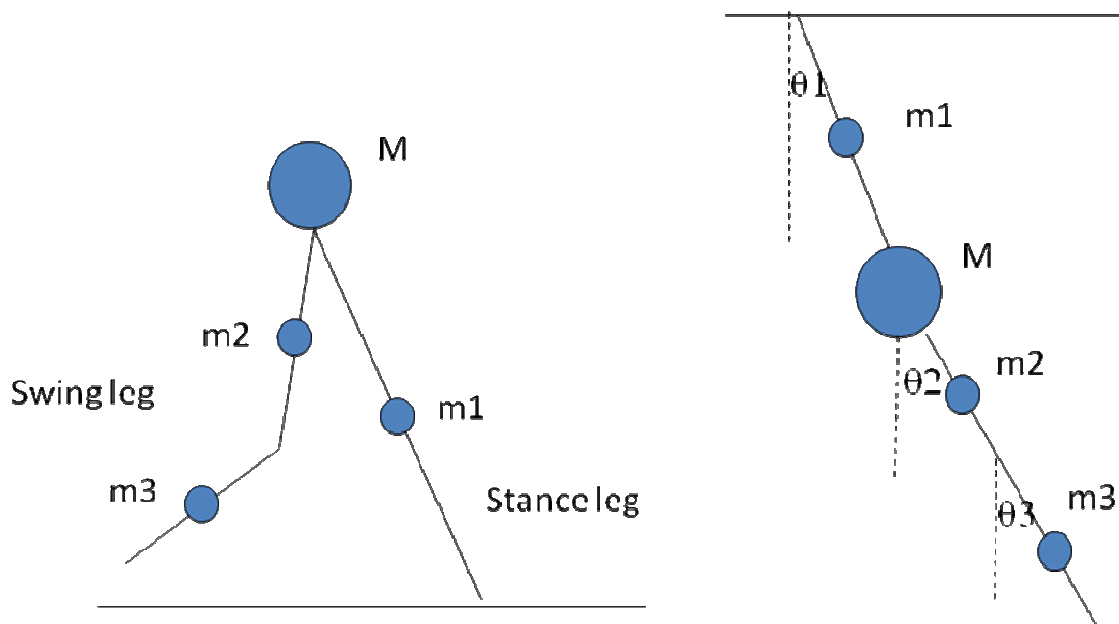
Figure 3. 3. A mathematical model of a passive walker with knee (left) and its inverted pendulum model (right).

A three segments (one straight leg and one leg with knee) model is constructed to simulate biped walking (Figure 3.3). This model has leg mass, m_{1-3}, for each segment and HAT (head, Arms, and trunk) mass, M, at the joint of two legs (Table 3.3). Three time-dependent angles determine the equations of motion, which are the stance leg, hip, and knee angles. The

governing equations of motion are derived from the Lagrange's equation (McGeer 1990). The

equations are given by Equation 3.5:

$$I(\theta)\ddot{\theta} + C(\theta)\dot{\theta}^2 + G(\theta) = 0 \qquad\qquad \text{Equation 3.5}$$

Where

$$I = \begin{bmatrix} m_1 c_1^2 + (M + m_1 + m_2)L_1^2 & m_2(R_1's_1)\cdot(R_2'c_2) + m_3(R_1's_1)\cdot(R_2's_2) & m_3(R_1's_1)\cdot(R_3'c_3) \\ m_2(R_1's_1)\cdot(R_2'c_2) + m_3(R_1's_1)\cdot(R_2's_2) & m_2 c_2^2 + m_3 L_2^2 & m_3(R_2's_2)\cdot(R_3'c_3) \\ m_3(R_1's_1)\cdot(R_3'c_3) & m_3(R_2's_2)\cdot(R_3'c_3) & m_3 c_3^2 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & m_2(R_1's_1)\cdot(R_2''c_2) + m_3(R_1's_1)\cdot(R_2''s_2) & m_3(R_1's_1)\cdot(R_3''c_3) \\ m_2(R_1''s_1)\cdot(R_2'c_2) + m_3(R_1''s_1)\cdot(R_2's_2) & 0 & m_3(R_2's_2)\cdot(R_3''c_3) \\ m_3(R_1''s_1)\cdot(R_3'c_3) & m_3(R_2''s_2)\cdot(R_3'c_3) & 0 \end{bmatrix}$$

$$G = \begin{bmatrix} m_1(R_1'c_1)\cdot g + (M + m_2 + m_3)(R_1's_1)\cdot g \\ m_2(R_2'c_2)\cdot g + m_3(R_2's_2)\cdot g \\ m_3(R_3'c_3)\cdot g \end{bmatrix}$$

Table 3. 3. Notations and numerical settings.

Var	Description	value	unit
M	HAT mass	50, 70, 100	kg
m_1	leg mass	2	kg
m_2	lower part of the leg	1	kg
m_3	upper part of the leg	1	m
L_1	leg length	1	m
L_2	lower part of the leg	0.5	m
L_3	upper part of the leg	0.5	m
s_1	Vector from ground to m_1	0.5	m
s_2	Vector from ground to M	1	m
s_3	Vector from ground to m_2	1.25	m
s_4	Vector from ground to m_3	1.75	m
c_1	Vector to m_1	0.5	m
c_2	Vector from M to m_2	0.25	m
c_3	Vector from knee to m_3	0.25	m
R	rotation matrix		

Constraint

Constraint equation ($R_1s_1 + R_2s_2 + R_3s_3$ =constant) is added to Equation 3.5.

This will yield:

$$\begin{bmatrix} I & -J' \\ -J' & 0 \end{bmatrix}\begin{bmatrix} \ddot{\theta} \\ \lambda \end{bmatrix} + \begin{bmatrix} C \\ -H \end{bmatrix}\begin{bmatrix} \dot{\theta}^2 \\ \lambda \end{bmatrix} + \begin{bmatrix} G \\ 0 \end{bmatrix} = 0 \qquad \text{Equation 3.6}$$

where
$$J = \begin{bmatrix} R_1's_1 & R_2's_2 & R_3's_3 \end{bmatrix}$$
$$H = \begin{bmatrix} R_1''s_1 & R_2''s_2 & R_3''s_3 \end{bmatrix}$$

This constraint equation restricts the movement of the foot. Therefore, it will represent the

double stance during walking.

(A)
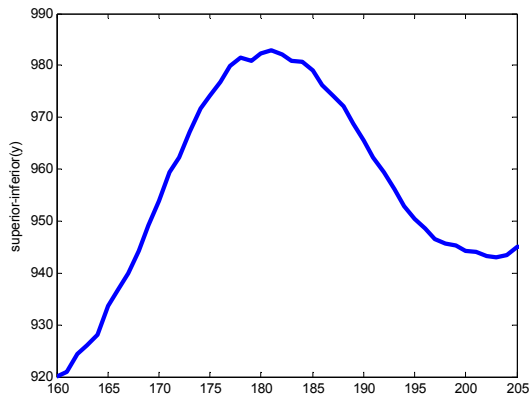
(B)
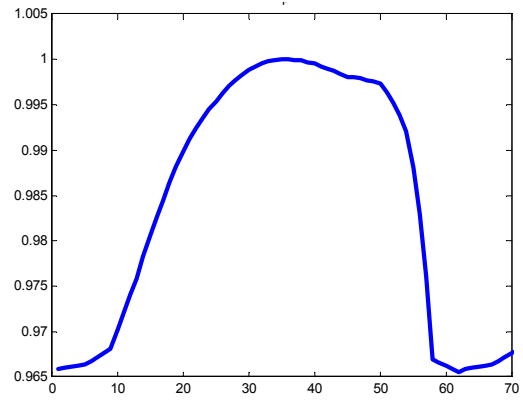
(C)
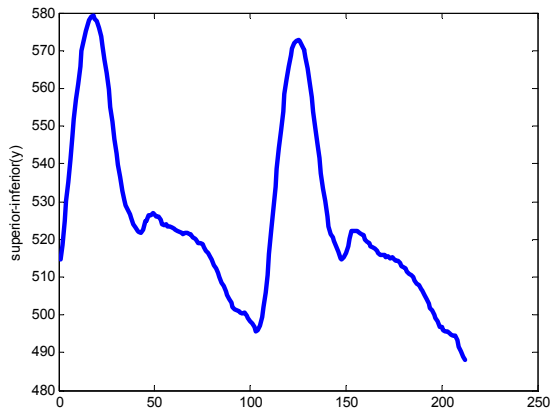
(D)
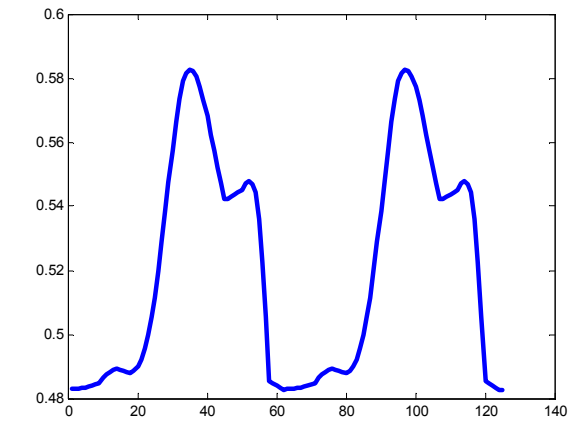
(E)
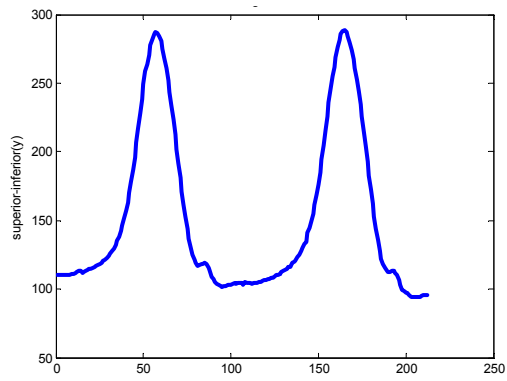
(F)
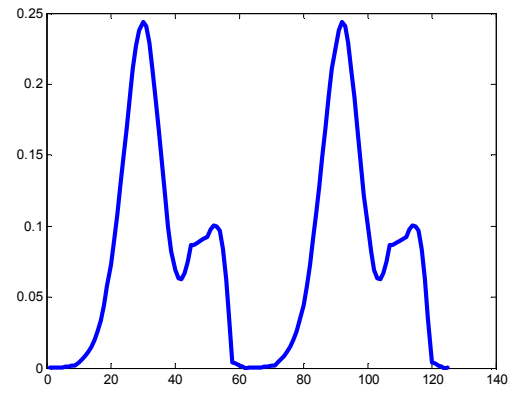
Figure 3. 4. Joint angles: (A) hip angle from experimental data, (B) hip angle from the mathematical model, (C) knee angle from experimental data, (D) knee angle from the mathematical model, (E) ankle angle from experimental data, (F) ankle angle from the mathematical model.

Results from a mathematical model have similar trends compared to joint angles from experimental data when considering it is a simplified model (Figure 3.4). Therefore, it can be used to simulate various load conditions. For this matter, the torso mass, M, is changed as to represent different load carriage which is 50, 70, and 100kg. Then, the vertical locations of joints including hip, knee and ankle are compared with real human joint movements. Specifically, standard deviations of joint vertical positions are shown in Figure 3.5 since the experimental data shows a consistent trend with external loads. However, the standard deviation for the hip joint is quite different. The reason may be that the hip joint in the mathematical model does not include all the upper body motion as in human walking. The results indicate that there are less joint vertical movements when carrying a heavier load compared to unloaded or light loads. It suggests there are energy-efficient mechanisms in humans which suppress vertical motion when carrying a heavy external load, particularly in the mathematical model.

(A)
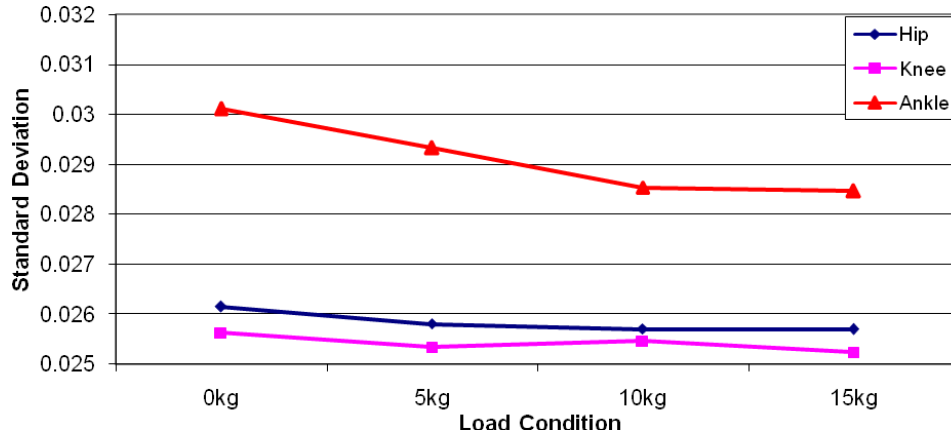
(B)
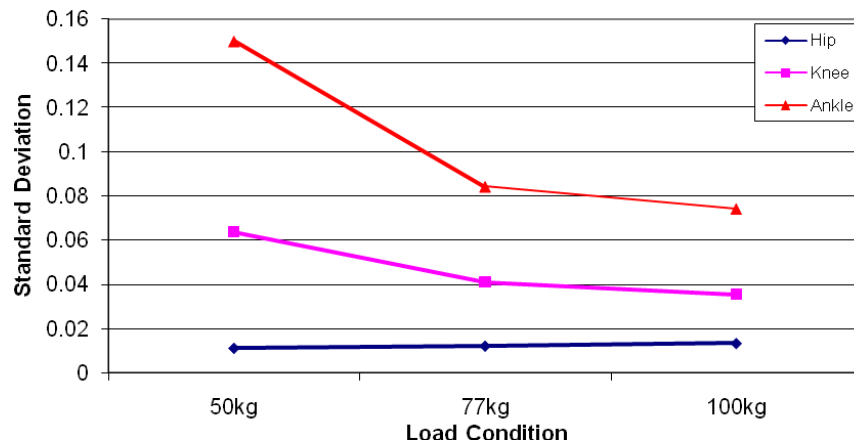
Figure 3. 5. Comparison of the standard deviations from experimental data (A) and the mathematical model (B).

The mathematical model in this section shows a potential to investigate the effects of external loads. For more realistic results, it would be necessary to develop the model with a foot and an active controller to generate torque in the ankle joint.

Chapter 4 - Intra-Session Reliability of the Gait Kinematic Variables in Loaded and Unloaded Walking

Minhyung Lee [a], Michael Roan [a] and Thurmon E. Lockhart [b]

[a] Vibration and Acoustics Laboratories, Department of Mechanical Engineering, Virginia
  Polytechnic Institute and State University, Blacksburg, VA 24061, USA

[b] Locomotion Research Laboratory, Grado Department of Industrial Systems Engineering,
  Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, USA

Correspondence:

     Minhyung Lee, M.S.

     Vibration and Acoustics Laboratories

     Department of Mechanical Engineering

     Virginia Polytechnic Institute and State University

     134 Durham Hall

     Blacksburg, VA 24061, USA

     Phone: 1-540-231-4022

     Fax: 1-540-231-8836

     minlee@vt.edu

4.1. Abstract

The work performed in this manuscript has two main goals: first, to quantify the reliability of lower body phase angles and continuous relative phase (CRP) measurements in gait analysis and second, to determine the number of required trials to achieve statistical reliability of these measurements. A difficult gait classification test case (unloaded vs. loaded walking with evenly distributed front-back loading) is used to illustrate the reliability analysis. Three treadmill trials in each load condition (unloaded or 12.5kg loaded) from 16 healthy subjects were analyzed.

The lower body movement was quantified by path length of phase angles and cross-correlation from a continuous relative phase (CRP). Then, Intra-class correlation coefficients, ICC(2, 1), were calculated for each load condition. The ICC(2, 1) values showed moderate reliability that varied between 0.61 to 0.82. The reliability decrement for the loaded walking condition indicates that stability was compromised when carrying a load. The results suggest that 3 trials are sufficient to determine lower body kinematics under two external load conditions.

4.2. Introduction

The nature of gait and the effects of various factors on gait have been investigated in many previous studies (Kinoshita 1985; Hong and Brueggemann 2000; Chow, Kwok et al. 2005). These studies have mostly analyzed linear spatial-temporal measurements such as stance duration, stride/step length, joint angles and trunk inclination. Recently, Haddad et al. (Haddad, van Emmerik et al. 2006) examined the intralimb and interlimb adaptations with a unilateral leg load. Continuous relative phase (CRP) analysis was used to evaluate how lower body movements were coordinated. The advantage of using relative phase analysis is that it converts four variables (two positions and two velocities) into one measurement. This makes the relative phase very useful for investigating human movement and its complexity using a reduced set of metrics. The path length of the phase portrait can be used to determine the effectiveness of the postural system in controlling the lower body stability and steadiness similar to distance measures of the whole body center-of-pressure (COP) in sway balance control tests (Prieto, Myklebust et al. 1996). However, we are not aware of any reports to characterize how reliable these kinematic quantities are or the required number of trials for assessments of reliable gait characterization.

The goal of this study was 1) To determine the reliability of measurements from phase portraits and CRP, and 2) To calculate the number of repeated trials required to obtain a statistically reliable measure of lower body kinematic quantities. Intra-class correlation (ICC) measures are reported during walking with two external load conditions: unloaded and moderate loaded (12.5kg). It was hypothesized that lower body kinematics can be reliably quantified using path lengths from phase portraits and cross-correlations from CRP analysis.

4.3. Methods

4.3.1. Subjects and experimental setup

Sixteen subjects, 12 male and 4 female, (mean age = 22.94 ± 3.84 years) participated in the study. All subjects gave their informed consent prior to participation as defined by the Committee for Participants of Investigative Projects at the Virginia Tech. The subject mean body heights and weights were 177.38 ± 7.01 cm and 75.39 ± 17.07 kg. To determine a subject's normal walking speed, the treadmill was started and the velocity gradually increased so as to achieve a subject's most comfortable walking speed. This walking speed was used for the two loading conditions on the treadmill.

A total of 23 reflective markers (Lockhart, Woldstad et al. 2003; Chow, Kwok et al. 2005) were attached to the subjects' anatomical landmarks (top of the head, base of second toe, malleolus, epicondyle, greater trochanter, clavicle, styloid process of ulna, lateral epicondyle of humerus, greater tubercle, acromion, anterior portion of temporal bone, and center of the calcaneus) to capture subjects' 3D motion using a ProReflex system (Qualisys, Gothenburg, Sweden) at the sampling rate of 120 Hz. However, only lower body markers' data were analyzed to focus on changes of lower body kinematics. Treadmill walking was performed for 30 s sessions with subjects wearing a 12.5 kg vest type mass (evenly distributed front and back) and without any external load (unloaded walking). The vest was attached to the subjects' body using two shoulder straps and three side straps so that it did not obstruct any upper or lower body movements. Five trials were repeated in each load condition. However, the first 2 trials were considered as practical sets to attain a physiological steady state and the rest of 3 trials were only

analyzed. Also, the order of external load conditions in each subject was completely randomized to reduce any order effects

.

