

JOINT MOMENT ESTIMATION FROM ELECTROMYOGRAPHY  
OF PATIENTS WITH OSTEOARTHRITIS

by

Kathryn Bernadine O'Keefe

A thesis submitted in partial fulfillment  
of the requirements for the degree

of

Master of Science

in

Health and Human Development

MONTANA STATE UNIVERSITY  
Bozeman, Montana

November 2007

© COPYRIGHT

by

Kathryn Bernadine O'Keefe

2007

All Rights Reserved

APPROVAL

of a thesis submitted by  
Kathryn Bernadine O'Keefe

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the Division of Graduate Education.

Dr. Michael E. Hahn

Approved for the Department of Health and Human Development

Dr. Timothy A. Dunnagan

Approved for the Division of Graduate Education

Dr. Carl A. Fox

STATEMENT OF PERMISSION TO USE

In presenting this thesis in partial fulfillment of the requirements for a master's degree at Montana State University, I agree that the Library shall make it available to borrowers under rules of the Library.

If I have indicated my intention to copyright this thesis by including a copyright notice page, copying is allowable only for scholarly purposes, consistent with "fair use" as prescribed in the U.S. Copyright Law. Requests for permission for extended quotation from or reproduction of this thesis in whole or in parts may be granted only by the copyright holder.

Kathryn Bernadine O'Keefe

November 2007

## TABLE OF CONTENTS

1. INTRODUCTION.....	1
Development of the Problem.....	1
Background.....	2
Statement of Purpose.....	4
Aims of the Study.....	4
Hypothesis.....	4
Assumptions.....	5
Limitations.....	5
Operational Definitions.....	5
2. LITERATURE REVIEW.....	7
Introduction.....	7
Traditional Gait Analysis.....	8
EMG-Muscle Force Modeling.....	9
Artificial Neural Networks – Applications in Biomechanics.....	10
3. METHODOLOGY.....	15
Subjects.....	15
Procedures.....	16
Instrumentation.....	18
EMG Recording System.....	18
3-D Motion Capture System.....	18
Force Platforms.....	19
Post-Processing.....	19
Analysis.....	23
4. RESULTS.....	25
Subjects.....	25
ANN Model.....	26
5. DISCUSSION.....	39
Introduction.....	39
ANN Model.....	39

TABLE OF CONTENTS – CONTINUED

Future Work.....	41
6. CONCLUSION .....	43
REFERENCES CITED.....	45
APPENDICES.....	49
APPENDIX A: Subject Consent Form.....	50
APPENDIX B: Video Consent Form.....	55
APPENDIX C: WOMAC Index.....	57

## LIST OF TABLES

Table	Page
3.1 Specific input data for the ankle, knee and hip joints.....	20
3.2 ANN training routines – twelve cases.....	21
4.1 Subject specific characteristics.....	26
4.2 T-test results for output correlation coefficients for cases 1-6.....	28
4.3 T-test results for output correlation coefficients for cases 7-12.....	28
4.4 Coefficient of determination ( $r^2$ ) values for each curve-fitting example.....	29
4.5 Absolute estimation error for the amplitude and timing of peaks A1 and A2 from the selected ankle joint moment curves.....	29
4.6 Absolute estimation error for the amplitude and timing of peaks K1, K2, K3, and K4 from the selected knee joint moment curves.....	32
4.7 Absolute estimation error for the amplitude and timing of peaks H1 and H2 from the selected hip joint moment curves.....	35

## LIST OF FIGURES

Figure	Page
2.1 An example of a multilayer feed-forward neural network.....	11
3.1 Detailed example of the three layer feed-forward ANN structure.....	20
3.2 Detailed ANN structure showing synaptic weights and biases as well as transfer functions.....	22
4.1 Ankle joint moment curves for case 1: (a) good curve-fitting example ( $r^2 > 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.96$ ).....	30
4.2 Ankle joint moment curves for case 12: (a) good curve-fitting example ( $r^2 > 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.98$ ).....	31
4.3 Knee joint moment curves for case 1: (a) good curve-fitting example ( $r^2 = 0.91$ ), (b) poor curve-fitting example ( $r^2 = 0.82$ ).....	33
4.4 Knee joint moment curves for case 12: (a) good curve-fitting example ( $r^2 = 0.96$ ), (b) poor curve-fitting example ( $r^2 = 0.82$ ).....	34
4.5 Hip joint moment curves for case 1: (a) good curve-fitting example ( $r^2 = 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.86$ ).....	36
4.6 Hip joint moment curves for case 12: (a) good curve-fitting example ( $r^2 = 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.87$ ).....	37
A.1 Surface electrode placement on seven muscles of the leg.....	52