4.3.2. Analysis

Consecutive left heel contacts determined the period of one stride in this study. Thus, one stride includes both a left and a right step. Left heel contacts were determined using the vertical velocity changes of heel markers to identify gait periods (Mickelborough, van der Linden et al. 2000). Two consecutive left strides were averaged for the analysis. Then, the kinematic data were filtered using a low pass, fourth-order Butterworth filter with 7 Hz cutoff frequency, and normalized by subjects' height. All following angles were measured in sagittal plane. Hip angles were defined from horizontal to the thigh segment. Knee angles were determined between the thigh segment and the shank segment, and ankle angles were between the shank segment and the foot (Harman, Han et al. 2000). Segmental angular velocities were calculated from the sagittal plane angles using a first central difference method (Haddad, van Emmerik et al. 2006). These angular positions and velocities were then used to compute continuous relative phase from the position-velocity phase portrait.

4.3.3. Continuous Relative Phase (CRP)

CRP was assessed over two interlimb couplings, CRP_{H-K} and CRP_{K-A} which indicate CRP between hip and knee (subscript H-K) angles and CRP between knee and ankle (subscript K-A) angles, respectively. The phase angles used in this study were determined from the angular position ($\theta(t)$) vs. angular velocity ($\dot{\theta}(t)$) on the phase portrait (Figure 4.1). From the resulting

phase-planes, the phase angle at each time was calculated relative to the right horizontal using

Equation 4.1 (Kurz and Stergiou 2002).

$$\psi(t) = \tan^{-1}\left(\frac{\dot{\theta}(t)}{\theta(t)}\right)$$

Equation 4.1

(A)

Phase Plot of Hip

(B)

Phase Plot of Hip

(C)

Phase Plot of Knee

(D)

Phase Plot of Knee

(E)   (F)

Phase Plot of Ankle

Angular Velocity

0.04
0.03
0.02
0.01
0
-0.01
-0.02
1.4 1.5 1.6 1.7 1.8 1.9 2
Angular Position

Phase Plot of Ankle

Angular Velocity

0.04
0.03
0.02
0.01
0
-0.01
-0.02
1.4 1.5 1.6 1.7 1.8 1.9 2
Angular Position
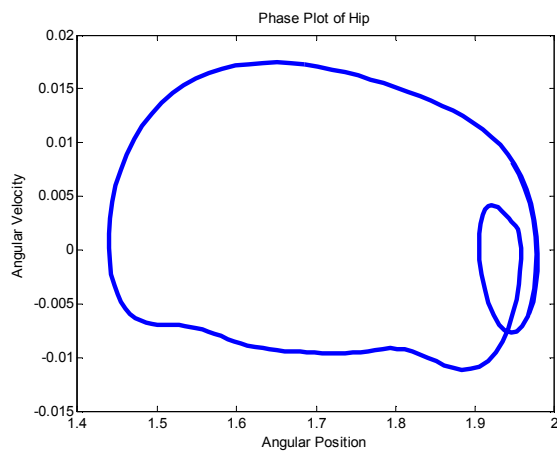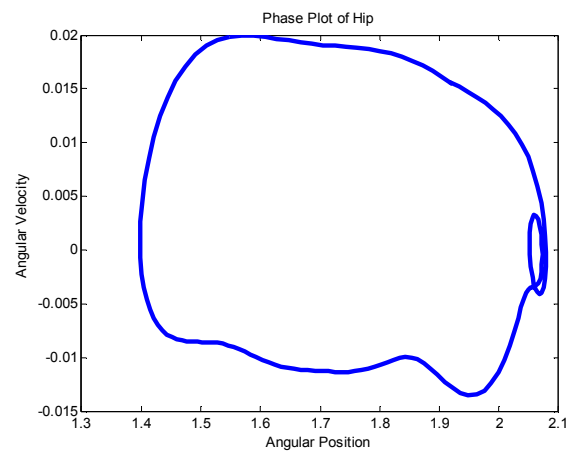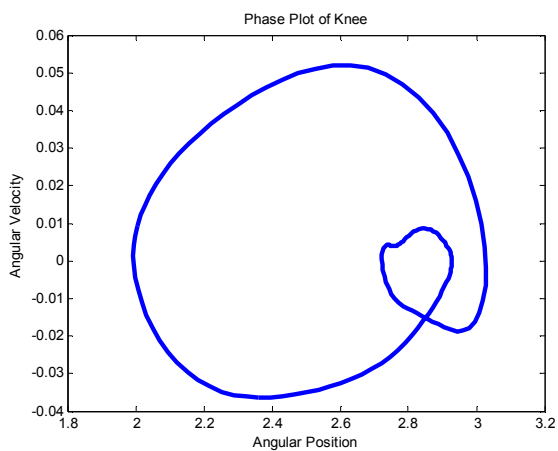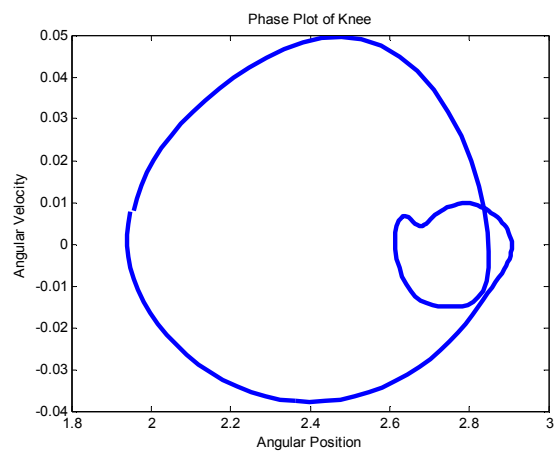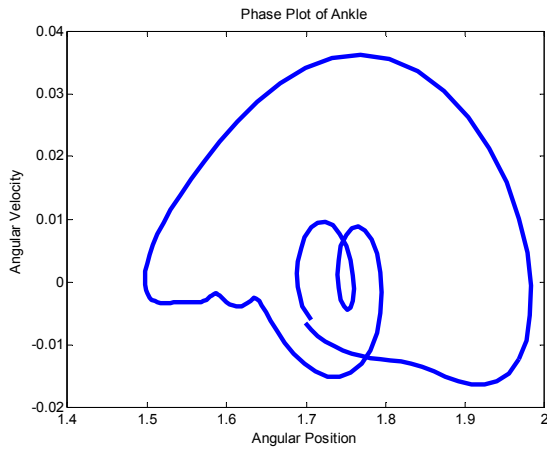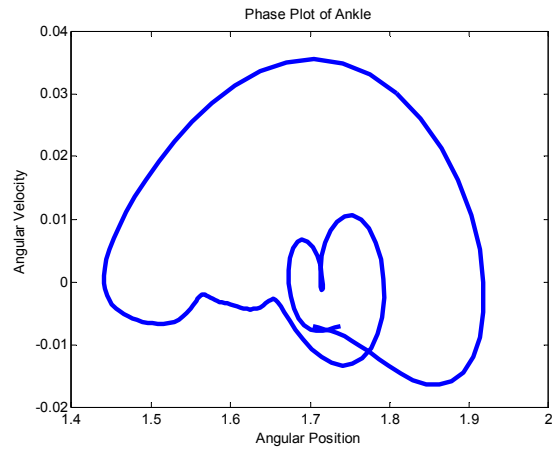
Figure 4. 1. Phase Portraits of hip, knee, and ankle angles from one typical subject (A) hip phase in unloaded walking condition, (B) hip phase in loaded, (C) knee phase in unloaded walking, (D) knee phase in loaded, (E) ankle phase in unloaded walking, and (F) ankle phase in loaded.

CRP was computed using the differences between the phase angle of hip-knee and knee-ankle using Equation 4.2. More detailed information about phase angle and CRP can be found in (Burgess-Limerick, Abernethy et al. 1991; Burgess-Limerick, Abernethy et al. 1993; Hamill, Haddad et al. 2000; Kurz and Stergiou 2002).

$$CRP_{H-K} = \psi_{Hip} - \psi_{Knee}$$
$$CRP_{K-A} = \psi_{Knee} - \psi_{Ankle}$$

Equation 4.2

where subscripts indicate the phase angles of each joint.

Cross-correlations were calculated for cross-body CRPs using Equation 4.3. These cross-correlation values show the similarity of relative movements between left and right legs. Therefore, smaller values indicate less similar movements between inter-leg dynamics.

$$XCorr_{H-K} = mean(xcorr(CRP_{H-K,R}, CRP_{H-K,L}))$$
$$XCorr_{K-A} = mean(xcorr(CRP_{K-A,R}, CRP_{K-A,L}))$$

<div align="right">Equation 4.3</div>

where subscripts R and L indicate the right and left sides' values, respectively.

4.3.4. Path length (PL) of Phase Portrait

From the phase-planes, path length (Equation 4.4) is estimated as the sum of the straight line distances between consecutive points for hip, knee and ankle joints (PL_{Hip}, PL_{Knee} and PL_{Ankle}). These values were used to quantify the magnitude and velocity of joint angular movement as function of time over a gait cycle.

$$PL = \sum_{i=1}^{n-1} \sqrt{(\theta(i+1) - \theta(i))^2 + (\dot{\theta}(i+1) - \dot{\theta}(i))^2}$$

<div align="right">Equation 4.4</div>

4.3.5. Intra-session reliability

Intra-class correlation coefficients with two-way random effect, ICC(2,1), were computed using the three trials from 16 subjects by Equation 4.5 (Shrout and Fleiss 1979):

$$ICC(2,1) = \frac{BMS - EMS}{BMS + (k-1) \cdot EMS + \dfrac{k \cdot (JMS - EMS)}{n}}$$

<div align="right">Equation 4.5</div>

In this equation, BMS is the between-targets (subjects) mean square, EMS is the error mean square, JMS is the between-judges mean square, k is the number of trials (judges) and n is the

number of targets. More information about ICC(2,1) can be found in (Landis and Koch 1977; Shrout and Fleiss 1979). Furthermore, Landis and Koch (Landis and Koch 1977) have characterized values of reliability coefficients as follows: slight (0-0.20), fair (0.21-0.40), moderate (0.41-0.60), substantial (0.61-0.80) and almost perfect (0.81-1.00). The number of trials (k) was calculated by the Spearman-Brown formula (Shrout and Fleiss 1979; Corriveau, Hebert et al. 2000) in Equation 4.6;

$$k = \frac{\rho^*(1-\rho)}{\rho(1-\rho^*)}$$

Equation 4.6

Where $\rho^* = 0.81$ in this study is set up for the desired reliability coefficient and ρ is the ICC values from the current study. Statistical analyses were performed using SPSS (v.13, SPSS Inc., Chicago, IL).

4.4. Results

All ICC values for loaded and unloaded conditions showed at least moderate reliability (Table 4.1). Also, unloaded walking was found to have greater ICC values. This indicates that the measurements taken in the unloaded condition are more reliable than for loaded walking for an equal number of trials.

Table 4. 1. Reliability ICC(2,1) coefficients for the gait kinematics in unloaded and loaded walking. Bolded values indicate "substantial" reliable category and * indicates "almost perfect" reliable category. CI indicates the confidence interval.

Variable	Unloaded			Loaded			p-value
	Mean (±SD)	ICC	95% CI of ICC	Mean (±SD)	ICC	95% CI of ICC	
$XCorr_{H-K}$	590554 ± 28733	**0.764**	$0.554\sim0.901$	572603 ± 42128	**0.744**	$0.518\sim0.892$	**< 0.05**
$XCorr_{K-A}$	590499 ± 28669	**0.768**	$0.560\sim0.902$	572601 ± 42111	**0.747**	$0.522\sim0.893$	**< 0.05**
PL_{Hip}	0.4459 ± 0.0820	**0.689**	$0.441\sim0.864$	0.4800 ± 0.0624	0.605	$0.330\sim0.820$	**< 0.01**
PL_{Knee}	2.5828 ± 0.2919	**0.819***	$0.641\sim0.926$	2.5698 ± 0.2607	0.606	$0.324\sim0.822$	0.69
PL_{Ankle}	0.6885 ± 0.7033	**0.689**	$0.441\sim0.864$	0.7280 ± 0.0503	0.605	$0.330\sim0.820$	**< 0.01**

The number of recommended trials to obtain almost perfect reliability (ICC=0.81) are summarized in Table 4.2. All measurements required at most 3 trials to have almost perfect reliability.

Table 4. 2. Number of recommended trials per load condition to achieve almost perfect (ICC=0.81) assessment. Results are based on the Spearman-Brown prophecy formula sufficient.

	$XCorr_{H-K}$	$XCorr_{K-A}$	PL_{Hip}	PL_{Knee}	PL_{Ankle}
Loaded	2	2	3	3	3
Unloaded	2	2	2	1	2

4.5. Discussion

The main objective of this study was to determine reliability of path length from phase portraits and cross-correlation from CRP and how many trials are necessary to obtain a reliable measure for lower body kinematics. Previous studies indicate that ICC values above 0.61 are the indication of substantial reliability (Landis and Koch 1977). The results in the current study showed that lower body kinematic quantities under loaded and unloaded walking conditions were within this range. This is comparable to previous studies (Wall and Crosbie 1996; Stolze, Kuhtz-Buschbeck et al. 1998; Maynard, Bakheit et al. 2003; Kang and Dingwell 2006). Thus, path length of phase portrait and cross-correlation of CRP can be used as reliable metrics to quantify lower body joint movements. In addition, the ICC values in loaded walking condition were lower than in unloaded walking condition implying that measurements were less reliable and needed more trials to obtain good reliability. All subjects stated that they were comfortable with the external load. However, it is possible that being unaccustomed to the load caused less balance stability due to an increased body weight (Hue, Simoneau et al. 2007). This may cause more variability across trials as subjects modify or adapt their gait patterns to the loaded condition (Kinoshita 1985).

Significantly smaller cross-correlation values in loaded walking condition may indicate that this condition is more asymmetry in lower body relative movements between left and right

legs than unloaded walking condition (Table 4.1). As presented in (Sadeghi, Allard et al. 2000; Chow, Kwok et al. 2005), this asymmetry is related to the contribution of each limb to propulsion and control tasks rather than abnormality, which probably causing greater energy costs (Reisman, Block et al. 2005). In addition, path lengths of ankle and hip joints are significantly greater in loaded walking condition than unloaded walking condition. The possible reason is that the additional mass causes more angular changes of each joint including angular velocity changes to produce more power during gait cycles that costs more energy due to external loads.

The number of trials necessary to obtain almost perfect reliability varied from 1 for PL_{Knee} in unloaded walking up to 3 for PL values in either loading conditions. Therefore, 3 trials for each load condition are sufficient for the lower body kinematic quantities such as path length from phase portraits and cross-correlation from CRP with two load conditions including 12.5kg loaded walking as reliable measurements. It may be possible to obtain more reliable measurements with additional trials, which are time-consuming. However, at least 3 trials can ensure that kinematic quantities are reliable.

In this study, the same self-selected walking speed was used for both unloaded and loaded walking on the treadmill. This may cause atypical walking in the loaded condition. Therefore, future work will assess to use two self-selected walking speed for each load condition to determine the changes of the ICC values with respect to the walking speed.

46

Acknowledgements

4.6. References

Burgess-Limerick, R., B. Abernethy, et al. (1991). "Note: A statistical problem in testing invariance of movement using the phase plane model." Journal of Motor Behavior **23**(4): 301-303.

Burgess-Limerick, R., B. Abernethy, et al. (1993). "Relative phase quantifies interjoint coordination." J Biomech **26**(1): 91-4.

Chow, D. H., M. L. Kwok, et al. (2005). "The effect of backpack load on the gait of normal adolescent girls." Ergonomics **48**(6): 642-656.

Corriveau, H., R. Hebert, et al. (2000). "Intrasession reliability of the "center of pressure minus center of mass" variable of postural control in the healthy elderly." Arch Phys Med Rehabil **81**(1): 45-8.

Haddad, J. M., R. van Emmerik, et al. (2006). "Adaptations in interlimb and intralimb coordination to asymmetrical loading in human walking." Gait and Posture **23**: 429–434.

Hamill, J., J. M. Haddad, et al. (2000). "Issues in quantifying variability from a dynamical systems perspective." Journal of Applied Biomechanics **16**: 407-418.

Harman, E. A., K. H. Han, et al. (2000). "The effects of backpack weight on the biomechanics of load carriage." US Army Research Institute of Environmental Medicine, Natick, MA.

Hong, Y. and G. P. Brueggemann (2000). "Changes in gait patterns in 10-year-old boys with increasing loads when walking on a treadmill." Gait Posture **11**(3): 254-9.

Hue, O., M. Simoneau, et al. (2007). "Body weight is a strong predictor of postural stability." Gait Posture **26**(1): 32-8.

Kang, H. G. and J. B. Dingwell (2006). "Intra-session reliability of local dynamic stability of walking." Gait Posture **24**(3): 386-90.

Kinoshita, H. (1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait." Ergonomics **28**(9): 1347-62.

Kurz, M. J. and N. Stergiou (2002). "Effect of normalization and phase angle calculations on continuous relative phase." Journal of Biomechanics **35**: 369–374.

Landis, J. R. and G. G. Koch (1977). "The measurement of observer agreement for categorical data." Biometrics **33**(1): 159-74.

Lockhart, T. E., J. C. Woldstad, et al. (2003). "Effects of age-related gait changes on the biomechanics of slips and falls." Ergonomics **46**(12): 1136-60.

Maynard, V., A. M. Bakheit, et al. (2003). "Intra-rater and inter-rater reliability of gait measurements with CODA mpx30 motion analysis system." Gait Posture **17**(1): 59-67.

Mickelborough, J., M. L. van der Linden, et al. (2000). "Validity and reliability of a kinematic protocol for determining foot contact events." Gait Posture **11**(1): 32-7.

Prieto, T. E., J. B. Myklebust, et al. (1996). "Measures of postural steadiness: differences between healthy young and elderly adults." IEEE Trans Biomed Eng **43**(9): 956-66.

Reisman, D. S., H. J. Block, et al. (2005). "Interlimb Coordination During Locomotion: What Can be Adapted and Stored?" J Neurophysiol **94**(4): 2403-2415.

Sadeghi, H., P. Allard, et al. (2000). "Symmetry and limb dominance in able-bodied gait: a review." Gait Posture **12**(1): 34-45.

Shrout, P. E. and J. L. Fleiss (1979). "Intraclass correlations: Uses in assessing rater reliability." Psychological Bulletin **86**(2): 420-8.

Stolze, H., J. P. Kuhtz-Buschbeck, et al. (1998). "Retest reliability of spatiotemporal gait parameters in children and adults." Gait Posture **7**(2): 125-130.

Wall, J. C. and J. Crosbie (1996). "Accuracy and reliability of temporal gait measurement." Gait and Posture **4**: 293-6.