## ABSTRACT

Biomechanical gait analysis may be used to determine treatment options, evaluate the success of rehabilitation programs or post-surgery recuperation, and provide insight for surgical planning, including functional outcomes for patients. However, gait analysis requires expensive equipment – a limiting factor for many clinical settings. One alternative that has been examined is the utilization of an artificial neural network (ANN) to model nonlinear relationships of gait. Researchers have shown initial success in ANN predictions of pathological conditions in gait as well as modeling other parameters. The purpose of this study was to evaluate the performance of a previously developed three layer feed-forward ANN model at estimating ankle, knee and hip joint moments for subjects with osteoarthritis (OA) from surface electromyography (EMG) signals. The broader purpose was to further validate the use of the ANN model as an alternative, less expensive method to traditional gait analysis. Eighteen subjects (13 female, 5 male) with physician diagnosed OA participated in this study. Each subject completed a full gait analysis session. Data from surface EMGs located on seven muscles of their symptomatic lower limb was recorded as well as kinematic and ground reaction force data. After post-processing, this data was entered into the ANN model and the model's ability to estimate lower extremity joint moments was evaluated. The ANN was able to accurately map the joint moments of subjects with OA. For the ankle, the mean correlation coefficients between the experimental joint moment and the estimated joint moment were between 0.97 and  $> 0.99$ . For the knee, the values ranged between 0.89-0.97, and for the hip, the values were between 0.91 and 0.97. Additionally, the ANN's ability to accurately map the lower extremity joint moments was demonstrated through the evaluation of case-specific joint moment time-series curves. Results have been presented in this study to show that the ANN model is adaptive to a subject group with more diversity than the previously tested group of young, healthy subjects. These findings further support the supposition that the ANN model may provide an alternative to traditional gait analysis methods.

## CHAPTER ONE

### INTRODUCTION

#### Development of the Problem

Degenerative joint disease (DJD) is associated with deterioration of cartilage and connective tissue in joints. Individuals who suffer from DJD may be limited in their daily functions and forced to quit recreational activities. One DJD that arises from inflammation of joints, cartilage and connective tissue is osteoarthritis (OA). This condition can be especially problematic for older individuals. A survey performed in 2002 estimated that one in every five Americans has been diagnosed with arthritis, and nearly 50% of the population over the age of 65 has been diagnosed with arthritis (Lethbridge-Ceiku, Schiller, and Bernadel, 2004). Specifically, it has been estimated that 12% of Americans over the age of 25 have been diagnosed with OA (National Institutes of Health [NIH], 2002). With an increasing elderly population, an even greater number of individuals are likely to be affected by OA.

Along with exercise, relaxation, and weight management, the most common treatment for OA is anti-inflammatory medications. However, for more severe cases, joint arthroplasty or total joint replacement surgeries may be recommended. The primary indicator for total knee replacement (TKR) and total hip replacement (THR) is joint failure due to OA (NIH, 2001; NIH, 2003). The number of TKR and THR surgeries

related to OA in the United States in 1997 was reported to be 256,000 and 117,000, respectively (Lethbridge-Ceiku et al., 2004).

Impaired joints of the lower extremity contribute to abnormal gait patterns. Biomechanical gait analysis may be used to determine treatment options and evaluate the success of rehabilitation programs or post-surgery recuperation (Davis, 1997). Gait analysis also provides insight for surgical planning, including functional outcomes for patients. However, gait analysis requires expensive equipment – a limiting factor for many clinical settings. One alternative that has been examined is the utilization of an artificial neural network (ANN) to model nonlinear relationships of gait. Researchers have shown initial success in ANN predictions of pathological conditions in gait as well as modeling other parameters (Chau, 2001; Schollhorn, 2004). Specifically, ANNs have been used to model the relationships between muscle activation from electromyography (EMG) signals to isokinetic joint torque (Hahn, 2007) and joint moments during gait (Hahn, Allen, and O’Keefe, 2006; Sepulveda, Wells, and Vaughn, 1993). By further developing techniques to model the nonlinear relationships of gait for both normal and abnormal patterns, researchers may be able to design an alternative, less expensive method for clinical gait evaluation.

### Background

Arthritis is defined as the inflammation of one or more joints, the surrounding cartilage, or connective tissue causing pain, swelling, and limited mobility. Osteoarthritis is one of the most common forms of arthritis, caused by the deterioration of cartilage within the joints, allowing excessive bone contact and increased inflammation and pain.

When OA occurs in the lower extremity, it often leads to abnormal gait. Abnormal gait and joint pain cause dynamic instability in individuals, being especially problematic within the elderly population who are susceptible to falls and further injury. It is therefore important to understand joint health as it relates to gait in order to maximize rehabilitation or post-surgical recovery.

Biomechanical gait analysis is used to measure parameters of normal and abnormal gait. The goal is to determine how gait differs from normal patterns, and if significant, identify the potential causes and recommend treatments (Davis, 1997). Primarily, gait analysis utilizes three-dimensional (3-D) video analysis along with force platforms to analyze joint kinetics and kinematics. Electromyography signals measuring dynamic muscle activation are also common to gait analysis, allowing neuromuscular function to be assessed. Both the 3-D motion capture system and force platforms are costly and require large laboratories, restricting widespread gait analysis.

It has been noted that while clinical gait analysis is continually advancing, improved quantitative methods are still needed for evaluating complex relationships within gait (Davis, 1997). Artificial neural networks capable of modeling nonlinear relationships may provide a way to address this need. One application of ANNs in biomechanics has been the estimation of isometric elbow joint torques (Wang and Buchanan, 2002; Luh, Chang, Cheng, Lai, and Kuo, 1999). For gait analysis, ANN applications have focused on classifying normal versus abnormal gait patterns (Barton and Lees, 1997; Holzreiter and Kohle, 1993; Lafuente, Belda, Sanchez-Lacuesta, Soler, and Pratt, 1997; Sepulveda et al., 1993; Wu and Su, 2000). Only a few attempts have been made using ANNs to map the EMG-joint moment relationships of the lower

extremities during isokinetic motion (Hahn, 2007) and during gait (Hahn et al., 2006; Sepulveda et al., 1993). This lack of lower extremity application is puzzling, as the estimation of joint kinetics is essential for improving knowledge of abnormal gait patterns (Davis, 1997). By using an ANN to model the EMG-joint moment relationship during gait, researchers may further elucidate the relationships between EMG, joint moments and gait abnormalities.

### Statement of Purpose

A previously designed ANN model has shown initial success in predicting lower extremity joint moments accurately for young, healthy subjects from recorded EMG data during gait. The purpose of this study was to determine if the neural network previously used to evaluate young, healthy subjects could estimate joint moments for a sample of patients with OA.

### Aims of the Study

The aim of this study was to validate the use of a previously designed model in the estimation of gait parameters in a sample of patients with OA.

### Hypothesis

It was hypothesized that the ANN model would accurately predict joint moments of the ankle, knee and hip joints of patients with OA.

$$H_0: \mu \leq 0.95$$

$$H_a: \mu > 0.95$$

The variable  $\mu$  represents the mean population correlation coefficient for the joint moment estimations. Testing the mean population correlation coefficient against 0.95 was determined by previous work in our lab in which values of 0.95-0.98 were obtained. Additionally, past researchers have generally accepted correlation coefficient values greater than 0.80 for this type of modeling.

### Assumptions

It was assumed that research subjects were representative of their population. It was also assumed that the patient's level of pain, swelling, and limited mobility caused by osteoarthritis did not change during the duration of this study.

### Limitations

Limitations of this study were the number of subjects as well as the possibility that the subject group may not have been a true representation of the general population with OA.

### Operational Definitions

*Arthritis*: inflammation of one or more joints causing pain, swelling, and limited mobility.

*Artificial Neural Network (ANN)*: a mathematical representation of a biological system modeled with a group of neurons interconnected through input, hidden, and output layers.

*Back-propagation*: a learning algorithm used to train artificial neural networks by working backwards and adjusting the weights of each neuron after initial outputs are obtained to provide solution convergence to the desired error limit.

*Electromyography (EMG)*: measurement of the electrical discharge produced from activated muscle motor units.

*Feed-forward*: referring to ANN structure, a process in which outputs are specified and learning proceeds in a forward direction from the input layers to the output.

*Hidden layer*: middle layer of a neural network where input-output relationships are mapped by means of back-propagation

*Input layer*: point at which data is entered into the ANN model.

*Inverse Dynamics*: an approach to determine the kinetics of motion from known kinematic variables.

*Joint moment*: the angular effect of forces acting about a joint, which is the resultant of the cross product between the distance the net force acts from the rotational axis and the net force.

*Muscle force*: amount of force produced by muscular tissue

*Neurons*: fundamental processing unit of the artificial neural network.

*Osteoarthritis (OA)*: arthritis caused by the deterioration of the cartilage within the joints, allowing excessive bone contact and increased inflammation and pain.

*Output layer*: point at which the output data from the ANN model is represented

## CHAPTER TWO

### LITERATURE REVIEW

#### Introduction

Degenerative joint diseases including OA impair lower extremity joints, often leading to abnormal gait patterns. It has been estimated that as many as one in five American's have been diagnosed with arthritis (Lethbridge-Ceiku et al., 2004) with 12% of Americans over the age of 25 being diagnosed specifically with OA (NIH, 2002). Many of these individuals suffer from complications of OA that limit their daily activities including work and recreation. Common remedies rely on exercise, relaxation, and weight management as well as anti-inflammatory medications. However, a more costly treatment option is joint repair or joint replacement surgery. Treatment options are chosen and evaluated by tracking the disease as well as evaluating pain and joint functionality. Gait analysis may be employed to evaluate treatment options as well as measure the success of rehabilitation programs. Full gait analysis is time consuming and requires expensive laboratory equipment, thus limiting its application in a typical non-research clinical environment. As an alternative, it has been suggested that the use of ANNs in gait evaluation will be economical and efficient with precision similar to current techniques, making gait analysis more feasible for clinical settings (Schollhorn, 2004).

### Traditional Gait Analysis

The focus of clinical gait analysis is often to determine how pathological gait differs from normal gait and the significance of such differences. By researching pathologies in this manner the potential causes of gait abnormalities may be identified, leading to treatment options. Researched gait pathologies have included, but are not limited to, patients with amputation, degenerative joint disease, multiple sclerosis, cerebral palsy, and rheumatoid arthritis (Davis, 1997).

By measuring pre- and post-operative pathological gait, the successful outcomes of an operation can be measured. Gait is commonly used in this way to measure the success of hip replacement surgeries. For instance, in research presented by Bennett, Ogonda, Elliott, Humphreys, and Beverland (2006), pre- and post-operative hip replacement gait was evaluated. They compared the traditional hip replacement procedure to the more modern minimally invasive techniques. It was determined that there were no significant differences in post-operation gait kinematics between the minimally invasive techniques and traditional surgery procedures.