Chapter 5 - Gait Analysis to Classify External Load Conditions Using Linear Discriminant Analysis

Original Article

Minhyung Lee [a], Michael Roan [a], Benjamin Smith [a] and Thurmon E. Lockhart [b]

[a] Vibration and Acoustics Laboratories, Department of Mechanical Engineering, Virginia
  Polytechnic Institute and State University, Blacksburg, VA 24061, USA
[b] Locomotion Research Laboratory, Grado Department of Industrial and Systems Engineering,
Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, USA

Correspondence:

Minhyung Lee, M.S.

Vibration and Acoustics Laboratories

Department of Mechanical Engineering

Virginia Polytechnic Institute and State University

134 Durham Hall

Blacksburg, VA 24061, USA

Phone: 1-540-231-4022

Fax: 1-540-231-8836

minlee@vt.edu

5.1. Abstract

There are many instances where it is desirable to determine, at a distance, whether a subject is carrying a hidden load. Automated detection systems based on gait analysis have been proposed to detect subjects that carry hidden loads. However, very little baseline gait kinematic analysis has been performed to determine the load carriage effect while ambulating with an evenly distributed (front to back) loads on human gait. The work in this paper establishes, via high resolution motion capture trials, the baseline separability of load carriage conditions into loaded and unloaded categories using several standard lower body kinematic parameters. A total of 23 subjects (19 for training and 4 for testing) were studied. Satisfactory classification of subjects into the correct loading condition was achieved in this paper by resorting to linear discriminant analysis (LDA). Six lower body kinematics including ranges of motion and path lengths from the phase portraits were used to train the LDA which can discriminate loaded and unloaded walking conditions. This baseline performance from 4 subjects who were not included in training data sets shows that the use of LDA provides an 88.9% correct classification over two loaded and unloaded walking conditions. The results suggest that there are gait pattern changes due to external loads, and LDA could be applied successfully to classify the gait patterns with an unknown load condition.

5.2. Introduction

There are many instances where it is desirable to determine, at a distance, whether a subject is carrying a hidden load. Several sensor modalities (e.g. imaging and radar) have been considered for this application. Many of these proposed methods rely on the assumption that a subject's gait is altered in a detectable way due to the load. The work in this paper establishes, via high resolution motion capture trials with 19 subjects for training and 4 subjects to validate the absolute baseline separability of subjects into loaded and unloaded categories utilizing several common lower body kinematic quantities. Any practical hidden load detection system based on gait analysis, such as video, will have performance poorer than that established in this paper because any "real world" system will extract noisier kinematic measurements than motion capture systems. Even using motion capture, it is difficult to correctly classify loading condition based on lower body kinematics when the load is distributed evenly from front to back. However, satisfactory classification of subjects into the correct loading condition was achieved in this paper by resorting to linear discriminant analysis (LDA). Many researchers have widely used discriminant analysis for image-processing (Han and Bhanu 2006; Boulgouris and Chi 2007) and face recognition (Yu and Yang 2001). In this paper, we explore the applicability of LDA to gait pattern classification. The LDA classifier developed in this paper establishes an 88.9% correct classification (loaded vs. unloaded) baseline performance for any detection system that uses the same kinematic quantities as those used in this paper.

There are many previous studies that characterize the nature of gait and the effects of various factors (such as loading condition) on gait patterns. One such study showed that the duration of the double stance increased as loads were heavier, but single stance duration

decreased in 10 healthy males (Kinoshita 1985) and in 15 boys (Hong and Brueggemann 2000). Also, it was shown that the normal walking pattern was significantly modified by external load conditions: backpack or double-pack (Kinoshita 1985). Backpack loading has a more significant effect on gait pattern than doublepack loading. For example, forward leaning of the trunk is a natural behavior to help keep the whole body center-of-mass (COM) over the feet with backpacking (Knapik, Harman et al. 1996; Harman, Han et al. 2000; Hong and Brueggemann 2000). There is, however, no forward leaning when ambulating with an evenly distributed front-to-back load carriage system (Kinoshita 1985). It was found that forward inclination considerably increased as weight increased in order to minimize energy cost (Inman, Ralston et al. 1981)(Inman et al., 1981; (Luttgens and Wells 1982). This minimized energy expenditure resulted in the decrease of vertical positions at the knee and ankle with added weight (Wittman, Ward et al. 2005). Several published studies indicated that ankle rotation increased in the sagittal plane under loaded conditions (Kinoshita 1985; Knapik, Harman et al. 1996). These studies also showed that knee flexion after impact was greater when carrying loads in order to absorb increased impact forces.

The previous studies, however, analyzed mostly linear spatial-temporal measurements such as stride length, stance duration, etc. Recently, Haddad et al. (Haddad, van Emmerik et al. 2006) examined the intralimb and interlimb adaptations with a unilateral leg load. Relative phase plot was used to evaluate how lower body movements were coordinated. The advantage of using relative phase analysis is that it can convert four variables (two positions and two velocities) into one measurement. This makes the relative phase plot very useful for investigating human movement and its complexity using a reduced set of measurements or metrics. The path length of the phase portrait can be used to determine the effectiveness of the postural system in controlling

the lower body stability and steadiness similar to distance measures of center-of-pressure (COP) in sway balance control tests (Prieto, Myklebust et al. 1996). Previous studies neither analyzed these quantities for walkers with and without an evenly distributed load nor do they establish the baseline performance of classification methods for determining loaded vs. unloaded walking. The only previous work to differentiate between loaded vs. unloaded subjects (BenAbdelkader and Davis 2002) used video as a sensing modality. This work used metrics that measured swinging periodicity of legs and arms. Another metric to differentiate carrying vs. not carrying an object were the medians of the time series for lower parts of body. The study used a simple "and" type classifier that classifies as natural-walking if all criteria were met. If any of the criteria was violated, then the state was classified as loaded walking. A significant difference between the work in BenAbdelkader and Davis and work in this study is that the type of loading in BenAbdelkader and Davis study was not evenly distributed loads.

Although much has been learned over the last few decades about external load effects on gait patterns, development of discriminant techniques to classify evenly distributed external loads is lacking. As such, the two primary goals of this study were: 1) To establish the upper bound on performance of classification of loading condition using LDA. 2) Provide pre and post loading analysis of several common gait kinematic discriminants that also serve as inputs to the LDA classifier. It was hypothesized that there will be significant differences in lower body joint kinenmatic quantities while carrying an evenly distributed load, and classification of unknown subject's loading condition would be possible based on the these quantities.

5.3. Methods

5.3.1. Subjects and experimental setup

Twenty three subjects, 14 male and 9 female, (mean age = 22.52 ± 3.84 years) participated in the study. They were randomly grouped to 19 (12 male and 7 female) subjects for training and 4 (2 male and 2 female) subjects for testing. All subjects gave their informed consent prior to participation as defined by the Committee for Participants of Investigative Projects at the Virginia Tech. The subject mean body heights and weights were 175.16 ± 8.51 cm, 73.31 ± 16.56 kg for the training group, and 174.43 ± 7.94 cm, 73.04 ± 15.40 kg for the testing group, respectively. To determine a subject's normal walking speed, the treadmill was started and the velocity gradually increased so as to achieve a subject's most comfortable walking speed. This walking speed was used for the two loading conditions on the treadmill.

A total of 23 reflective markers (Lockhart, Woldstad et al. 2003; Chow, Kwok et al. 2005) were attached to the subjects' anatomical landmarks (top of the head, base of second toe, malleolus, epicondyle, greater trochanter, clavicle, styloid process of ulna, lateral epicondyle of humerus, greater tubercle, acromion, anterior portion of temporal bone, and center of the calcaneus) to capture subjects' 3D motion using a ProReflex system (Qualisys, Gothenburg, Sweden) at the sampling rate of 120 Hz. However, only lower body markers' data were analyzed to focus on changes of lower body kinematics. Treadmill walking was performed for 30 s sessions with subjects wearing a 12.5 kg vest type mass (evenly distributed front and back) and without any external load (unloaded walking). The vest was attached to the subjects' body using two shoulder straps and three side straps so that it did not obstruct any upper or lower body

movements. Five trials were repeated in each load condition and the order of external load

conditions in each subject was completely randomized to reduce any order effects.

5.3.2. Analysis

Consecutive left heel contacts determined the period of one stride in this study. Thus, one

stride included both a left and a right step. Left heel contacts were determined using the vertical

velocity changes of heel markers to identify gait periods (Mickelborough, van der Linden et al.

2000). Two consecutive left strides were averaged for the analysis. Then, the kinematic data

were filtered using a low pass, fourth-order Butterworth filter with 7 Hz cutoff frequency and

normalized by subjects' height. All following angles were measured in sagittal plane. Hip angles

were defined from horizontal to the thigh segment. Knee angles were determined between the

thigh segment and the shank segment, and ankle angles were between the shank segment and the

foot (Harman, Han et al. 2000). Then, sagittal plane joint ranges of motion (ROM) were

calculated as the difference between peak flexion and peak extension (LaFiandra, Holt et al.

2002) at hip, knee and ankle joints (Hip ROM, Knee ROM and Ankle ROM). These values were

used to quantify the magnitude of joint angular movement over gait cycle.

5.3.3. Phase Portrait Path length (PL)

The phase portrait (Figure 5.1) used in this study were determined from the angular

position ($\theta(t)$) vs. angular velocity ($\dot{\theta}(t)$). Segmental angular velocities were calculated from

the sagittal plane angles utilizing a first central difference method (Haddad, van Emmerik et al.

2006). From the resulting phase-planes, path length (Equation 5.1) is estimated as the sum of the

straight line distances between consecutive points for hip, knee and ankle phases (PL_{Hip}, PL_{Knee}

and PL$_{Ankle}$). These values were used to quantify the magnitude and velocity of joint angular
movement as function of time over a gait cycle.

$$PL = \sum_{i=1}^{n-1} \sqrt{\left(\theta(i+1) - \theta(i)\right)^2 + \left(\dot{\theta}(i+1) - \dot{\theta}(i)\right)^2}$$ Equation 5.1

(A)   (B)

(C)   (D)
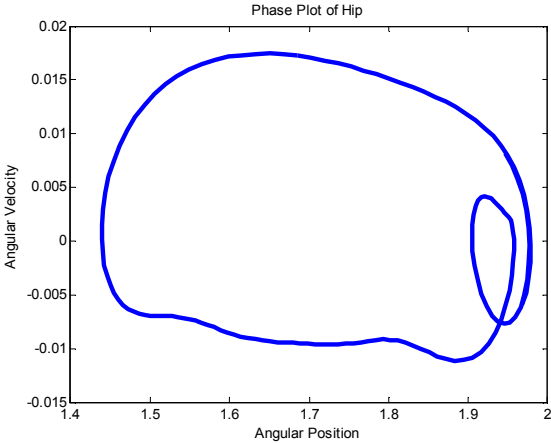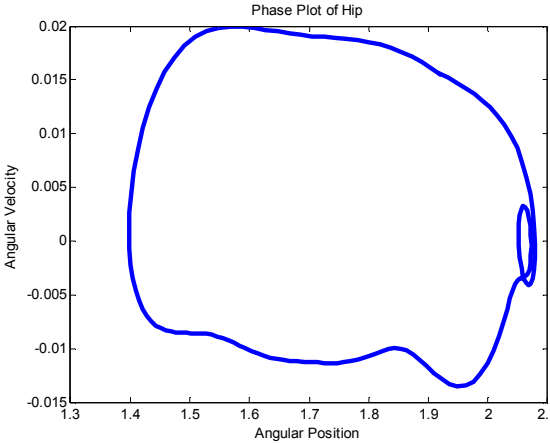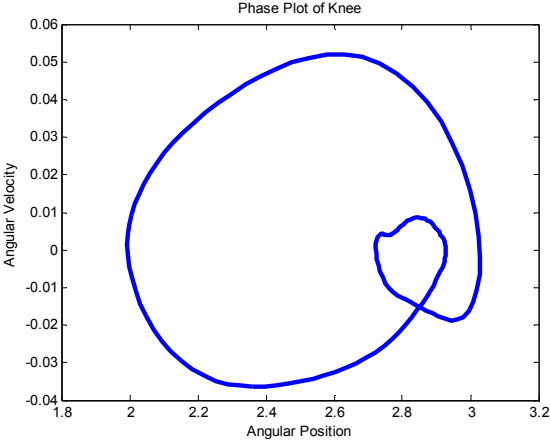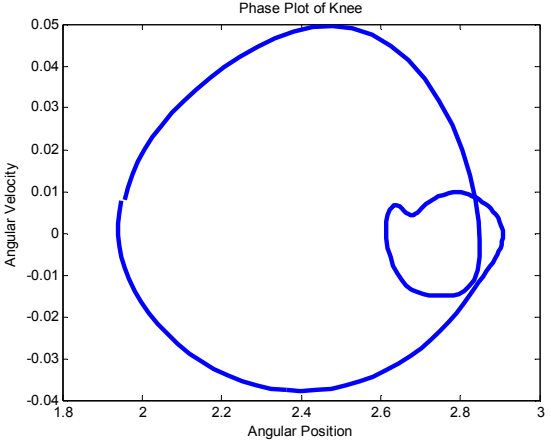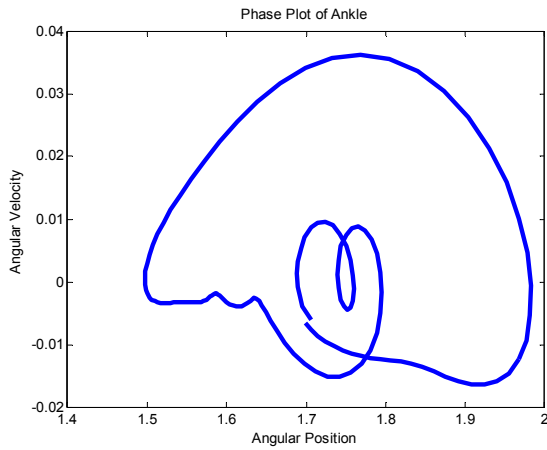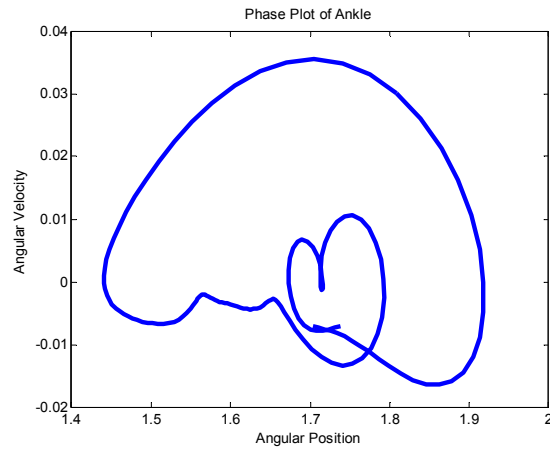
Figure 5. 1. Phase Portraits of hip, knee, and ankle angles from one typical subject (A) hip phase in unloaded walking condition, (B) hip phase in loaded, (C) knee phase in unloaded walking, (D) knee phase in loaded, (E) ankle phase in unloaded walking, and (F) ankle phase in loaded.

5.3.4. Statistics and Linear Discriminant Analysis (LDA)

Analysis of Variance (ANOVA) was used to test for the main effects of load condition (2 levels) on the dependent variables (Hip ROM, Knee ROM, Ankle ROM, PL_{Hip}, PL_{Knee}, and PL_{Ankle}). A p-value less than 0.05 indicates a statistically significant difference between loaded and unloaded walking for a given variable. Results showed that three variables (Hip ROM, PL_{Hip}, and PL_{Ankle}) indicated statistically significant differences between unloaded and loaded walking (Table 1). Therefore, only these variables were used as inputs to the LDA classifier, and the other three variables (Knee ROM, Ankle ROM, and PL_{Knee}) were not used.

Table 5. 1. The averages and S.D. of joint ranges of motion in the sagittal plane and path lengths under two loading conditions (unloaded and 12.5kg loaded) from 19 training subjects. * indicate a statistically significant load effect – ANOVA.

Variable	Unloaded	Loaded	p-values
Hip ROM (°)	38.491 ± 3.833	41.731 ± 3.285	**0.008***
Knee ROM (°)	59.432 ± 5.529	56.826 ± 7.537	0.232
Ankle ROM (°)	28.298 ± 3.384	29.767 ± 4.275	0.248
PL_{Hip}	1.362 ± 0.130	1.466 ± 0.105	**0.010***
PL_{Knee}	2.564 ± 0.265	2.553 ± 0.220	0.699
PL_{Ankle}	0.681 ± 0.065	0.733 ± 0.053	**0.010***

For this study, linear discriminant analysis (LDA) was implemented to find a classification boundary between loaded and unloaded conditions using three kinematic variables (or calculated from the measurements). LDA is closely related to ANOVA and regression analysis. These methods also attempt to express a dependent variable as a linear combination of other measured features (Sharma 1996). More information on LDA and its application can be found in (Yu and Yang 2001; Boulgouris and Chi 2007). For the classification, LDA is trained using 19 subjects' experimental data. The effectiveness of this analysis is then determined using the untrained trials from the sequestered 4 subjects. The overall processing flow is shown in Figure 5.2.
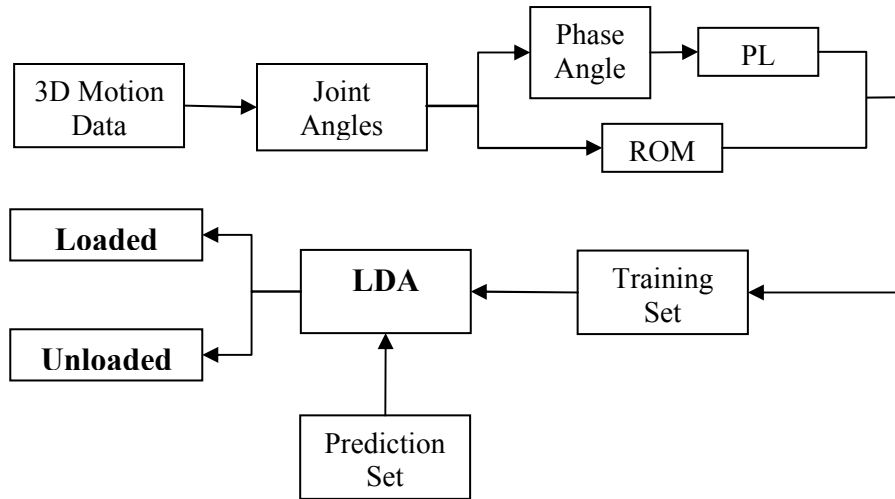
Figure 5. 2. A summarized processing flow to classify loaded or unloaded walking conditions.