Gait analysis may also provide insight for protecting joints from injury and disease. Specifically, Chang et al. (2005) studied the hip abduction moment as a means of protecting against medial tibiofemoral OA. The researchers found that the hip abductor moment provided protection against loading of the medial tibiofemoral compartment. They also confirmed that the moment's magnitude is a factor of hip muscle strength. Their findings indicated that future studies focusing on strengthening hip abductors might lead to disease modifying rehabilitation strategies.

Gait analysis primarily involves 3-D segment position data synchronized with force platform data to calculate joint kinetics and kinematics. Electromyography signals are also a common tool for gait analysis, providing a means of assessing dynamic muscle activations. The use of EMG signals as a measurement tool for gait analysis has allowed researchers to focus their activities on dynamic muscle force and joint moment models. One such study (Bogey, Perry, and Gitter, 2005) found a close correlation (0.97) between using inverse dynamics and an EMG-force model to estimate ankle moments. Gait analysis is constantly evolving, and advancements like modeling joint moments from EMG signals has led to the conclusion that a better quantitative tool is needed to model the complex relationships within both normal and abnormal gait (Davis, 1997).

#### EMG-Muscle Force Modeling

A few researchers have attempted to model the complex EMG-muscle force relationships (Amarantini and Martin, 2004; Hof, Pronk, and Van Best, 1987; Manal and Buchanan, 2003; Olney and Winter, 1985). For example, Amarantini and Martin (2004) modeled joint moments from EMG signals during dynamic stepping tasks of the lower extremity. The researchers noted that an alternative to inverse dynamics was needed to model this relationship. They utilized numerical optimization techniques and found that the EMG-moment relationship was most accurately modeled using a nonlinear least-squares curve-fitting approach. The researchers determined that this optimization technique improved their dynamic muscle moment estimations and provided an estimate that was physiologically feasible. Another group (Manal and Buchanan, 2003) accounted for non-linearities between EMG and muscle force about the elbow using a curvilinear

technique to model the relationship between neural activation and muscle activation. The researchers were able to improve the accuracy of their elbow joint torque estimations using this model. In conclusion, they determined joint moment models could be improved by accounting for the non-linearities within the EMG-muscle force relationship.

In summary, several researchers investigating EMG-muscle force relationships have concluded that for dynamic movements, the relationship is nonlinear. Furthermore, it has been concluded that these non-linearities need to be accounted for when modeling EMG and muscle force (Amarantini and Martin, 2004; Hof et al., 1987; Manal and Buchanan, 2003; Olney and Winter, 1985).

#### Artificial Neural Networks – Applications in Biomechanics

Artificial neural network models are designed to represent the biological neural network system that communicates via synapses through neurons to complete functions, or reach an output. ANNs have been used as tools to estimate an output based on some input assuming that a relationship exists between the input and output (Chau, 2001). Specifically, ANNs have proven successful at mapping non-linear relationships between input and output variables, making them practical for many applications in biomechanics. Over the past 10 years, the use of ANNs in the field of biomechanics has increased (Chau, 2001). Specific applications of ANNs have been gait classification (i.e. normal vs. pathological), biomechanical modeling, and mapping EMG-muscle force relationships. The success of ANNs as a modeling tool has made them the most common non-traditional method for analyzing gait (Chau, 2001).

For biomechanical analysis, the most common ANN structure utilized has been the multilayer feed-forward neural network (Chau, 2001). This structure has an input layer, a processing layer (called the hidden layer), and an output layer. See Figure 2.1 for an example of the ANN structure.

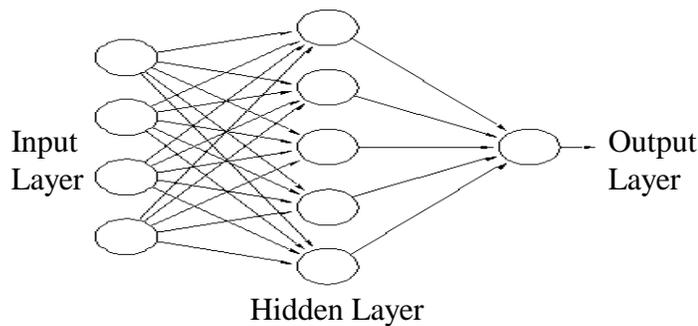


Figure 2.1: An example of a multilayer feed-forward neural network.

Data is entered into this structure at the input layer and sent forward to the hidden layer for processing. The result of this processing is recorded in the output layer and evaluated for accuracy. To optimize the relationships between the independent variables in the input layer and the variable of the output layer, learning algorithms are used that adjust the internal parameters of the hidden layer to enhance the network's predictive accuracy. Training the ANN encompasses these steps and is done by randomly selecting a proportion of the full dataset to use for each training session, and the remainder of the data set is used for testing the model's predictive ability (Haykin, 1994).

The inputs for many ANNs used to model gait have been ground reaction forces (GRF) measured from force platforms. Holzreiter and Kohle (1993) evaluated normal versus pathological gait in this manner. In their study, the vertical reaction force was the sole input for the neural network, and was collected from gait trials of 94 healthy subjects

and 131 patients with compromised gait. The output was a number between zero (indicating healthy) and one (indicating patient). The highest success rate for classification came close to 95%; however, this accuracy was not consistent for all data sets used for network training.