5.4. Results

There were statistically significant differences on Hip ROM, PL_{Hip}, and PL_{Ankle}; the other dependent variables did not show significant differences. Carrying an evenly distributed load resulted in increased hip ROM and path lengths of hip and ankle (Table 1). The LDA classifier was trained using 19 subjects. The performance of the classifier was tested using 36 trials from 4 subjects that were not used for training. The LDA classifier achieved an 88.9% correct classification rate (32 out of 36), which means that 88.9% of the unknown load conditions were assigned to the correct category (Figure 5.3). The false alarm rate, which is the rate that classifies unloaded walking as loaded one, is 8.3% (3 out of 36).
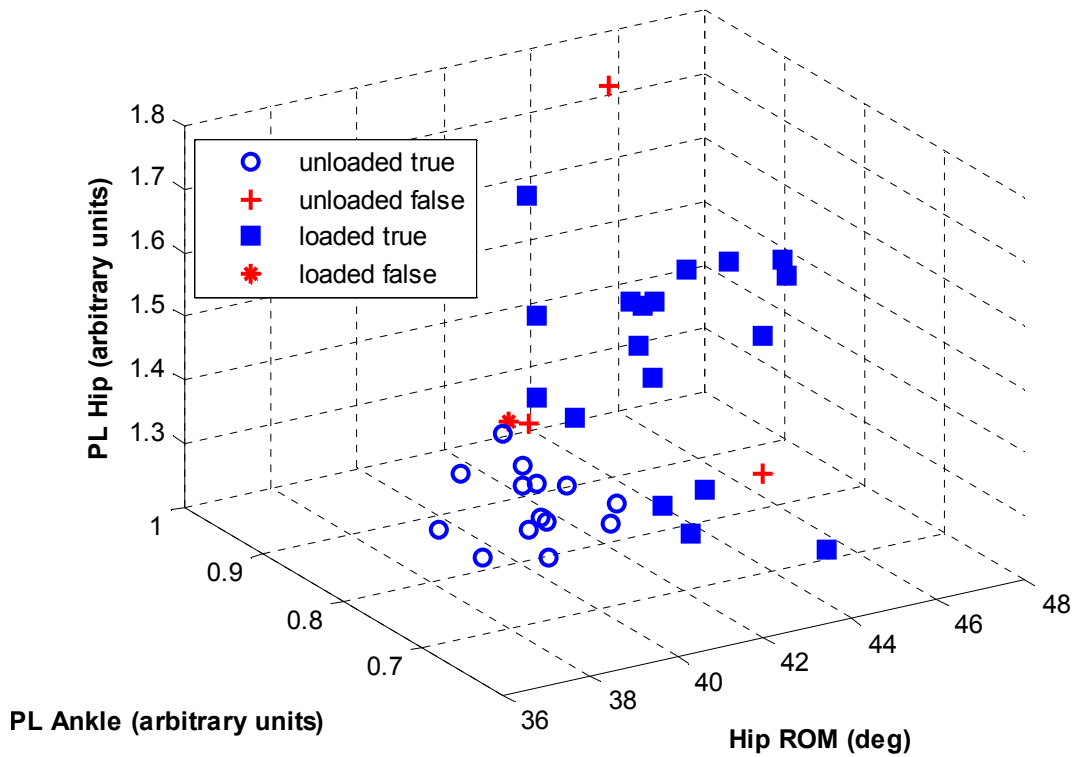
Figure 5. 3. Scatter plots of load classification after linear discriminant analysis (LDA). An 88.9% (32 out of 36) correct classification rate was achieved when using three variables. True is the correct and false is the incorrect classification after linear discriminant analysis.

5.5. Discussion

We present classification results (loaded/unloaded) with simple linear discriminant analysis classifier that analyzes the motion capture data as training data sets from 19 subjects. This classifier gives a baseline performance of 88.9% correct classification from 4 untrained subjects of loaded vs. unloaded walking conditions when load is evenly distributed on the upper body. Our results confirm that a measurable difference exists between loaded and unloaded walking conditions using the gait kinematics. It is important to note that any real world systems that non-invasively measures the same variables used in this paper should have poorer

61

performance than our results. It may not even be practical to obtain these types of measurements in the real world settings such as utilizing video capture systems.

The kinematic variables in Figure 5.3 illustrate the possibility of gait pattern separation for subjects not included in the training data sets. The differences between unloaded and loaded walking are noticeable, which indicates that these three variables would be sufficient to classify the conditions on a statistical basis. Thus, the results suggest that the use of these variables (if at all possible) in a video camera system may also lead to the advanced real-time classification. Three of the 4 incorrect classifications are caused by points appearing at the boundary between the two conditions.

All joint ranges of motions were similar to previous studies (Kerrigan, Todd et al. 1998; Harman, Han et al. 2000; LaFiandra, Holt et al. 2002; Chow, Kwok et al. 2005). It was found that the gait adaptation of external loads would result in the angular changes of hip joint (Table 1). Several studies (Harman, Han et al. 2000; LaFiandra, Holt et al. 2002; Chow, Kwok et al. 2005) also reported that increased hip ROM was to generate and absorb the power when carrying a load. No significant changes in knee and ankle kinematics were found up to 15% of body weight, but there was a load effect of ankle with 15 to 20% of body weight (Chow, Kwok et al. 2005) which had similar values in this study. This implies that external loads may require more angular momentum or power for propulsion. It was also found that the increased path lengths of hip and ankle joints (Table 1) would indicate that more angular velocity changes (the vertical direction in Figure 5.1) due to external loads. It may support the shorter single stance time (Kinoshita 1985; Hong and Brueggemann 2000; Wang, Pascoe et al. 2001; Chow, Kwok et al. 2005) and the faster cadence in previous studies (Harman, Han et al. 2000; LaFiandra, Wagenaar

et al. 2003). This results in decreased transversal pelvic rotation (LaFiandra, Wagenaar et al. 2003). However, this study is limited to an investigation of sagittal plane kinematics.

In this study, the same treadmill speed was used (set for each subject's normal walking speed) for both loaded and unloaded conditions. This ensures that both walking conditions were close to identical in terms of spatio-temporal measurements, i.e. nearly constant stride frequency at a given speed. Further study would be necessary to find the effects of walking speed by having each subject walk at a normal walking speed for each load condition over ground vs. treadmill walking. Another important result found in this study is that it is not required to have a priori knowledge of individual's gait kinematics to correctly classify loaded vs. unloaded walking conditions assuming the "real world" system can extract the kinematic quantities with high enough fidelity and enough training data exists.

Acknowledgements

5.6. References

BenAbdelkader, C. and L. Davis (2002). "Detection of people carrying objects: A motion-based recognition approach." Fifth IEEE International Conference on Automatic Face and Gesture Recognition **p. 0378**.

Boulgouris, N. V. and Z. X. Chi (2007). "Gait recognition using radon transform and linear discriminant analysis." IEEE Trans Image Process **16**(3): 731-40.

Chow, D. H., M. L. Kwok, et al. (2005). "The effect of backpack load on the gait of normal adolescent girls." Ergonomics **48**(6): 642-656.

Haddad, J. M., R. van Emmerik, et al. (2006). "Adaptations in interlimb and intralimb coordination to asymmetrical loading in human walking." Gait and Posture **23**: 429–434.

Han, J. and B. Bhanu (2006). "Individual recognition using gait energy image." IEEE Trans Pattern Anal Mach Intell **28**(2): 316-22.

Harman, E. A., K. H. Han, et al. (2000). "The effects of backpack weight on the biomechanics of load carriage." US Army Research Institute of Environmental Medicine, Natick, MA.

Hong, Y. and G. P. Brueggemann (2000). "Changes in gait patterns in 10-year-old boys with increasing loads when walking on a treadmill." Gait Posture **11**(3): 254-9.

Inman, V., H. J. Ralston, et al. (1981). Human Walking, Williams and Wilkins.

Kerrigan, D. C., M. K. Todd, et al. (1998). "Gender differences in joint biomechanics during walking: normative study in young adults." Am J Phys Med Rehabil **77**(1): 2-7.

Kinoshita, H. (1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait." Ergonomics **28**(9): 1347-62.

Knapik, J. J., E. A. Harman, et al. (1996). "Load carriage using packs: A review of physiological, biomechanical and medical aspects " Applied Ergonomics **27**(3): 207-216.

LaFiandra, M., K. G. Holt, et al. (2002). "Transverse plane kinetics during treadmill walking with and without a load." Clinical Biomechanics **17**: 116-122.

LaFiandra, M., R. C. Wagenaar, et al. (2003). "How do load carriage and walking speed influence trunk coordination and stride parameters?" Journal of Biomechanics **36**: 87-95.

Lockhart, T. E., J. C. Woldstad, et al. (2003). "Effects of age-related gait changes on the biomechanics of slips and falls." Ergonomics **46**(12): 1136-60.

Luttgens, K. and K. Wells (1982). Kinesiology: scientific basis of human motion, Saunders College Publishing.

Mickelborough, J., M. L. van der Linden, et al. (2000). "Validity and reliability of a kinematic protocol for determining foot contact events." Gait Posture **11**(1): 32-7.

Prieto, T. E., J. B. Myklebust, et al. (1996). "Measures of postural steadiness: differences between healthy young and elderly adults." IEEE Trans Biomed Eng **43**(9): 956-66.

Sharma, S. (1996). Applied Multivariate Techniques, John Wiley & Sons, Inc.

Wang, Y. T., D. D. Pascoe, et al. (2001). "Evaluation of book backpack load during walking." ERGONOMICS **44**(9): 858-869.

Wittman, M. G., J. M. Ward, et al. (2005). "Visual analysis of the effects of load carriage on gait." Proceedings of the SPIE **5779**: 15-22

Yu, H. and J. Yang (2001). "A direct LDA algorithm for high-dimensional data -- with application to face recognition." Pattern Recognition **34**(10): 2067-2070.

Chapter 6 - The effect of evenly distributed load carrying on lower body gait dynamics for normal weight and overweight subjects

Minhyung Lee, Michael Roan, and Benjamin Smith

Department of Mechanical Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, USA

Correspondence:

      Minhyung Lee, M.S.

      Department of Mechanical Engineering

      Virginia Polytechnic Institute and State University

      134 Durham Hall

      Blacksburg, VA 24061, USA

      Phone: 1-540-231-4022

      Fax: 1-540-231-8836

      minlee@vt.edu

6.1. Abstract

The carrying of extra weight can cause significant injuries. This extra weight can be in the form of an external load carried by an individual or excessive body weight carried by an overweight individual. This study attempts to define the differences in lower body gait patterns caused by either external load carriage, excessive body weight, or a combination of both.

Twenty three subjects generated one hundred fifteen trials of motion capture data for each loading condition. Path lengths of the phase portrait and the ranges of joint motions (hip, knee and ankle) were used to quantify subgroup differences.

The study found significant gait differences due to external load carriage and excessive body weight. Within each class of normal weight and overweight subjects, differences were found in the hip and ankle path lengths when a subject carried an evenly distributed external load. This implies that these joints may be more prone to injury due to external load carriage.

6.2. Introduction

Load carrying is a common cause of injuries including knee and lower back (Dalen A, Nilsson J et al. 1978; Knapik, Reynolds et al. 1992). This has motivated previous studies that characterize the human effects of load carrying including the effect on gait patterns. According to these studies, the duration of the double stance increased with increased loads, while the single stance duration decreased (in 10 healthy males (Kinoshita 1985) and in 15 boys (Hong and Brueggemann 2000)). Significant gait differences were observed between loaded and unloaded walking. The nature of the changes depended on whether the load was backpack or double-pack. For example, with backpacking, forward leaning of the trunk is a natural behavior to help keep the center of mass over the feet. It was found that the forward inclination considerably increased with load weight to minimize energy cost (Knapik, Harman et al. 1996). The goal of minimized energy expenditure resulted in the decrease of vertical positions at the knee and ankle with the added weight (Wittman, Ward et al. 2005). Several published studies indicated that pelvic rotation reduced and ankle rotation increased in the sagittal plane under loaded conditions (Kinoshita 1985; Knapik, Harman et al. 1996). These studies also showed that knee flexion after impact was greater when carrying loads in order to absorb increased impact forces.

Excessive body weight has also been linked to large number of health problems such as cardiovascular disease, stroke, hypertension, and diabetes as well as numerous gait related injuries (Must and Strauss 1999). A limited amount of work has been done to investigate the injury related gait kinematics of overweight individuals. The kinematic deviations include slower velocity, shorter step length, increased double support time, decreased knee range of motion, and larger ground reaction forces compared to normal weight individuals (Hills and Parker 1991;

Messier 1994; Stephen P. Messier, Walter H. Ettinger et al. 1996; McGraw, McClenaghan et al. 2000).

Body mass index (BMI) is a standard measure of obesity level. It is a measure of body fat based on height and weight that applies to both adult men and women (Hall and Cole 2006). In this work BMI is used to separate subjects into normal weight and overweight categories. This follows the standard convention (BMI > 25 kg/m^2 overweight, BMI<25 kg/m^2 normal weight).

Little work has been done to study the effects of external load carriage and excessive body weight. The previous studies focus on external load carriage by normal weight individuals using mostly linear spatial-temporal measurements. Recently, Haddad and Emmerik (Haddad, van Emmerik et al. 2006) examined the intralimb and interlimb adaptations with a unilateral leg load. Continuous relative phase (CRP) analysis was used to evaluate limb coordination. The advantage of using phase analysis is that it can convert four variables (two positions and two velocities) into one measurement. This makes phase analysis very useful for investigating human movement and its complexity using a reduced set of measurements or metrics. The path length of the phase portrait has been used to determine the effectiveness of the postural control system in controlling the lower body stability and steadiness similar to distance measures of center of pressure (COP) in sway balance control tests (Prieto, Myklebust et al. 1996). To the best of our knowledge, gait adaptations due to external loads have not been compared using measures extracted from phase portraits in normal weight vs. overweight subjects in order to quantify gait differences within these groups.

The present study investigated kinematic gait measures to quantify gait adaptations due to external loads for overweight and normal weight groups. Our primary hypothesis was that external loads will affect the lower body movements of the two groups differently. Establishing

gait differences between BMI classes due to external loads can be useful for determining

maximum acceptable occupational load conditions as function of BMI.

6.3. Methods

6.3.1. Subjects and experimental setup

Twenty three subjects, 16 normal weight (BMI < 24.99 kg/m^2) and 7 overweight (BMI >

25 kg/m^2), generated a total of 115 treadmill trials for each loading condition. All subjects gave

their informed consent prior to participation as defined by the Committee for Participants of

Investigative Projects at the Virginia Tech. The only statistically significant difference between

two groups is weight related variables, i.e. weight, the weight of the load as a percentage of the

subject body mass (% BM), and BMI. The subject demographics are summarized in Table 6.1.

To determine a subject's normal walking speed, the treadmill was started and the velocity

gradually increased so as to achieve a subject's most comfortable walking speed. This walking

speed was used for the two loading conditions.

Table 6. 1. A total of twenty three subjects demographics (mean ± SD). Bolded values indicate statistically significant difference (p < 0.05) between normal weight and overweight groups.

Variable	Normal weight (n = 16)	Overweight (n = 7)	p-value
Age (yrs)	21.59 ± 3.14	25.17 ± 4.67	0.12
Height (m)	1.74 ± 0.08	1.75 ± 0.08	0.94
Weight (kg)	67.08 ± 8.50	89.95 ± 18.68	**0.02**
% BM	18.62 ± 2.05	15.67 ± 4.08	**0.01**
BMI (kg/m^2)	22.04 ± 2.10	29.20 ± 3.42	**0.01**

n: number of subjects
% BM: the weight of the load as a percentage of the subject body mass
Normal weight: BMI < 24.99 kg/m^2,   Overweight: BMI > 25.00 kg/m^2

A total of 23 reflective markers (Lockhart, Woldstad et al. 2003; Chow, Kwok et al. 2005) were attached to the subjects' anatomical landmarks (top of the head, base of second toe, malleolus, epicondyle, greater trochanter, clavicle, styloid process of ulna, lateral epicondyle of humerus, greater tubercle, acromion, anterior portion of temporal bone, and center of the calcaneus) to capture subjects' 3D motion using a ProReflex system (Qualisys, Gothenburg, Sweden) at the sampling rate of 120 Hz. However, in this study only lower body data were analyzed to focus on changes in lower body kinematics. Treadmill walking was performed for 30 s sessions with subjects wearing a 12.5 kg vest type mass (evenly distributed front and back) and without any external load (unloaded walking). The vest was attached to the subjects' body using two shoulder straps and three side straps so that it did not obstruct any upper or lower body movements. Five trials were repeated in each load condition and the order of external load conditions in each subject was completely randomized to reduce any order effects.

6.*3.2. Analysis*

Consecutive left heel contacts determined the period of one stride in this study. Thus, one stride includes both a left and a right step. Left heel contacts were determined using the vertical velocity changes of heel markers to identify gait periods (Mickelborough, van der Linden et al. 2000). Two consecutive left strides were averaged for the analysis. Then, the kinematic data were filtered using a low pass, fourth-order Butterworth filter with 7 Hz cutoff frequency and normalized by subjects' height. All angles were measured in the sagittal plane. Hip angles were defined from horizontal to the thigh segment. Knee angles were determined between the thigh segment and the shank segment, and ankle angles were between the shank segment and the foot (Harman, Han et al. 2000). Sagittal plane joint ranges of motion (ROM) were calculated as the

71

difference between peak flexion and peak extension (LaFiandra, Holt et al. 2002) at hip, knee

and ankle joints (Hip ROM, Knee ROM and Ankle ROM). Segmental angular velocities were

calculated from the sagittal plane angles using a first central difference method (Haddad, van

Emmerik et al. 2006). These angular positions and velocities were then used to compute

continuous relative phase from the position-velocity phase portrait. From the resulting phase-

planes, the phase angle at each time was calculated relative to the right horizontal using Equation

6.1 (Kurz and Stergiou 2002).

$$\psi(t) = \tan^{-1}\left(\frac{\dot{\theta}(t)}{\theta(t)}\right) \qquad \text{Equation 6.1}$$

6.3.3. Path length (PL) of Phase Portrait

From the resulting phase-planes, path length (Equation 6.2) is estimated as the sum of the

straight line distances between consecutive points for hip, knee and ankle phases (PL_{Hip}, PL_{Knee}

and PL_{Ankle}). These values were used to quantify the magnitude and velocity of joint angular

movement as function of time over a gait cycle, i.e. large values of PL suggest more joint angular

movements.

$$PL = \sum_{i=1}^{n-1} \sqrt{\left(\theta(i+1) - \theta(i)\right)^2 + \left(\dot{\theta}(i+1) - \dot{\theta}(i)\right)^2} \qquad \text{Equation 6.2}$$

6.3.4. Statistical Analysis

Two-way analysis of variance (BMI by load) was used and results were considered to be significant at the $p < 0.05$ level of confidence. Statistical analyses were completed using the SPSS statistical package (v.13, SPSS Inc., Chicago, IL).

6.4. Results

Two-way analysis of variance (BMI by load) indicated no significant ($p>0.05$) two-way interaction for lower body movements, implying that the overall trend in these responses was similar in normal weight vs. overweight individuals. No significant effect of load was found in the knee path length, and knee and ankle ROMs (Table 6.2). However, there were statistically significant increased path lengths of ankle and hip joints ($p<0.001$), and hip ROM ($p<0.05$) in the loaded walking condition for all subjects.

Table 6. 2. ANOVA results (mean ± SD) from pooled loading conditions between unloaded and loaded walking conditions for all subjects. Bolded values indicate statistically significant difference ($p < 0.05$) between unloaded and loaded walking conditions.

Variable	Unloaded	Loaded	p-value
PL_{Ankle}	0.6856 ± 0.0642	0.7515 ± 0.0593	**0.001**
PL_{Hip}	1.3713 ± 0.1283	1.5031 ± 0.1185	**0.001**
PL_{Knee}	2.5602 ± 0.2131	2.6418 ± 0.2234	0.211
Hip ROM (°)	38.6058 ± 3.5124	41.8693 ± 3.0355	**0.019**
Knee ROM (°)	60.3562 ± 5.0004	57.9842 ± 6.4828	0.172
Ankle ROM (°)	28.5638 ± 4.0134	29.9843 ± 5.0475	0.297

Figure 6.1 illustrates the overall experiment, broken down into the specific groups and loading conditions studied. Each of the statistical tests conducted between the groups and loading conditions is labeled as A-F. Individual results for each comparison in Figure 6.1 are;

A: Comparison between two BMI groups over all external loading conditions found a statistically significant difference in hip ROM (Table 6.3).

B: Comparison between two BMI groups for the unloaded walking condition found no statistically significant difference ($p>0.05$) in gait variables.

C: Comparison between two BMI groups for the loaded walking condition found no statistically significant difference ($p>0.05$) in gait variables.

D: Comparison between the loaded normal weight subjects and unloaded overweight subjects found no statistically significant difference in gait variables.

E: Comparison between two loading conditions for the normal weight group found a statistically significant difference ($p>0.05$) in the hip and ankle path lengths (also in Figure 6.2).

F: Comparison between two loading conditions for the overweight group found a statistically significant difference in the hip and ankle path lengths (also in Figure 6.2).

Table 6. 3. ANOVA results (mean ± SD) from pooled loading conditions between normal weight and overweight subjects. Bolded values indicates statistically significant difference ($p < 0.05$) between normal weight and overweight groups.

Variable	Normal weight	Overweight	p-value
PL_{Ankle}	0.7076 ± 0.0758	0.7437 ± 0.0453	0.106
PL_{Hip}	1.4152 ± 0.1517	1.4874 ± 0.0907	0.106
PL_{Knee}	2.5932 ± 0.2418	2.6189 ± 0.1655	0.720
Hip ROM (°)	39.5170 ± 3.9068	41.8845 ± 2.3013	**0.041**
Knee ROM (°)	59.6105 ± 4.1115	58.1638 ± 3.7484	0.446
Ankle ROM (°)	29.5389 ± 4.6397	28.6686 ± 4.5010	0.558
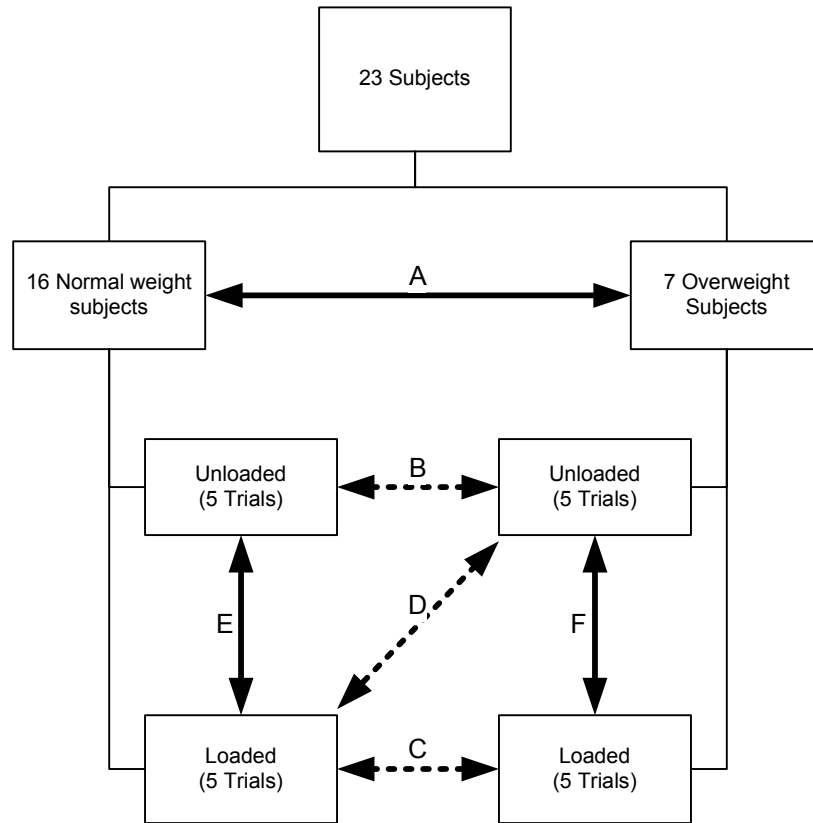
Figure 6. 1. A summary of group differences in terms of path length (PL) and joint range of motion (ROM) variables.

A: a statistically significant difference (p < 0.05) in hip ROM between two groups over two

loading conditions (solid).

B and *C:* no significant differences (p>0.05) in gait variables between BMI groups within each

loading condition (dashed).

D: no significant difference (p>0.05) in gait variables between loaded normal weight subjects

and unloaded overweight subjects (dashed).

E and *F:* statistically significant differences (p<0.05) in PL of ankle and hip within each BMI

group (solid).

(A)
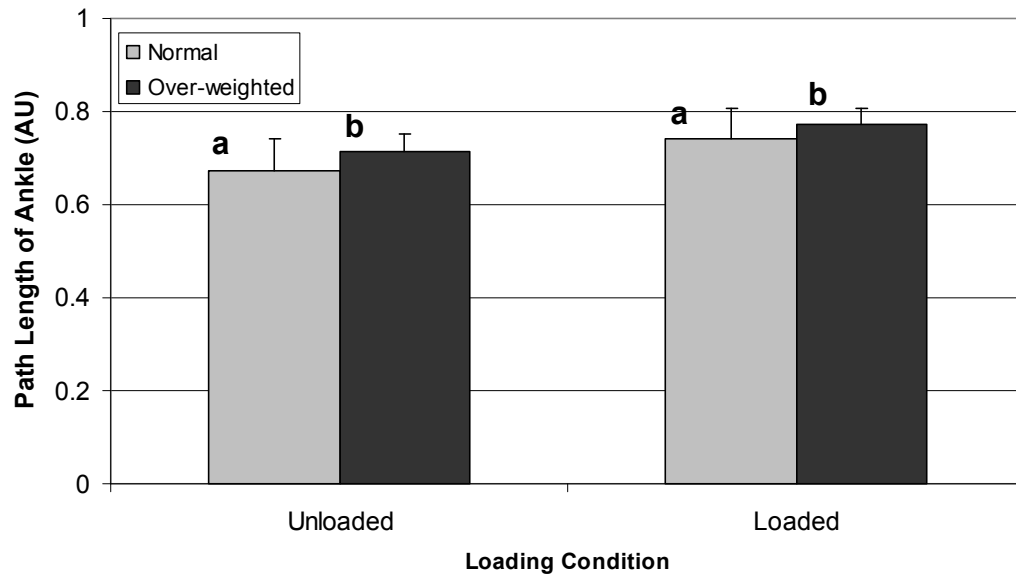
(B)
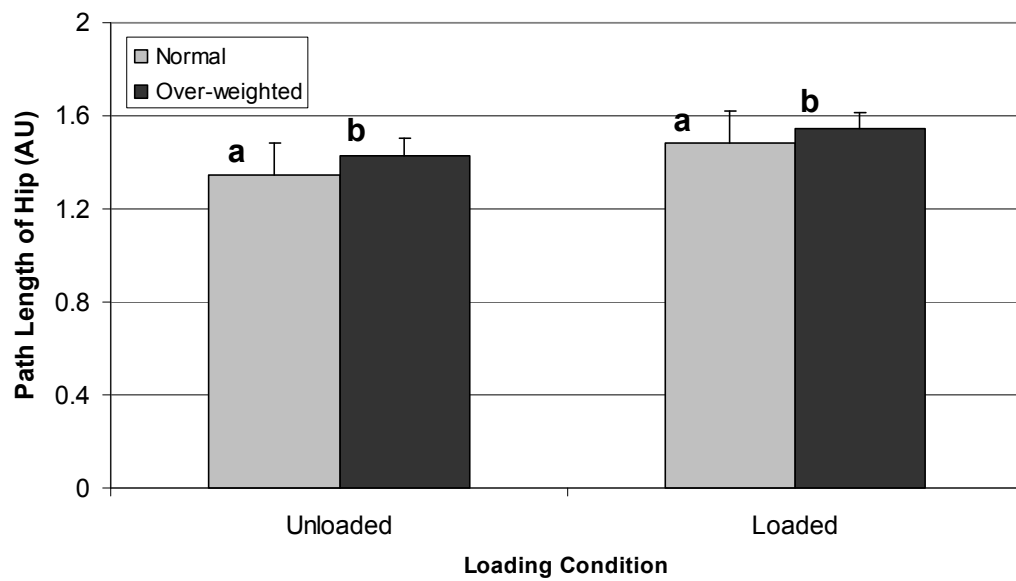
Figure 6. 2. Kinematic changes due to loading conditions in normal weight and overweight subjects. (A) path length of ankle and (B) path length of hip. *a* indicates a statistically significant difference in normal weight subjects between unloaded and loaded walking conditions ($p<0.05$). *b* indicates a statistically significant difference in overweight subject between unloaded and loaded walking conditions ($p<0.05$).

6.5. Discussion

The purpose of this study was to compare lower extremity kinematics between BMI classes (normal weight vs. overweight) during unloaded and loaded walking conditions. The hypothesis was that evenly distributed external loads will affect the lower body movements of each group differently. The main conclusion of the study is that there are significant differences in path lengths of hip and ankle joints between loading conditions within each subgroup, normal weight and overweight.

Hip ROM, ankle path length, and hip path length are significantly greater in loaded walking than unloaded walking (Table 6.2) for all subjects. However, no knee and ankle ROM differences are found. A similar result has been reported in (Harman, Han et al. 2000) including the significantly greater hip ROM as an external load increases. External load carriage obviously requires more energy expenditure (Griffin, Roberts et al. 2003). Our study indicates that ankle and hip joints are the focus of the energy expenditure due to greater path lengths under the loaded condition. In addition, this trend is same for both overweight and normal weight subjects.

Different movement patterns between normal weight and overweight subjects are observed in only hip ROM (Table 6.3). The increased hip ROM in overweight subjects leads to greater vertical movement of the hip (Whittle 2007). This may indicate that there is greater energy expenditure at preferred walking speed in overweight subjects as shown in (Foster, Wadden et al. 1995; Stefano, Yves et al. 2003; Browning, Modica et al. 2007). A previous study (Berrigan, Simoneau et al. 2006) reported that controlling balance reduced the efficiency of overweight subjects. Although the ROM difference between two groups is statistically significant, it is very small (less than 3°). Moreover, there is no significant difference in other variables between normal weight and overweight groups. It has been shown that obese subjects

adapt certain neuromuscular functions to produce a gait pattern with less load in lower body joints (Spyropoulos, Pisciotta et al. 1991). Spyropoulos et al. (Spyropoulos, Pisciotta et al. 1991) also reported that obese gait is characterized by a normal pattern of sagittal and transverse plane movement. More importantly, external loads are different from additional body weight. It is shown that external loads affect both groups' (normal weight and overweight) lower body movements in ankle and hip as shown in Figure 6.2. However, no path length differences exist between the two groups in either load condition as shown in Figure 6.1-D. In other words, if additional bodyweight and external loads were to have similar effects on gait, then the differences between loading conditions would be the same as differences between normal weight and overweight groups. This proved not to be the case.

In conclusion, statistically significant differences were found in hip and ankle path lengths when a subject carried an evenly distributed external load. These differences were found regardless of the subjects' BMI. The hip and ankle likely pay for the increased energy cost to carry the load via increased path lengths. This implies that these joints may be more prone to injury due to external load carriage.

Acknowledgements

6.6. References

Berrigan, F., M. Simoneau, et al. (2006). "Influence of obesity on accurate and rapid arm movement performed from a standing posture." Int J Obes (Lond) **30**(12): 1750-7.

Browning, R. C., J. R. Modica, et al. (2007). "The effects of adding mass to the legs on the energetics and biomechanics of walking." Med Sci Sports Exerc **39**(3): 515-25.

Chow, D. H., M. L. Kwok, et al. (2005). "The effect of backpack load on the gait of normal adolescent girls." Ergonomics **48**(6): 642-656.

Dalen A, Nilsson J, et al. (1978). "Factors Influencing a Prolonged Foot March." Stockholm, Sweden, Karolinska Institute **FOA report C50601-H6.** .

Foster, G. D., T. A. Wadden, et al. (1995). "The energy cost of walking before and after significant weight loss." Med Sci Sports Exerc **27**(6): 888-94.

Griffin, T. M., T. J. Roberts, et al. (2003). "Metabolic cost of generating muscular force in human walking: insights from load-carrying and speed experiments." J Appl Physiol **95**(1): 172-83.

Haddad, J. M., R. van Emmerik, et al. (2006). "Adaptations in interlimb and intralimb coordination to asymmetrical loading in human walking." Gait and Posture **23**: 429–434.

Hall, D. M. and T. J. Cole (2006). "What use is the BMI?" Arch Dis Child **91**(4): 283-6.

Harman, E. A., K. H. Han, et al. (2000). "The effects of backpack weight on the biomechanics of load carriage." US Army Research Institute of Environmental Medicine, Natick, MA.

Hills, A. P. and A. W. Parker (1991). "Gait characteristics of obese children." <u>Arch Phys Med Rehabil</u> **72**(6): 403-7.

Hong, Y. and G. P. Brueggemann (2000). "Changes in gait patterns in 10-year-old boys with increasing loads when walking on a treadmill." <u>Gait Posture</u> **11**(3): 254-9.

Kinoshita, H. (1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait." <u>Ergonomics</u> **28**(9): 1347-62.

Knapik, J., K. Reynolds, et al. (1992). "Injuries associated with strenuous road marching." <u>Mil Med</u> **157**(2): 64-7.

Knapik, J. J., E. A. Harman, et al. (1996). "Load carriage using packs: A review of physiological, biomechanical and medical aspects " <u>Applied Ergonomics</u> **27**(3): 207-216.

Kurz, M. J. and N. Stergiou (2002). "Effect of normalization and phase angle calculations on continuous relative phase." <u>Journal of Biomechanics</u> **35**: 369–374.

LaFiandra, M., K. G. Holt, et al. (2002). "Transverse plane kinetics during treadmill walking with and without a load." <u>Clinical Biomechanics</u> **17**: 116-122.

Lockhart, T. E., J. C. Woldstad, et al. (2003). "Effects of age-related gait changes on the biomechanics of slips and falls." <u>Ergonomics</u> **46**(12): 1136-60.

McGraw, B., B. A. McClenaghan, et al. (2000). "Gait and postural stability in obese and nonobese prepubertal boys." <u>Arch Phys Med Rehabil</u> **81**(4): 484-9.

Messier, S. P. (1994). "Osteoarthritis of the knee and associated factors of age and obesity: effects on gait." <u>Med Sci Sports Exerc</u> **26**(12): 1446-52.

Mickelborough, J., M. L. van der Linden, et al. (2000). "Validity and reliability of a kinematic protocol for determining foot contact events." <u>Gait Posture</u> **11**(1): 32-7.

Must, A. and R. S. Strauss (1999). "Risks and consequences of childhood and adolescent

    obesity." <u>Int J Obes Relat Metab Disord</u> **23 Suppl 2**: S2-11.

Prieto, T. E., J. B. Myklebust, et al. (1996). "Measures of postural steadiness: differences

    between healthy young and elderly adults." <u>IEEE Trans Biomed Eng</u> **43**(9): 956-66.

Spyropoulos, P., J. Pisciotta, et al. (1991). "Biomechanical gait analysis in obese men." <u>Arch</u>

    <u>Phys Med Rehabil</u> **72**: 1065-70.

Stefano, L., B. Yves, et al. (2003). "Assessment of energy expenditure associated with physical

    activities in free-living obese and nonobese adolescents." <u>The American journal of</u>

    <u>clinical nutrition </u>**78**: 471-479.

Stephen P. Messier, Walter H. Ettinger, et al. (1996). "Obesity: Effects on Gait in an

    Osteoarthritic Population." <u>Journal of Applied Biomechanics</u> **12**(2): 161-172.

Whittle, M. (2007). <u>Gait analysis: an introduction</u>, Butterworth-Heinemann.

Wittman, M. G., J. M. Ward, et al. (2005). "Visual analysis of the effects of load carriage on

    gait." <u>Proceedings of the SPIE</u> **5779**: 15-22.

Chapter 7 - An application of principal component analysis for lower body kinematics between loaded and unloaded walking

Original Article

Minhyung Lee, Michael Roan, and Benjamin Smith

Department of Mechanical Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, USA

Correspondence:

Minhyung Lee, M.S.

Department of Mechanical Engineering

Virginia Polytechnic Institute and State University

134 Durham Hall

Blacksburg, VA 24061, USA

Phone: 1-540-231-4022

Fax: 1-540-231-8836

minlee@vt.edu

7.1. Abstract

Load carriage is a very common daily activity at home and in the workplace. Generally, the load is in the form of an external load carried by an individual, it could also be the excessive body mass carried by an overweight individual. To quantify the effects of carrying extra weight, whether in the form of an external load or excess body mass, motion capture data was generated for a diverse subject set. This consisted of twenty three subjects generating one hundred fifteen trials for each loading condition. This study applied Principal Component Analysis (PCA) to motion capture data in order to analyze the lower body gait patterns for four loading conditions: normal weight unloaded, normal weight loaded, overweight unloaded and overweight loaded.

PCA has been shown to be a powerful tool for analyzing complex gait data. In this analysis, it is shown that in order to quantify the effects of external loads for both normal weight and overweight subjects, only two principal components (PCs) are needed. For the work in this paper, PCs were generated from lower body joint angle data. The PC1 of the hip angle and PC2 of the knee angle are shown to be an indicator of external load effects on temporal gait data.

7.2. Introduction

Load carriage is one of the most common tasks in daily activities as well as in the workplace. There are many previous studies that characterize the effects of load carrying on gait. These showed that the duration of the double stance increased with heavier backpack loading, but single stance duration decreased (in 10 healthy males (Kinoshita 1985) and in 15 boys (Hong and Brueggemann 2000)). An evenly distributed external load, i.e. double-packing, has a reduced effect on human movements including less trunk inclination (Kinoshita 1985) and energy expenditure than front or backpack loading (Ramanthan 1972). Most gait studies for load carriage rely on direct statistical analysis of measures such as muscle activation, metabolic cost, kinematics and kinetics of the human body (Harman, Han et al. 1992; Harman, Han et al. 2000; Hsiang 2002; Griffin, Roberts et al. 2003). However, subspace analysis techniques, such as Principal Component Analysis (PCA), can also be brought to bear to better understand the nature of load induced changes in gait.