Other researchers have shown that using more inputs enhances prediction results (Begg and Kamruzzaman, 2005; Lafuente et al., 1997; Wu and Su, 2000). For instance, Wu and Su (2000) used normalized maximum forces of all three GRF components and their normalized time events as the input parameters for the neural network. This yielded recognition accuracies of up to 95.8% between healthy subjects and patients with ankle arthrodesis. Another research group (Begg and Kamruzzaman, 2005) found that while using basic gait variables (i.e. cadence, walking velocity), the accuracy of distinguishing between young and elderly gait patterns only reached 62.5%. However, using a combination of kinetic and kinematic data yielded accuracies of 91.7%. Similarly, Lafuente et al. (1997) focused on optimizing the number of inputs by using a stepwise Fisher's Discriminate Analysis. Cadence, walking velocity, and GRF components were all utilized. Seventy-six parameters were evaluated, of which 30 were chosen as inputs. It was determined that these inputs were the most critical in distinguishing between patients with OA and healthy control subjects.

While many researchers used GRF components as key parameters in classifying gait patterns, other relationships have been modeled. Barton and Lees (1997) used hip-knee joint angle diagrams in a neural network to distinguish healthy versus pathological gait patterns. The classification in this case involved simulating disorders from the original data set such as leg length difference and leg weight difference. The overall

correct recognition was 75%, while the four best neural networks had an average of 83.3% correct classification.

Only Sepulveda et al. (1993) has attempted to use EMG signals to predict joint angles and joint moments for gait analysis using an ANN. In their study, they compared modeling EMG-joint angle and EMG-joint moment relationships in two separate neural networks. Their test was to classify simulated pathological conditions (cerebral palsy) and determine the effects of simulated treatments with each model. Their test conditions reflected treatments for cerebral palsy such as reducing the soleus EMG activity by 30% and eliminating EMG activity of the rectus femoris. Overall, the second neural network (EMG-joint moment) was more successful than the first (EMG-joint angle) at mapping the relationship. The authors suggested comparing pre- and post-surgery gait of cerebral palsy children to enhance the validity of the neural network. Since this seminal work however, no further studies have reported progress in the clinical application of such ANN models.

While only a limited number of researchers have attempted to estimate joint moments from EMG signals during gait using ANNs, others have utilized ANNs to create muscle force models from EMG signals of feline gait (Liu, Herzog, and Savelberg, 1999), human upper extremity movement (Wang and Buchanan, 2002), and isokinetic knee torque (Hahn, 2007). Specifically, Liu et al. (1999) used ANNs to successfully predict dynamic forces of feline gait from EMG signals exclusively. With EMG signals as the sole input to the ANN, the researchers were able to predict muscle force at varying gait speeds with correlation coefficients of 0.93 to 0.95. Wang and Buchanan (2002) used an ANN to map the EMG-muscle activation relationship of the human upper extremity.

Using ANN-estimated muscle activations, they were able to predict elbow joint moments successfully. It is important to note however that a different neural network was created for each subject, limiting the overall generalizability of the findings. Hahn (2007) evaluated the feasibility of modeling the EMG-joint torque relationship for isokinetic knee torque using an ANN. The success of the ANN model was evaluated by comparing the torque estimations to values obtained using a stepwise regression model. It was found that the ANN model had higher accuracy than the regression model, proving the model feasible for estimating knee joint torque.

Researchers using ANNs have shown initial success at mapping a variety of relationships regarding muscle activations as measured by EMG electrodes; yet, there remains a lack of studies utilizing ANNs to predict joint moments from EMG signals. Further research is needed to justify using ANN models with EMG data for eventual application in gait analysis.

## CHAPTER THREE

## METHODOLOGY

Subjects

The number of subjects recruited was determined by using a heuristic sampling rule that has been generally accepted in the computer science community for neural network models. The recommendation is that the number of data points used to train an ANN model should be 10 times greater than the number of network connections (Haykin, 1994). For example, the ANN used for this study had up to 15 input units, 30 hidden units and a single output unit, totaling 455 connections. Thus, 4550 data points were required to train the model. If four 100% time-normalized trials per subject are used (400 data points per subject), then more than 11 subjects are needed to train the ANN model. However, the model still needs to be tested on additional data. The k-fold re-sampling technique used trains on 90% of the data and tests on the remaining 10%, and this procedure is repeated until all data has been used for training and testing (this technique is described further in the post-processing section). Therefore, an additional 2 subjects are needed for testing the model, or a minimum of 13 subjects. To ensure the sampling guideline was met, 22 individuals (15 female, 7 male) with physician-diagnosed OA were recruited from the Bozeman area to participate in this study.

Subject recruitment followed Institutional Review Board (IRB) guidelines and involved physician referral as well as recruitment from local exercise clubs, the senior

center and a health forum on osteoarthritis hosted by the Bozeman Deaconess hospital.

The target age group was between 35-75 years old. Patients receiving corticosteroid treatments or hyaluronic injections within the last three months were excluded.