PCA is a useful technique that has found application in fields such as face recognition (Oravec and Pavlovicova 2004) and image compression (Meyer-Baese 2000). It is as a common technique for finding patterns in data of high dimension (Daffertshofer, Lamoth et al. 2004). PCA finds the greatest sources of variation in the data and allows the effects of these variations to be isolated. PCA can also be used to remove unwanted sources of data variation and provide information that may greatly increase classification accuracy (Deluzio and Astephen 2007). PCA has previously been used in Biomechanics. According to Wrigley et al. (Wrigley, Albert et al. 2006), PCA was used to quantify clinically relevant differences in kinetic lifting waveforms. Sadeghi et al. (Sadeghi, Allard et al. 1997; Sadeghi, Prince et al. 2000; Sadeghi, Allard et al.

84

2002) reported that PCA could be used to identify main functional contributions of muscle powers and mechanical energies. Also, Olney et al. (Olney, Griffin et al. 1998) successfully applied PCA to dimensionally reduced gait data. Deluzio et al. (Delaney, Foroughi et al. 1997; Deluzio, Wyss et al. 1999; Deluzio and Astephen 2007) reported that PCA could be used for gait data reduction when comparing the gait patterns of normal and osteoarthritis subjects. Temporal waveforms such as joint angles, forces and moments were used to determine group differences. However, there are no previous studies using PCA to analyze the effect of external loads on human gait.

The present study investigates gait kinematic adaptations due to evenly distributed external load using PCA. The primary hypothesis is that PCA could be used to characterize the main features of the evenly distributed external load conditions in gait data. In other words, principal components (PCs) were extracted to determine features of variation that could be used to quantify differences in gait patterns between unloaded and loaded walking conditions. In addition, tests were conducted to investigate whether these changes manifest themselves differently between normal weight (BMI < 24 kg/m^2) and overweight subjects (BMI > 24 kg/m^2). Excessive body mass has been linked to kinematic deviations which include slower velocity, shorter step length, increased double support time, decreased knee range of motion, and larger ground reaction forces compared to normal weight individuals (Hills and Parker 1991; Messier 1994; Stephen P. Messier, Walter H. Ettinger et al. 1996; McGraw, McClenaghan et al. 2000). Establishing gait differences between BMI classes due to external loads will be useful to determine whether characteristics of each group's gait come from the external loads or excessive body weight. To explore these hypotheses, data from the sagittal plane were selected because the major movements occur in this plane.

7.3. Methods

7.3.1. Subjects and experimental setup

Twenty three subjects, 14 (7 male and 7 female) normal weight (BMI < 24 kg/m^2) and 9 (7 male and 2 female) overweight (BMI > 24 kg/m^2), participated in the study. All subjects gave their informed consent prior to participation as defined by the Committee for Participants of Investigative Projects at the Virginia Tech. The subject demographics are summarized in Table 7.1.

Table 7. 1. A total of twenty three subjects demographics (mean ± SD). Bolded values indicate statistically significant difference ($p < 0.05$) between normal and overweight groups.

Variable	Normal weight (n = 14)	Overweight (n = 9)	p-value
Age (yrs)	21.79 ± 3.12	23.67 ± 4.72	0.31
Height (m)	1.75 ± 0.08	1.73 ± 0.08	0.50
Weight (kg)	66.29 ± 8.93	83.54 ± 17.87	**< 0.05**
% BM	19.16 ± 2.45	15.49 ± 2.83	**< 0.05**
BMI (kg/m^2)	21.51 ± 1.90	27.65 ± 3.57	**< 0.01**

n: number of subjects
% BM: the weight of the load as a percentage of the subject body mass
Normal weight: BMI < 24.99 kg/m^2 (7 males and 7 females)
Overweight: BMI > 25.00 kg/m^2 (7 males and 2 females)

To determine a subject's normal walking speed, the treadmill was started and the velocity gradually increased so as to achieve a self-selected comfortable walking speed. This walking speed was used for the two loading conditions on the treadmill. Note that a treadmill is often used in gait research due to its controllability and test repeatability. In addition, it is convenient because it requires only a small area to use motion capture equipment while allowing

measurement of many gait cycles. However, there may be discrepancies between treadmill and overground walking. Treadmill walking has a higher cadence to maintain the same self-selected walking speed than overground walking (Strathy, Chao et al. 1983). In this study, the same normal walking speed was used for both loading conditions to control any speed-related changes such as dynamic stability (England and Granata 2007), metabolic costs (Griffin, Roberts et al. 2003), and so on.

A total of 23 reflective markers (Lockhart, Woldstad et al. 2003; Chow, Kwok et al. 2005) were attached to the subjects' anatomical landmarks (top of the head, base of second toe, malleolus, epicondyle, greater trochanter, clavicle, styloid process of ulna, lateral epicondyle of humerus, greater tubercle, acromion, anterior portion of temporal bone, and center of the calcaneus) to capture subjects' 3D motion using a ProReflex system (Qualisys, Gothenburg, Sweden) at the sampling rate of 120 Hz. However, only lower body markers' data were analyzed to focus on changes of lower body kinematics. Treadmill walking was performed for 30 s sessions with subjects wearing a 12.5 kg vest type mass (evenly distributed front and back) and without any external load (unloaded walking). The vest was attached to the subjects' body using two shoulder straps and three side straps so that it did not obstruct any upper or lower body movements. Five trials were repeated in each load condition and the order of external load conditions in each subject was completely randomized to reduce any order effects.

7.3.2. Analysis

Consecutive left heel contacts determined the period of one stride in this study. Thus, one stride includes both a left and a right step. Left heel contacts were determined using the vertical velocity changes of heel markers to identify gait periods (Mickelborough, van der Linden et al.

87

2000). The kinematic data were filtered using a low pass, fourth-order Butterworth filter with 7

Hz cutoff frequency. All following angles were measured in sagittal plane. Hip angles were

defined from horizontal to the thigh segment. Knee flexion angles and ankle angles (between the

shank segment and the foot) were used. These three angles are used as the input temporal

variables. In addition, sagittal plane joint ranges of motion (ROM) were calculated as the

difference between peak flexion and peak extension at hip, knee and ankle joints.

7.3.3. PCA background

PCA is a powerful tool for summarizing high dimensional data via a set of orthogonal

vectors onto which the data is projected. Mathematically, PCA consists of an orthogonal

transformation that converts the input variables into the new uncorrelated PCs (Jolliffe 2002).

The objective of PCA is to reduce the dimensionality (number of variables) of the dataset but

retain most of the original variability in the data. The first principal component (PC1) accounts

for as much of the variability in the data as possible, and each succeeding component accounts

for as much of the remaining variability as possible (Sadeghi, Prince et al. 2000; Daffertshofer,

Lamoth et al. 2004). A brief mathematical discussion of PCA is given below.

Consider a m-dimensional random vector $X = (X_1, X_2, ..., X_m)$. n principal components (n<m) of

X are n (univariate) random variables $Y_1, Y_2, ..., Y_n$ which are defined by the equation,

$Y = U^t X$ (Delaney, Foroughi et al. 1997). The coefficient vectors, $U = (U_1, U_2, ..., U_n)$, are the

eigenvectors of the covariance matrix of X. The data is described by m linear combinations of

the principal components (Z). Typically, the first few components explain most of the variance in

the original data. In the current work only the first two PCs are needed. PC1 is the axis with the

most variation and PC2 is orthogonal to PC1 and has the second largest variation (Jolliffe 2002).

The magnitude of the eigenvalues of U is the lengths of the corresponding components.

In this study, the input variables are lower body joint (hip, knee, and ankle) angles. Ninety

percent of the data variation is represented by the first two PCs corresponding to the two largest

eigenvalues. Excellent explanations of PCA applied to gait waveform data can be found in

(Delaney, Foroughi et al. 1997; Deluzio, Wyss et al. 1999; Sadeghi, Prince et al. 2000; Deluzio

and Astephen 2007).

7.4. Results

Principal component analysis was conducted for the hip, knee, and ankle angles. PC

scores were generated for each subject for both loaded and unloaded conditions. In order to

quantify statistical differences between loading conditions and BMI classes, Student's t-test was

applied to joint angle PC scores and actual joint ranges of motion. The p-values of each PC are

provided in Table 7.3. Figure 7.1 and 7.2 show mean joint angle waveforms, PC loading vectors,

and waveforms corresponding to the high and low PC scores. The ankle angle showed no

significant differences in any groups for either PCA or ROM. Also, no significant effect of load

was found in the actual knee ROM (Table 7.2).

Table 7. 2. A summary of Student's t-tests results (mean ± SD) between unloaded and loaded walking conditions for all subjects. Bolded values indicate statistically significant difference ($p < 0.05$) between unloaded and loaded walking conditions.

Variable	Unloaded	Loaded	p-value
Hip ROM (°)	38.6058 ± 3.5124	41.8693 ± 3.0355	**< 0.05**
Knee ROM (°)	60.3562 ± 5.0004	57.9842 ± 6.4828	0.172
Ankle ROM (°)	28.5638 ± 4.0134	29.9843 ± 5.0475	0.297

(A)
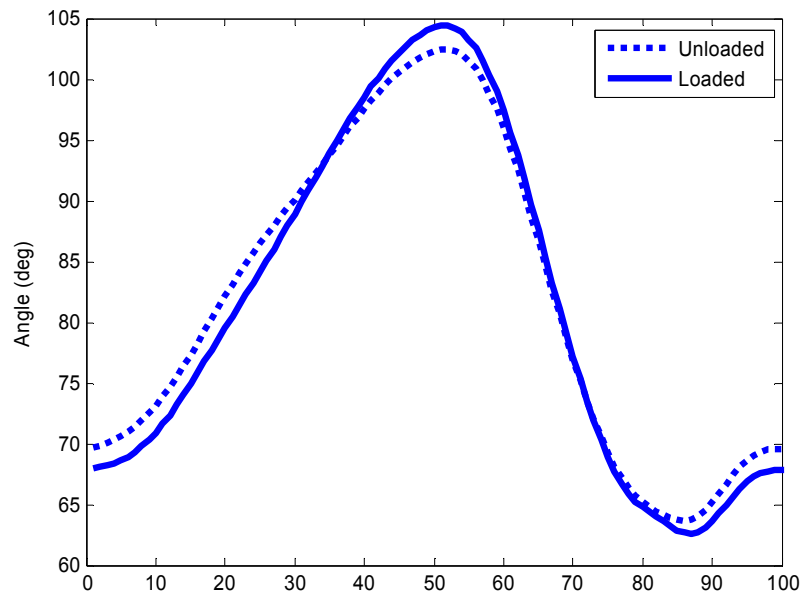
(B)
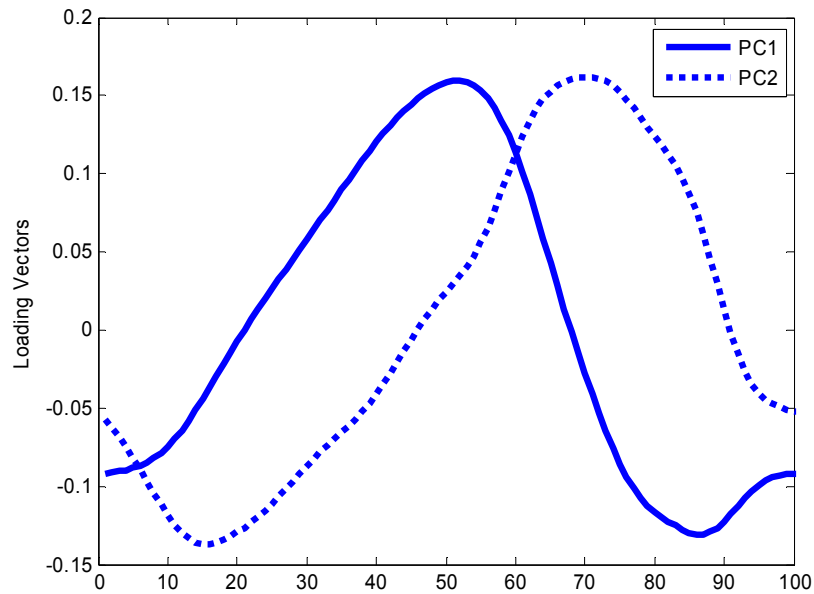
(C)

Figure 7. 1. (A) Mean hip angle waveform data for unloaded (dashed) and loaded walking (solid). (B) The loading vectors for the first two principal components, PC1 (solid) and PC2 (dashed). (C) Hip angle waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC1 scores.

There were several measures, however, where significant statistical differences between groups did exist. The first PC of hip angle showed significant differences between unloaded and loaded walking conditions (Table 7.3 and Figure 7.1). The first PC has positive values in late stance and large negative values during early stance and swing (Figure 7.1B). Therefore, it is a measure of the range of motion of the hip joint (Deluzio and Astephen 2007). Figure 1C shows the waveform data according to the high and low PC1 scores. PC1 score statistical analysis showed that unloaded walking had, on average, less hip angular motion (p<0.001). The same result was found in actual hip ROM as shown in Table 7.2. No significant difference was found between unloaded and loaded walking with respect to PC2.

Table 7. 3. A summary of Student's t-tests results (mean ± SD) comparing the PC scores between unloaded and loaded walking conditions. Bolded values indicate statistically significant difference (p < 0.05) between the two groups. Only significant contributions were shown.

Angle	*PC*	*Unloaded*	*Loaded*	p-value
Hip	PC1	-0.89 ± 0.19	-0.69 ± 0.19	**< 0.05**
	PC2	-0.06 ± 0.30	0.06 ± 0.28	0.177
Knee	PC1	0.34 ± 0.32	0.32 ± 0.30	0.835
	PC2	-0.09 ± 0.30	0.11 ± 0.32	**< 0.05**
Normal weight		*Unloaded*	*Loaded*	
Hip	PC1	-0.93 ± 0.22	-0.72 ± 0.22	**< 0.05**
Overweight		*Unloaded*	*Loaded*	
Hip	PC1	-0.84 ± 0.14	-0.64 ± 0.12	**< 0.01**

(A)
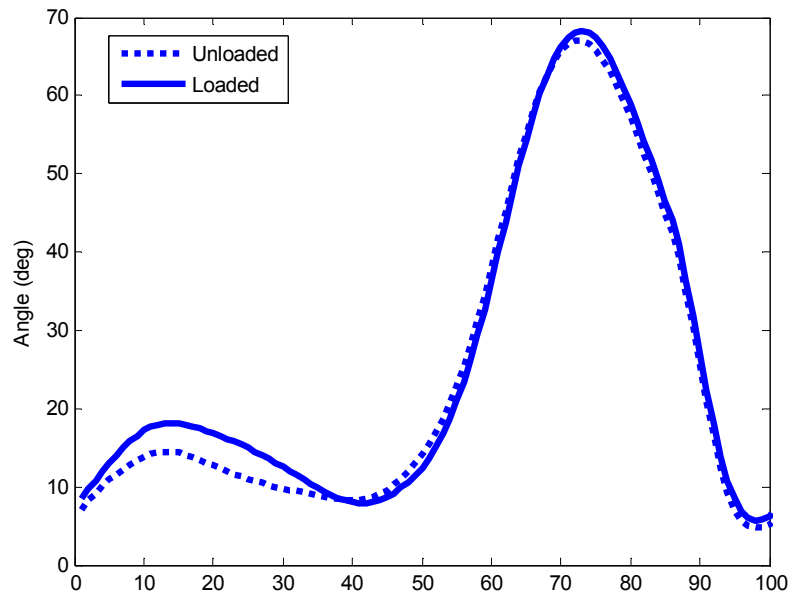
(B)
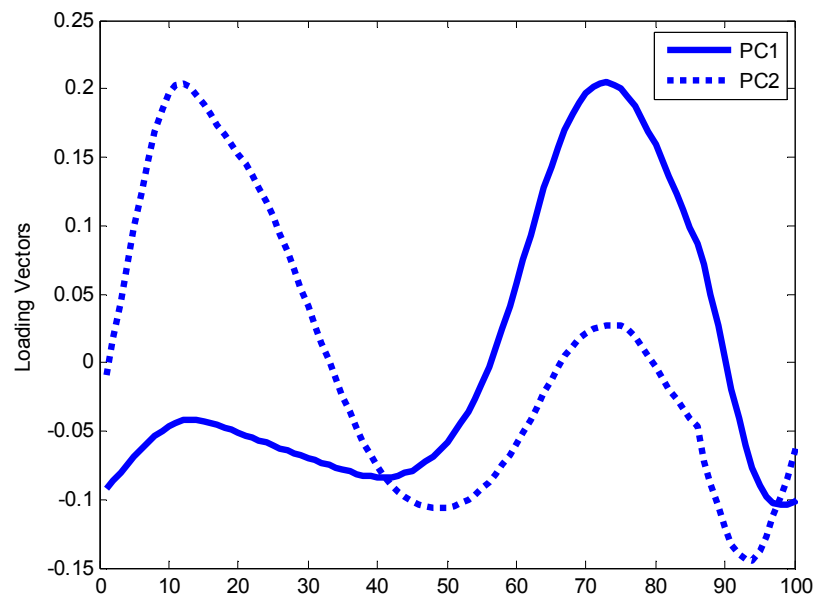
(C)
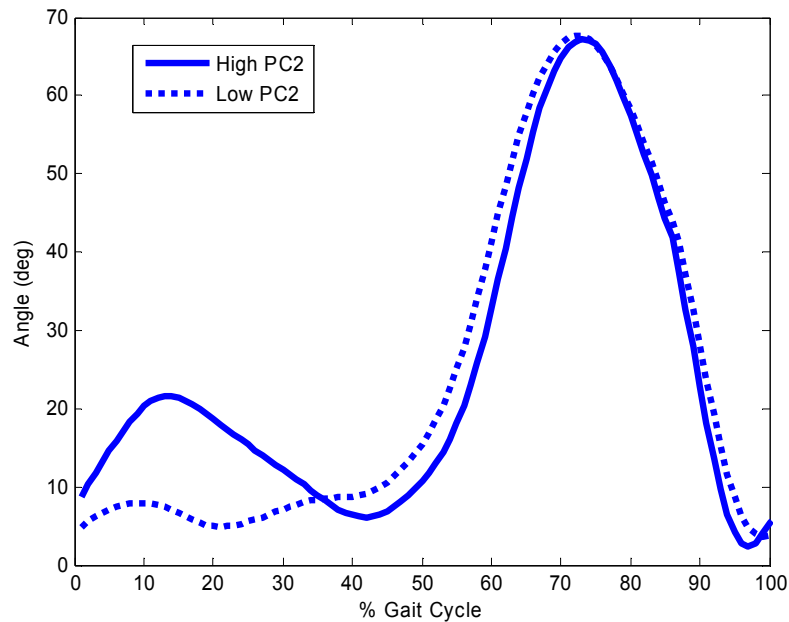
Figure 7. 2. (A) Mean knee angle waveform data for unloaded (dashed) and loaded walking (solid). (B) The loading vectors for the first two principal components, PC1 (solid) and PC2 (dashed). (C) Knee angle waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC2 scores.