Additionally, patients with impaired balance were excluded from the study. All subjects were asked to sign an informed consent before participation.

### Procedures

Subjects were asked to visit the laboratory twice--once for an introduction to the lab and to sign the informed consent (see Appendix A and B), and once for the gait analysis. The first session was brief, lasting thirty minutes, whereas the gait analysis session lasted two hours. Subjects were allowed to schedule the introductory session in conjunction with the gait analysis if necessary.

Demographic and anthropometric data were recorded prior to performing the walking trials. Also, a brief test for balance was completed prior to participation. The balance test entailed the subject standing on one foot for 30 seconds with their eyes open and repeating with the opposite foot. If a subject exhibited impaired balance, or had to place his or her opposite foot down during this test, they were excluded from the study.

Severity of OA was qualitatively assessed using the Western Ontario MacMaster (WOMAC) 3.1 Index. A scale of zero to four was used to score 24 parameters listed on the WOMAC index (see Appendix C). The parameters evaluated pain, stiffness, and physical dysfunction of daily tasks with zero indicating none and four indicating severe.

The general laboratory procedures involved placing passive surface electrodes and reflective markers on the lower limbs. First, the skin covering the gluteus maximus

(GMAX) above the gluteal fold, the gluteus medius (GMED) below the iliac crest, and the muscle bellies of the biceps femoris (BF), rectus femoris (RF), vastus lateralis (VL), tibialis anterior (TA), and medial gastrocnemius (MG) of the symptomatic limb was cleaned with alcohol wipes in preparation for placement of the passive surface EMG electrodes (see Figure A.1 in Appendix A). The electrodes were then connected to the Myopac Jr. system for data collection. In addition, a 3-D motion capture system was used to collect trajectories of 39 retro-reflective spherical markers placed on bony landmarks of the entire body. The lower extremity markers were placed bilaterally on the anterior superior iliac spine (ASIS), posterior superior iliac spine (PSIS), lateral thigh, lateral femoral epicondyle, lateral shank, lateral malleolus, heel and dorsum of the foot (distal 2<sup>nd</sup> metatarsal). These placements correspond to the standard bilateral full-body marker set used in gait analysis. Additionally, the ankle and knee flexion/extension axes were determined using a standard knee alignment device (KAD-12, Motion Lab Systems, Inc., Baton Rouge, LA, USA) and a medial malleolus marker during a static collection.

Each subject performed a series of level walking trials at their self-selected speed while wearing their own walking shoes. To obtain three to five good trials, subjects often completed ten or more trials. A trial was considered good if heel-strike and toe-off of the symptomatic side were detected with the force platform, all reflective markers were visible in the viewing screen and the EMG sensors were connected. Subjects were allowed up to three practice trials to become familiar with the walkway and equipment.

## Instrumentation

The following instrumentation was used for this study: an EMG recording system, a 3-D motion capture system, and two force platforms. Muscle activation patterns during gait were recorded using the EMG recording system. Lower extremity movement was recorded using the 3-D motion capture system and the force platforms were used to record ground reaction forces. During data collection, all instrumentation was synchronized.

### EMG Recording System

Blue Sensor passive surface electrodes (Ambu, Ballerup, Denmark) were used in this study. They were connected to the EMG recording system, Myopac Jr. (Run Technologies, Mission Viejo, CA), to record muscle activations of the GMAX, GMED, BF, RF, VL, TA, and MG muscles during gait. The sampling frequency for the Myopac Jr. recording system was 1,000 Hz with a bandwidth filter of 10-1,000 HZ. The Vicon Workstation (Vicon, Lake Forest, CA) was used to collect the EMG data.

### 3-D Motion Capture System

The 3-D position trajectories of the markers on the lower extremity were recorded using six infrared cameras and the Vicon Workstation (Vicon, Lake Forest, CA) sampling at 200 Hz.

### Force Platforms

The GRF components were recorded using two AMTI force platforms (AMTI, Watertown, MA) and Vicon Workstation (Vicon, Lake Forest, CA) at a sampling frequency of 1,000 Hz.

### Post –Processing

Before using the ANN to map the EMG-joint moment relationships, the EMG signals were full wave rectified. The signal was then smoothed, for easier interpretation, with a linear envelope using a fourth order Butterworth filter with a low pass cutoff frequency of 5 Hz. After rectifying and smoothing the signals, the EMG signals for each trial were normalized to the maximum magnitude of the trial. All signal processing was carried out using a customized Matlab program (The Mathworks, Inc., Natick, MA).

Plug-In Gait® software (Vicon, Lake Forest, CA) was used to process data and calculate joint centers, kinematics and kinetics. Specifically, this software was used to calculate the internal joint moments of the hip, knee and ankle. Plug-In Gait® software utilizes traditional inverse dynamics theory to calculate the joint moments from ground reaction force data, anthropometric measurements, and kinematics.

A three layer feed-forward ANN, created during previous research using Matlab's Neural Network Toolbox (The Mathworks, Inc., Natick, MA) was utilized after data collection and post-processing (see Figure 3.1 for an example of the ANN structure).

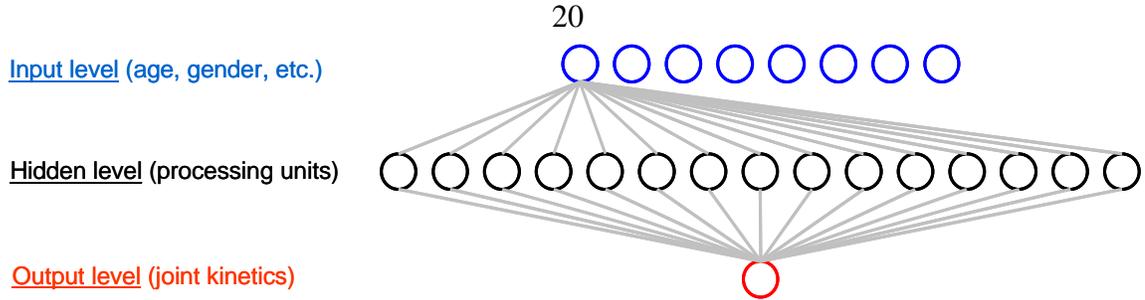


Figure 3.1: Detailed example of the three layer feed-forward ANN structure.

The inputs were demographic, anthropometric, kinematic and EMG data. The output was the time-normalized joint moments of the hip, knee and ankle (see Table 3.1 for detailed input data for each joint).

Table 3.1: Specific input data for the ankle, knee and hip joints.

	Hip	Knee	Ankle
<u>Demographic</u>	Age Gender	Age Gender	Age Gender
<u>Anthropometric*</u>	Body Height Body Mass $I_{th}$	Body Height Body Mass $I_{sh}$	Body Height Body Mass $I_{ft}$
<u>Kinematic**</u>	$\theta_h$ $\omega_h$ $\alpha_h$	$\theta_k$ $\omega_k$ $\alpha_k$	$\theta_a$ $\omega_a$ $\alpha_a$
<u>Electromyographic</u>	Gluteus Maximus Gluteus Medius Biceps Femoris Rectus Femoris	Rectus Femoris Vastus Lateralis Biceps Femoris Medial Gastrocnemius	Medial Gastrocnemius Tibialis Anterior

\* I is the mass moment of inertia

\*\*  $\theta$  is the angular position data,  $\omega$  is the angular velocity data,  
and  $\alpha$  is the angular acceleration data

Training goals of 0.1 and 0.01 mean-square error (MSE) between the experimental joint moment and estimated joint moment were chosen. The ANN was trained to these goals using back-propagation error correction, using the Levenberg-Marquardt algorithm

(Levenberg, 1944; Marquardt, 1963). The number of hidden units was set to five and increased to 30 using a five-point increment. This combination of training goals and hidden units yielded 12 (2 training goals x 6 hidden layer settings) different training routines, or cases, for the ANN (see Table 3.2).

Table 3.2: ANN training routines – twelve cases.

	MSE	Hidden Units
Case 1	0.1	5
Case 2	0.1	10
Case 3	0.1	15
Case 4	0.1	20
Case 5	0.1	25
Case 6	0.1	30
Case 7	0.01	5
Case 8	0.01	10
Case 9	0.01	15
Case 10	0.01	20
Case 11	0.01	25
Case 12	0.01	30

A k-fold re-sampling technique, where the data set is divided into k equal subsets, was used to select data for training and testing the ANN model. For this study, k=10 based on the total number of gait trials, 70. Therefore, each subset of data had seven gait trials. The model was trained on 90% of the data, or nine subsets, and tested on the remaining 10% of the data, or one subset. This was repeated until each subset of data had been used for testing the model. The correlation coefficient between the experimental joint moment and the estimated joint moment for each k-fold of the data set (or ten correlation coefficients) was recorded for all twelve training routines. Additionally, experimental and estimated joint moment data for each test set of data was saved for further analysis on the predictive ability of the ANN.

In training the ANN, the input data were processed in the hidden layer and an activation signal was derived (see Figure 3.2 for a detailed ANN structure).