The knee angle also revealed differences between unloaded and loaded walking conditions (Table 7.3 and Figure 7.2). No significant differen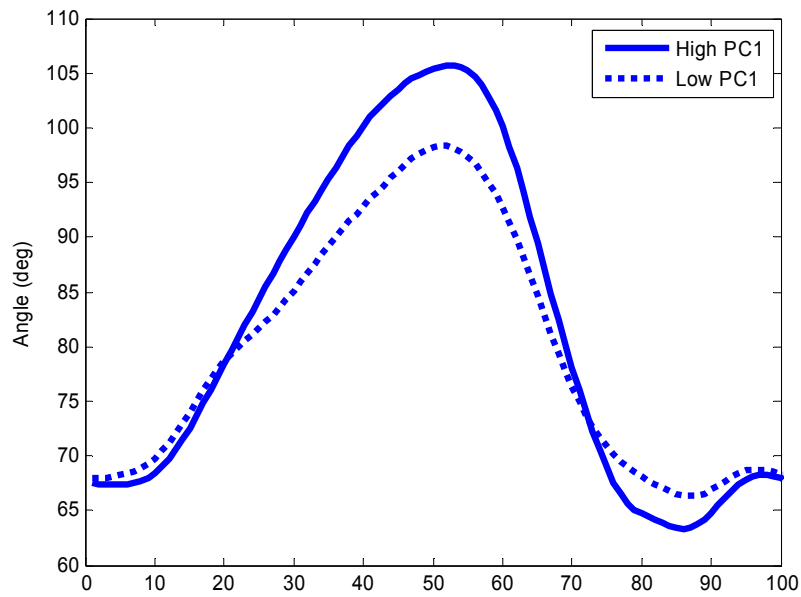ce was found in the PC1 score between unloaded and loaded walking. PC2 had large positive values in early stance and large negative values during late stance and swing. Unloaded walking was found to have a lower magnitude of knee flexion during early stance than loaded walking as shown in PC2 scores (Fig. 2B and C).

Above, PCA identified gait differences between loaded and unloaded walking for the general population. In this section, the analysis is further refined to include the effects of body mass on the gait adaptation due to external loads. This was accomplished by separating subjects into two BMI classes (normal weight < 24 kg/m^2 < overweight). The hip angle PC1 score for

94

normal weight subjects was found to be statistically different (p<0.05) between loaded and

unloaded walking. This relates to a reduction in hip angular motion during swing phase when

unloaded (Table 7.3 and Figure 7.3A). Similarly, the overweight group showed significantly

(p<0.01) lower hip angle PC1 score in unloaded walking than loaded walking (Table 7.3 and

Figure 7.3B).

(A)
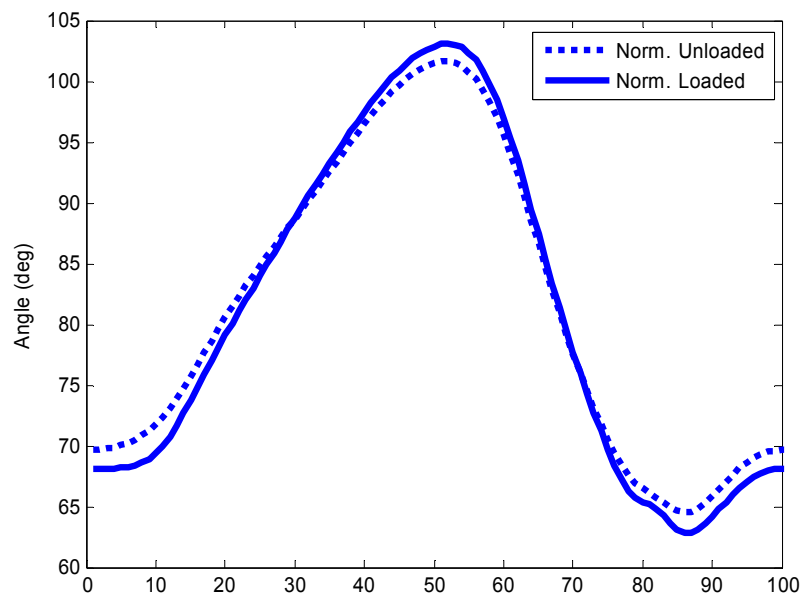
(B)
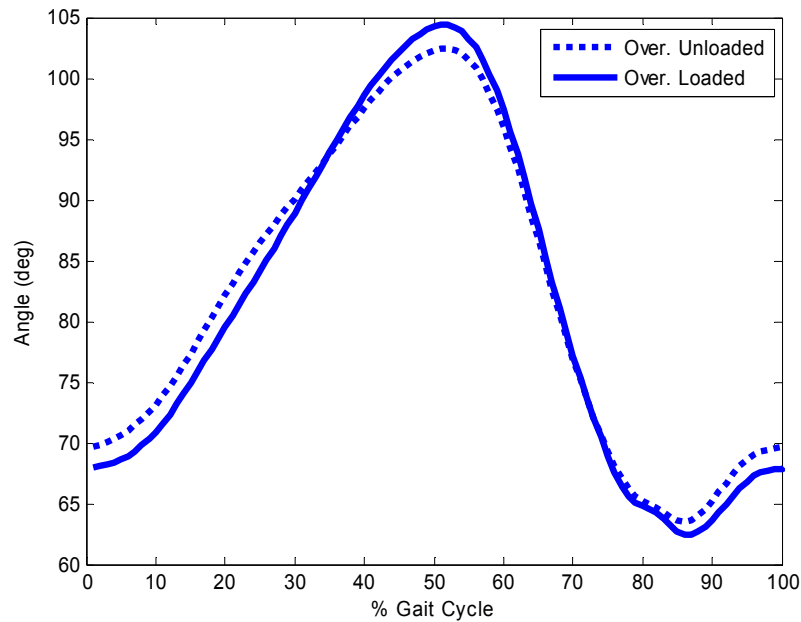
Figure 7. 3. (A) Mean hip angle waveform data of normal weight subjects for unloaded (dashed) and loaded walking (solid). (B) Mean hip angle waveform data of overweight subjects for unloaded (dashed) and loaded walking (solid). Unloaded: unloaded walking, Loaded: loaded walking, Norm: normal weight subjects, Over: overweight subject.

7.5. Discussion

The purpose of this study was to compare lower extremity kinematics between unloaded and loaded walking conditions using PCA. The hypothesis was that PCA could be used to characterize changes due to evenly distributed external loads. These changes are more subtle than one-sided loadings and require more sophisticated analysis. The main conclusion of the study is that gait data can be reduced into two highly informative PCs. The first PC (PC1) of hip angle and the second PC (PC2) of knee angle are the most informative in regard to the effect of external loads on lower body kinematics. However, no significant difference was found in the ankle angular movements. This indicates that the ankle joint is not sensitive enough to the 12.5kg

96

external load used in this study. Similar results were reported in (Harman, Han et al. 2000) with various one sided loading.

Principal component analysis of the sagittal hip angle revealed a significant PC1 score increase for loaded walking compared to unloaded walking. The PC1 score increase is consistent with the increase in actual measures of hip ROM as shown in Table 7.2. This indicates more angular hip motion when carrying a load. PC2 scores of the knee angle show that there is a significant increase in the knee flexion during stance in loaded walking than in unloaded walking. An increase in knee joint flexion after heel contact is expected when carrying a load (Chow, Kwok et al. 2005). The difference in knee flexion between loaded and unloaded walking is not significant during swing. Therefore, knee angular motion during the swing phase is not an indicator of load effects.

Normal weight and overweight subjects show similar external load adaptations. Both groups have increased hip ROM in loaded walking than in unloaded walking. The difference between unloaded and loaded walking is greatest during peak hip extension. However, a significant BMI effect was not found when comparing overweight and normal weight subjects. The effects of external loads are more significant than those caused by BMI differences when walking.

As shown in this study, PCA is an effective way of analyzing subtle changes in lower body joint angles caused by evenly distributed external loads. PCA was used to find significant differences in the knee joint angle between unloaded and loaded walking even though no statistical difference exists in knee ROM. PCA was not able to show a significant difference in any joint angles between normal weight and overweight groups. Subjects in this study had a relatively a short time to adapt to the external load. Larger kinematic changes may result without

a proper amount of adaptation time. The longer term adaptations of overweight subjects to their excessive body mass may result in more subtle differences in lower body joint angles. These changes cannot be analyzed using PCA because the small variations in joint angles are not captured in the first two PCs. Although a higher number of PCs might contain these variations, they are often dominated by noise.

In conclusion, PCA has been shown to be a powerful tool for analyzing complex gait data. It is shown that in order to quantify the effects of external loads, only two principal components were needed. For the work in this paper, PCs were generated from lower body joint angle data. PC1 of hip and PC2 of knee angle were shown to be indicators of external load effects on temporal gait data.

Acknowledgements

7.6. References

Chow, D. H., M. L. Kwok, et al. (2005). "The effect of backpack load on the gait of normal adolescent girls." Ergonomics **48**(6): 642-656.

Daffertshofer, A., C. J. C. Lamoth, et al. (2004). "PCA in studying coordination and variability: a tutorial." Clinical Biomechanics **19**(4): 415-428.

Delaney, M. M., A. Foroughi, et al. (1997). "Principal component models of knee kinematics and kinetics: Normal vs. pathological gait patterns " Human Movement Science **16**(2): 201-217.

Deluzio, K. J. and J. L. Astephen (2007). "Biomechanical features of gait waveform data associated with knee osteoarthritis: an application of principal component analysis." Gait Posture **25**(1): 86-93.

Deluzio, K. J., U. P. Wyss, et al. (1999). "Gait assessment in unicompartmental knee arthroplasty patients: Principal component modelling of gait waveforms and clinical status." Human Movement Science **18**: 701-11.

England, S. A. and K. P. Granata (2007). "The influence of gait speed on local dynamic stability of walking." Gait Posture **25**(2): 172-8.

Griffin, T. M., T. J. Roberts, et al. (2003). "Metabolic cost of generating muscular force in human walking: insights from load-carrying and speed experiments." J Appl Physiol **95**(1): 172-83.

Harman, E., K. H. Han, et al. (1992). " The effects on gait timing, kinetics, and muscle activity of various loads carried on the back." Medicine and Science in Sports and Exercise **24**: S129.

Harman, E. A., K. H. Han, et al. (2000). "The effects of backpack weight on the biomechanics of load carriage." US Army Research Institute of Environmental Medicine, Natick, MA.

Hills, A. P. and A. W. Parker (1991). "Gait characteristics of obese children." Arch Phys Med Rehabil **72**(6): 403-7.

Hong, Y. and G. P. Brueggemann (2000). "Changes in gait patterns in 10-year-old boys with increasing loads when walking on a treadmill." Gait Posture **11**(3): 254-9.

Hsiang, S. M., Chang, C. (2002). "The effect of gait speed and load carrying on the reliability of ground reaction forces." Safety Science **40**: 639-657.

Jolliffe, I. T. (2002). Principal component analysis, Springer.

Kinoshita, H. (1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait." Ergonomics **28**(9): 1347-62.

Lockhart, T. E., J. C. Woldstad, et al. (2003). "Effects of age-related gait changes on the biomechanics of slips and falls." Ergonomics **46**(12): 1136-60.

McGraw, B., B. A. McClenaghan, et al. (2000). "Gait and postural stability in obese and nonobese prepubertal boys." Arch Phys Med Rehabil **81**(4): 484-9.

Messier, S. P. (1994). "Osteoarthritis of the knee and associated factors of age and obesity: effects on gait." Med Sci Sports Exerc **26**(12): 1446-52.

Meyer-Baese, A. (2000). "Medical image compression by neura-gas network and principal component analysis." Neural Networks, Proceedings of the IEEE-INNS-ENNS International Joint Conference on **5**: 489-493.

Mickelborough, J., M. L. van der Linden, et al. (2000). "Validity and reliability of a kinematic protocol for determining foot contact events." Gait Posture **11**(1): 32-7.

Olney, S. J., M. P. Griffin, et al. (1998). "Multivariate examination of data from gait analysis of persons with stroke." PHYS THER **78**(8): 814-828.

Oravec, M. and J. Pavlovicova (2004). "Face recognition methods based on principal component analysis and feedforward neural networks." International Joint Conference on Neural Networks.

Ramanthan, N. L., Datta, S.R., Gupta, M.N (1972). "Biomechanics of various modes of load transport on level ground." Indian J Medical Research **60**: 1702-1710.

Sadeghi, H., P. Allard, et al. (2002). "Main functional roles of knee flexors/extensors in able-bodied gait using principal component analysis (I)." The Knee **9**(1): 47-53.

Sadeghi, H., P. Allard, et al. (1997). "Functional gait asymmetry in able-bodied subjects." Human Movement Science **16**(2-3): 243-258.

Sadeghi, H., F. Prince, et al. (2000). "Principal component analysis of the power developed in the flexion/extension muscles of the hip in able-bodied gait." Medical Engineering & Physics **22**(10): 703-710.

Stephen P. Messier, Walter H. Ettinger, et al. (1996). "Obesity: Effects on Gait in an Osteoarthritic Population." Journal of Applied Biomechanics **12**(2): 161-172.

Strathy, G. M., E. Y. Chao, et al. (1983). "Changes in knee function associated with treadmill ambulation." J Biomech **16**(7): 517-22.

Wrigley, A. T., W. J. Albert, et al. (2006). "Principal component analysis of lifting waveforms." Clinical Biomechanics **21**(6): 567-578.

Chapter 8 - Conclusions

8.1. Research summary

Gait analysis to classify unloaded and loaded walking was examined in this study. External loads were evenly-distributed with a weight of 12.5kg. Results of this study have demonstrated that external loads significantly affect kinematics of lower limbs. It was successfully quantified in this study by phase angles, path lengths from phase portraits, and joint angle ranges of motion. The actual classification for loading conditions is conducted by artificial neural networks (ANNs) and linear discriminant analysis (LDA). Also, principal component analysis (PCA) is used to characterize both loading conditions.

Reliability analysis was performed 1) to quantify the consistency of lower body kinematic measurements during gait, and 2) to determine the number of required trials. Intra-class correlation coefficients, ICC(2,1), were calculated for each loading condition. Results showed moderate reliability from 0.61 to 0.82. Lower ICC values in loaded walking suggest that a less reliable measure would be expected for such a loading condition.

Next, satisfactory classification of subjects into the correct loading condition was achieved by using LDA. LDA could successfully discriminated loaded and unloaded walking conditions using six lower body kinematic variables including joint angle ranges of motion and path lengths of joint movements. The results showed that external loads affected gait pattern changes and with a large amount of training data sets, it would be possible to classify an unknown person's gait patterns. However, another research question was asked: how are the

external loads different from the excessive body mass in overweight subjects. Therefore, a further study was conducted to define the differences in lower body gait patterns caused by external loading condition and excessive body mass. The study found significant gait adaptations caused by external load carriage rather than excessive body mass. A subspace analysis technique such as PCA was also performed to better understand the nature of load induced changes in gait. In this study, PCA was showed to be a powerful tool for analyzing complex gait data. With only two principal components, it was successfully characterized the effects of load carriage.

Biomechanical understanding of human movements, specifically gait patterns, can be a useful tool for the detection of a hidden load, clinical evaluations of patients, as well as movement control for bipedal robots.

8.2. Contributions and Future work

The new methods and results in this dissertation provide additional tools which may be applied for clinical evaluations as well as gait research. Specifically, the analysis from phase portraits can be used for an indication of the amount of angular displacement or velocity in individuals who have disabilities. It also estimates the stability of human motion and provides an analysis of adaptation methods caused by various perturbations. A lower tolerance to perturbations may place the person at higher risk of developing gait instabilities.

In addition, a simple classification method using linear discriminant analysis may be helpful in understanding characteristics of each class (i.e. unloaded and loaded walking in this study). It can be further compared with principal component analysis or neural networks to find the advantage of each method.

There are some limitations for this study. In the future, it would be essential to use various loading conditions, for example 5, 10, 15, and 20 kg, in order to find adaptation trends due to the loading conditions. Using this data, motion classifications can be generated for randomly selected individuals based on training data from a large number of people. In this dissertation, the same preferred walking speed for normal walking was used for both unloaded and loaded walking. This may cause atypical walking while carrying a load. Therefore, future work should use two different preferred walking speeds for both loading conditions to determine the changes of lower body kinematics with respect to the walking speed and external load at the same time.

Finally, a study will be necessary to relate the risk of injuries to kinematic changes due to external loads or excessive body mass. After verification with current experimental data, this can be further developed by a mathematical model which may anticipate kinematic changes due to severe external conditions. Applying torso and arms movements in the mathematical model will lead to much more realistic motion and can be used to find risk factors of those joints which are prone to injuries.

References

Begg, R. and M. Palaniswami (2006). <u>Computational intelligence for movement sciences: neural networks and other emerging techniques</u>. Hershey, PA, Idea Group Publishing.

BenAbdelkader, C. and L. Davis (2002). "Detection of people carrying objects: A motion-based recognition approach." <u>Fifth IEEE International Conference on Automatic Face and Gesture Recognition</u> **p. 0378**.

Berrigan, F., M. Simoneau, et al. (2006). "Influence of obesity on accurate and rapid arm movement performed from a standing posture." <u>Int J Obes (Lond)</u> **30**(12): 1750-7.

Bonett, D. G. (2002). "Sample size requirements for estimating intraclass correlations with desired precision." <u>Stat Med</u> **21**(9): 1331-5.

Boulgouris, N. V. and Z. X. Chi (2007). "Gait recognition using radon transform and linear discriminant analysis." <u>IEEE Trans Image Process</u> **16**(3): 731-40.

Boulgouris, N. V., D. Hatzinakos, et al. (2005). "Gait recognition: a challenging signal processing technology for biometric identification." <u>IEEE Signal Processing Magazine</u>: 78-90.

Browning, R. C., J. R. Modica, et al. (2007). "The effects of adding mass to the legs on the energetics and biomechanics of walking." <u>Med Sci Sports Exerc</u> **39**(3): 515-25.

Burgess-Limerick, R., B. Abernethy, et al. (1991). "Note: A statistical problem in testing invariance of movement using the phase plane model." <u>Journal of Motor Behavior</u> **23**(4): 301-303.

Burgess-Limerick, R., B. Abernethy, et al. (1993). "Relative phase quantifies interjoint coordination." <u>J Biomech</u> **26**(1): 91-4.

Chow, D. H., M. L. Kwok, et al. (2005). "The effect of backpack load on the gait of normal adolescent girls." <u>Ergonomics</u> **48**(6): 642-656.

Chow, D. H., M. L. Kwok, et al. (2006). "The effect of load carriage on the gait of girls with adolescent idiopathic scoliosis and normal controls." <u>Med Eng Phys</u> **28**(5): 430-7.

Clark, J. E. and S. J. Phillips (1993). "A longitudinal study of intralimb coordination in the first year of independent walking: a dynamical systems analysis." <u>Child Dev</u> **64**(4): 1143-57.