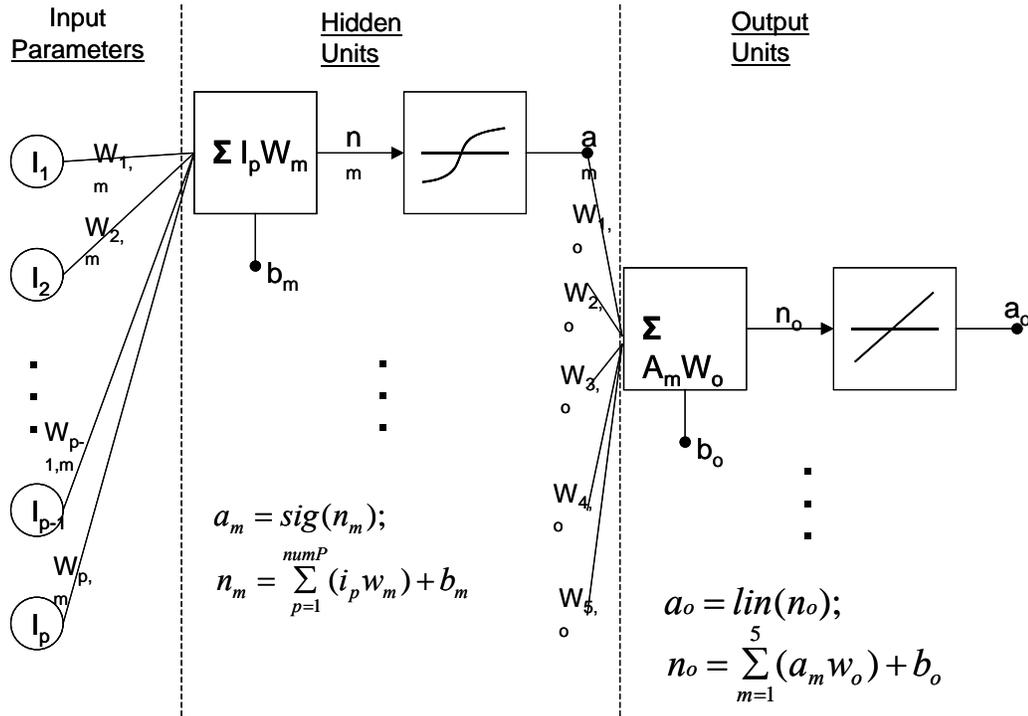


Figure 3.2: Detailed ANN structure showing synaptic weights and biases as well as transfer functions.

A sigmoid transfer function (equation 1) was used in the hidden layer to derive the activation signal from the summation of the inputs at each hidden unit.

$$a = \text{sig}(n) = 2/(1+e^{(-2*n)}) \quad (1)$$

where  $n$  is the result of the weight summation (equation 2);

$$\mathbf{n} = \sum_{p=1}^{\text{numP}} [(i_p w) + b] \quad (2)$$

$i_p$  is the input signal from each  $p$  parameter,  $w$  is the synaptic weight on each input signal, and  $b$  is the bias of the hidden unit.

The data was then processed in the output layer using a similar method. The activation signals of the output layer were calculated using a linear transfer function. Specifically, the output layer utilized the back-propagated error correction mentioned previously. During this step, the synaptic weights and biases were corrected. This was done using the Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963), which is generally described by the following equation

$$x_{k+1} = x_k - \alpha_k g_k \quad (3)$$

where  $x_k$  is the current vector of weights and biases,  $\alpha_k$  is the current learning rate,  $g_k$  is the current gradient value, and  $k$  is the iteration index. This algorithm controlled the rate of solution convergence by adjusting the learning rate. For example, major changes were made to the weights and biases initially. However, when the ANN was near solution convergence, the changes were minor, allowing the ANN to be fine-tuned.

### Analysis

Statistical analysis for the hypothesis involved a one-sample student t-test to test the mean correlation coefficient against the predetermined value of 0.95 for each of the

36 tests (12 cases per joint x three joints). A 95% confidence interval (CI) was then created for each t-test.

Further analysis on the predictive ability of the ANN involved determining case-specific coefficient of determination ( $r^2$ ) values between the experimental and estimated joint moment data and graphing representative joint moment curves. The  $r^2$  values were used to select both good and poor curve-fitting examples for each joint for case 1 (model setting: MSE = 0.1, hidden units = 5) and case 12 (model setting: MSE = 0.01, hidden units = 30). Case 1 and case 12 were selected based on what was expected to be the model setting to perform the worst (case 1) and the model setting that was expected to perform the best (case 12). Experimental joint moment data was plotted against the estimated data for the selected ankle, knee and hip joint moment examples, and the joint moment curves were used to evaluate the accuracy in amplitude and timing of key peaks.

## CHAPTER FOUR

### RESULTS

#### Subjects

A total of 22 subjects were recruited to participate in this study. Exclusion criteria required subjects to have good balance as well as physician-diagnosed OA in the hips, knees, or ankles without having recent corticosteroid or hyaluronic injections. One subject without physician diagnosed OA was disqualified. Difficult marker placement on another individual resulted in lost markers during the 3-D motion capture, thus disqualifying the subject from the study. Additionally, two participants did not complete the study. The eighteen remaining subjects (13 female, 5 male) completed the study and data from their gait trials were used to develop and test the ANN model (see Table 4.1 for subject characteristics).

All subjects had physician-diagnosed OA in at least one of their lower extremity joints. However, only the most affected joint of each subject was evaluated using the WOMAC index and the corresponding side was evaluated using the EMG recording system (see Table 4.1 for distribution of affected joints). All subjects were required to complete the WOMAC index, answering the questions in terms of the joint that was most problematic upon coming to the lab. WOMAC scores ranged from 6 to 58 out of a possible 96 points, with higher scores indicating worse physical function and higher perceived pain.

Table 4.1: Subject specific characteristics.

Subject	Gender	Age	Height (cm)	Body Mass (kg)	Womac Score	Affected Joint*
1	F	66	162	69.5	58	R. Knee
2	F	68	167	82.5	36	R. Knee
3	F	75	170	71.0	55	R. Knee
4	F	59	180	78.0	19	R. Knee
5	F	70	163	85.0	54	L. Ankle
6	F	52	171	86.0	27	R.Knee
7	F	59	165	88.7	29	L. Knee
8	M	49	199	120.5	21	L. Knee
9	M	74	173	83.5	28	L. Knee
10	M	57	181	113.9	51	L. Hip
11	F	