Corriveau, H., R. Hebert, et al. (2000). "Intrasession reliability of the "center of pressure minus center of mass" variable of postural control in the healthy elderly." <u>Arch Phys Med Rehabil</u> **81**(1): 45-8.

Daffertshofer, A., C. J. C. Lamoth, et al. (2004). "PCA in studying coordination and variability: a tutorial." <u>Clinical Biomechanics</u> **19**(4): 415-428.

Dalen A, Nilsson J, et al. (1978). "Factors Influencing a Prolonged Foot March." <u>Stockholm, Sweden, Karolinska Institute</u> **FOA report C50601-H6.** .

Delaney, M. M., A. Foroughi, et al. (1997). "Principal component models of knee kinematics and kinetics: Normal vs. pathological gait patterns " <u>Human Movement Science</u> **16**(2): 201-217.

Deluzio, K. J. and J. L. Astephen (2007). "Biomechanical features of gait waveform data associated with knee osteoarthritis: an application of principal component analysis." <u>Gait Posture</u> **25**(1): 86-93.

Deluzio, K. J., U. P. Wyss, et al. (1999). "Gait assessment in unicompartmental knee arthroplasty patients: Principal component modelling of gait waveforms and clinical status." <u>Human Movement Science</u> **18**: 701-11.

Donner, A. and M. Eliasziw (1987). "Sample size requirements for reliability studies." Stat Med **6**(4): 441-8.

England, S. A. and K. P. Granata (2007). "The influence of gait speed on local dynamic stability of walking." Gait Posture **25**(2): 172-8.

Foster, G. D., T. A. Wadden, et al. (1995). "The energy cost of walking before and after significant weight loss." Med Sci Sports Exerc **27**(6): 888-94.

Goswami, A., B. Espiau, et al. (1996). Limit cycles and their stability in a passive bipedal gait. Proc IEEE International Conference on Robotics and Automation.

Griffin, T. M., T. J. Roberts, et al. (2003). "Metabolic cost of generating muscular force in human walking: insights from load-carrying and speed experiments." J Appl Physiol **95**(1): 172-83.

Haddad, J. M., R. van Emmerik, et al. (2006). "Adaptations in interlimb and intralimb coordination to asymmetrical loading in human walking." Gait and Posture **23**: 429–434.

Hailey, D. and J. A. Tomie (2000). "An assessment of gait analysis in the rehabilitation of children with walking difficulties." Disabil Rehabil **22**(6): 275-80.

Hall, D. M. and T. J. Cole (2006). "What use is the BMI?" Arch Dis Child **91**(4): 283-6.

Hamill, J., J. M. Haddad, et al. (2000). "Issues in quantifying variability from a dynamical systems perspective." Journal of Applied Biomechanics **16**: 407-418.

Han, J. and B. Bhanu (2006). "Individual recognition using gait energy image." IEEE Trans Pattern Anal Mach Intell **28**(2): 316-22.

Harman, E., K. H. Han, et al. (1992). " The effects on gait timing, kinetics, and muscle activity of various loads carried on the back." Medicine and Science in Sports and Exercise **24**: S129.

Harman, E. A., K. H. Han, et al. (2000). "The effects of backpack weight on the biomechanics of load carriage." US Army Research Institute of Environmental Medicine, Natick, MA.

Herman, T., N. Giladi, et al. (2005). "Gait instability and fractal dynamics of older adults with a "cautious" gait: why do certain older adults walk fearfully?" Gait Posture 21(2): 178-85.

Hills, A. P. and A. W. Parker (1991). "Gait characteristics of obese children." Arch Phys Med Rehabil 72(6): 403-7.

Hong, Y. and G. P. Brueggemann (2000). "Changes in gait patterns in 10-year-old boys with increasing loads when walking on a treadmill." Gait Posture 11(3): 254-9.

Hsiang, S. M., Chang, C. (2002). "The effect of gait speed and load carrying on the reliability of ground reaction forces." Safety Science 40: 639-657.

Hue, O., M. Simoneau, et al. (2007). "Body weight is a strong predictor of postural stability." Gait Posture 26(1): 32-8.

Inman, V., H. J. Ralston, et al. (1981). Human Walking, Williams and Wilkins.

Johnson, R. A. and D. W. Wichern (1998). Applied multivariate statistical analysis, Prentice Hall.

Jolliffe, I. T. (2002). Principal component analysis, Springer.

Kale, A., N. Cuntoor, et al. (2003). "Gait analysis for human identification." in 4th Int. Conf. Audio-and-Video-Based Person Authentication, Guilford, UK: 706-714.

Kang, H. G. and J. B. Dingwell (2006). "Intra-session reliability of local dynamic stability of walking." Gait Posture 24(3): 386-90.

Kerrigan, D. C., M. K. Todd, et al. (1998). "Gender differences in joint biomechanics during walking: normative study in young adults." Am J Phys Med Rehabil 77(1): 2-7.

Kinoshita, H. (1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait." Ergonomics 28(9): 1347-62.

Kirtley, C. (2006). Clinical Gait Analysis: Theory and Practice, Churchill Livingstone.

Knapik, J., K. Reynolds, et al. (1992). "Injuries associated with strenuous road marching." Mil Med **157**(2): 64-7.

Knapik, J. J., E. A. Harman, et al. (1996). "Load carriage using packs: A review of physiological, biomechanical and medical aspects " Applied Ergonomics **27**(3): 207-216.

Kurz, M. J. and N. Stergiou (2002). "Effect of normalization and phase angle calculations on continuous relative phase." Journal of Biomechanics **35**: 369–374.

LaFiandra, M., K. G. Holt, et al. (2002). "Transverse plane kinetics during treadmill walking with and without a load." Clinical Biomechanics **17**: 116-122.

LaFiandra, M., R. C. Wagenaar, et al. (2003). "How do load carriage and walking speed influence trunk coordination and stride parameters?" Journal of Biomechanics **36**: 87-95.

Landis, J. R. and G. G. Koch (1977). "The measurement of observer agreement for categorical data." Biometrics **33**(1): 159-74.

Lehmann, J. and B. DeLateur (1990). Gait analysis: diagnosis and management Philadelphia, Saunders.

Lockhart, T. E., J. C. Woldstad, et al. (2003). "Effects of age-related gait changes on the biomechanics of slips and falls." Ergonomics **46**(12): 1136-60.

Luttgens, K. and K. Wells (1982). Kinesiology: scientific basis of human motion, Saunders College Publishing.

Lynch, S. (2004). Dynamical systems with applications using Matlab, Birkhäuser Boston.

Martin, P. E. and R. C. Nelson (1985). "The effect of carried loads on the combative movement performance of men and women." Mil Med **150**(7): 357-62.

Martin, P. E. and R. C. Nelson (1986). "The effect of carried loads on the walking patterns of men and women." Ergonomics **29**(10): 1191-202.

Maynard, V., A. M. Bakheit, et al. (2003). "Intra-rater and inter-rater reliability of gait measurements with CODA mpx30 motion analysis system." Gait Posture **17**(1): 59-67.

McGeer, T. (1990). "Passive dynamic walking." International Journal of Robotics Research **9**(2): 62-82.

McGeer, T. (1990). Passive walking with knees. IEEE Robotics and Automation Conference**:** 1640-1645.

McGraw, B., B. A. McClenaghan, et al. (2000). "Gait and postural stability in obese and nonobese prepubertal boys." Arch Phys Med Rehabil **81**(4): 484-9.

McGraw, K. O. and S. P. Wong (1996). "Forming inferences about some intraclass correlation coefficients." Psychological Methods **1**(1): 30-46.

McLachlan, G. J. (2004). Discriminant analysis and statistical pattern recognition, Wiley-Interscience.

Mehrotra, K., C. Mohan, et al. (1996). Elements of artificial neural networks, The MIT Press.

Messier, S. P. (1994). "Osteoarthritis of the knee and associated factors of age and obesity: effects on gait." Med Sci Sports Exerc **26**(12): 1446-52.

Meyer-Baese, A. (2000). "Medical image compression by neura-gas network and principal component analysis." Neural Networks, Proceedings of the IEEE-INNS-ENNS International Joint Conference on **5**: 489-493.

Mickelborough, J., M. L. van der Linden, et al. (2000). "Validity and reliability of a kinematic protocol for determining foot contact events." Gait Posture **11**(1): 32-7.

Mochon, S. and T. A. McMahon (1980). "Ballistic walking: an improved model." <u>Mathematical Biosciences</u> **52**(3-4): 241-260.

Mulder, T., B. Nienhuis, et al. (1998). "Clinical gait analysis in a rehabilitation context: some controversial issues." <u>Clin Rehabil</u> **12**(2): 99-106.

Must, A. and R. S. Strauss (1999). "Risks and consequences of childhood and adolescent obesity." <u>Int J Obes Relat Metab Disord</u> **23 Suppl 2**: S2-11.

Olney, S. J., M. P. Griffin, et al. (1998). "Multivariate examination of data from gait analysis of persons with stroke." <u>PHYS THER</u> **78**(8): 814-828.

Oravec, M. and J. Pavlovicova (2004). "Face recognition methods based on principal component analysis and feedforward neural networks." <u>International Joint Conference on Neural Networks</u>.

Perry, J. (1992). <u>Gait Analysis: Normal and Pathological Function</u>, Slack Incorporated.

Piecha, J. (2008). <u>Gait Motor Disturbances in Neurological Diseases Diagnosis</u>. Berlin, Springer.

Portney, L. G. and M. P. Watkins (2000). <u>Foundations of clinical research: applications to practice</u>, Prentice-Hall.

Prieto, T. E., J. B. Myklebust, et al. (1996). "Measures of postural steadiness: differences between healthy young and elderly adults." <u>IEEE Trans Biomed Eng</u> **43**(9): 956-66.

Ramanathan, N. L., S. R. Datta, et al. (1972). "Biomechanics of various modes of load transport on level ground." <u>Indian J Med Res</u> **60**(11): 1702-10.

Ramanthan, N. L., Datta, S.R., Gupta, M.N (1972). "Biomechanics of various modes of load transport on level ground." <u>Indian J Medical Research</u> **60**: 1702-1710.

Reisman, D. S., H. J. Block, et al. (2005). "Interlimb Coordination During Locomotion: What Can be Adapted and Stored?" <u>J Neurophysiol</u> **94**(4): 2403-2415.

Sadeghi, H., P. Allard, et al. (2002). "Main functional roles of knee flexors/extensors in able-bodied gait using principal component analysis (I)." The Knee **9**(1): 47-53.

Sadeghi, H., P. Allard, et al. (1997). "Functional gait asymmetry in able-bodied subjects." Human Movement Science **16**(2-3): 243-258.

Sadeghi, H., P. Allard, et al. (2000). "Symmetry and limb dominance in able-bodied gait: a review." Gait Posture **12**(1): 34-45.

Sadeghi, H., F. Prince, et al. (2000). "Principal component analysis of the power developed in the flexion/extension muscles of the hip in able-bodied gait." Medical Engineering & Physics **22**(10): 703-710.

Saunders, J. B., V. T. Inman, et al. (1953). "The major determinants in normal and pathological gait." J Bone Joint Surg Am **35-A**(3): 543-58.

Sharma, S. (1996). Applied Multivariate Techniques, John Wiley & Sons, Inc.

Shrout, P. E. and J. L. Fleiss (1979). "Intraclass correlations: Uses in assessing rater reliability." Psychological Bulletin **86**(2): 420-8.

Spyropoulos, P., J. Pisciotta, et al. (1991). "Biomechanical gait analysis in obese men." Arch Phys Med Rehabil **72**: 1065-70.

Stefano, L., B. Yves, et al. (2003). "Assessment of energy expenditure associated with physical activities in free-living obese and nonobese adolescents." The American journal of clinical nutrition **78**: 471-479.

Stephen P. Messier, Walter H. Ettinger, et al. (1996). "Obesity: Effects on Gait in an Osteoarthritic Population." Journal of Applied Biomechanics **12**(2): 161-172.

Stergiou, N. (2004). Innovative analysis of human movement: Analytical tools for human movement research, Human Kinetics

Stokes, V. P., C. Andersson, et al. (1989). "Rotational and translational movement features of the pelvis and thorax during adult human locomotion." <u>J Biomech</u> **22**(1): 43-50.

Stolze, H., J. P. Kuhtz-Buschbeck, et al. (1998). "Retest reliability of spatiotemporal gait parameters in children and adults." <u>Gait Posture</u> **7**(2): 125-130.

Strathy, G. M., E. Y. Chao, et al. (1983). "Changes in knee function associated with treadmill ambulation." <u>J Biomech</u> **16**(7): 517-22.

Wall, J. C. and J. Crosbie (1996). "Accuracy and reliability of temporal gait measurement." <u>Gait and Posture</u> **4**: 293-6.

Walter, S. D., M. Eliasziw, et al. (1998). "Sample size and optimal designs for reliability studies." <u>Stat Med</u> **17**(1): 101-10.

Wang, Y. T., D. D. Pascoe, et al. (2001). "Evaluation of book backpack load during walking." <u>ERGONOMICS</u> **44**(9): 858-869.

Whittle, M. (2002). <u>Gait analysis: an introduction</u>, Butterworth-Heinemann.

Whittle, M. (2007). <u>Gait analysis: an introduction</u>, Butterworth-Heinemann.

Winsmann, F. R. and R. F. Goldman (1976). "Methods for evaluation of load-carriage systems." <u>Percept Mot Skills</u> **43**: 1211-1218.

Winstein, C. J. and A. Garfinkel (1989). "Qualitative dynamics of disordered human locomotion: a preliminary investigation." <u>J Mot Behav</u> **21**(4): 373-91.

Wittman, M. G., J. M. Ward, et al. (2005). "Visual analysis of the effects of load carriage on gait." <u>Proceedings of the SPIE</u> **5779**: 15-22

Wrigley, A. T., W. J. Albert, et al. (2006). "Principal component analysis of lifting waveforms." <u>Clinical Biomechanics</u> **21**(6): 567-578.

Yu, H. and J. Yang (2001). "A direct LDA algorithm for high-dimensional data -- with application to face recognition." Pattern Recognition **34**(10): 2067-2070.

Appendix I. An IRB approved letter

VirginiaTech

Office of Research Compliance
Institutional Review Board
1880 Pratt Drive (0497)
Blacksburg, Virginia 24061
540/231-4991 Fax: 540/231-0959
E-mail: moored@vt.edu
www.irb.vt.edu
FWA00000572(expires 7/20/07)
IRB # is IRB00000667.

DATE: August 30, 2006

MEMORANDUM

TO: Thurmon E. Lockhart

Approval date: 8/29/2006
Continuing Review Due Date: 8/14/2007
Expiration Date: 8/28/2007

FROM: David M. Moore

SUBJECT: **IRB Expedited Approval:** "Gait Analysis to Detect Hidden External Loads", IRB # 06-460

This memo is regarding the above-mentioned protocol. The proposed research is eligible for expedited review according to the specifications authorized by 45 CFR 46.110 and 21 CFR 56.110. As Chair of the Virginia Tech Institutional Review Board, I have granted approval to the study for a period of 12 months, effective August 29, 2006.

As an investigator of human subjects, your responsibilities include the following:

1.   Report promptly proposed changes in previously approved human subject research activities to the IRB, including changes to your study forms, procedures and investigators, regardless of how minor. The proposed changes must not be initiated without IRB review and approval, except where necessary to eliminate apparent immediate hazards to the subjects.

2.   Report promptly to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

3.   Report promptly to the IRB of the study's closing (i.e., data collecting and data analysis complete at Virginia Tech). If the study is to continue past the expiration date (listed above), investigators must submit a request for continuing review prior to the continuing review due date (listed above). It is the researcher's responsibility to obtained re-approval from the IRB before the study's expiration date.

4.   If re-approval is not obtained (unless the study has been reported to the IRB as closed) prior to the expiration date, all activities involving human subjects and data analysis must cease immediately, except where necessary to eliminate apparent immediate hazards to the subjects.

Important:
If you are conducting **federally funded non-exempt research**, this approval letter must state that the IRB has compared the OSP grant application and IRB application and found the documents to be consistent. Otherwise, this approval letter is invalid for OSP to release funds. Visit our website at http://www.irb.vt.edu/pages/newstudy.htm#OSP for further information.

cc: File
    Department Reviewer:Thurmon E. Lockhart
    T. Coalson 0118

Invent the Future

VIRGINIA POLYTECHNIC INSTITUTE UNIVERSITY AND STATE UNIVERSITY
An equal opportunity, affirmative action institution

Appendix II. A consent form

Informed Consent for Participants of Investigative Projects
Grado Department of Industrial and Systems Engineering
Virginia Tech

TITLE: Gait Analysis to Detect Hidden External Loads

PRINCIPAL INVESTIGATOR: Thurmon E. Lockhart Ph.D.

PURPOSE
The purpose of this study is to evaluate gait characteristics associated with carrying a hidden load.

PROCEDURE
The test will be performed at Virginia Tech, Locomotion Research Laboratory. You will perform walking maneuvers while carrying a load (no-load, 5 kg, 10kg, 15kg, 20kg, and 25kg). While walking at natural and fast walking speed (120 steps/min) your gait parameters will be assessed utilizing the motion analysis system and video camcorder. Refractive markers will be attached to the joint centers and you will be instructed to walk on the treadmill with a safety harness. While walking data will be collected using the motion analysis and video camcorders. The entire experiment will take two hours.

RISKS OF PARTICIPATION
Minor muscle sprain (similar to those encountered in regular daily activities)

BENEFITS
The proposed research will provide an algorithm to detect hidden loads. This information can be used for security purposes in places such as airports and government buildings. The benefits to the subjects are a better understanding of hidden load detections.

COMPENSATION
Monetary compensation will be provided ($10.00 per hour).

ANOYNMITY AND CONFIDENTIALITY
The data from this study will be kept strictly confidential. No data will be released to anyone but the principal investigator and graduate students involved in the project without written consent of the subject. Data will be identified by subject number.

FREEDOM TO WITHDRAW
You are free to withdraw at any time from the study for any reason. Circumstances may come up that the researcher will determine that you should not continue as a subject in the study. For example, an illness could be a reason to have the researchers stop your participation in the study.

APPROVAL OF RESEARCH

This research has been approved, as required, by the Institutional Review Board for Research Involving Human Subjects at Virginia Tech, and by the Grado Department of Industrial and Systems Engineering. You will receive a copy of this form to take with you.

SUBJECT PERMISSION
I have read the informed consent and fully understand the procedures and conditions of the project. I have had all my questions answered, and I hereby give my voluntary consent to be a participant in this research study. I agree to abide by the rules of the project. I understand that I may withdraw from the study at any time.

If I have questions, I will contact:
　　　　Principal Investigator: Thurmon E. Lockhart, Assistant Professor, Grado Department of Industrial and Systems Engineering, 231-9088.
　　　　Chairman, Institutional Review Board for Research Involving Human Subjects: David Moore, 231-4991.

Signature of Subject _____ Date:

Signature of Project Director or his Authorized Representative:
_____ Date:

Signature of Witness to Oral Presentation:
_____ Date: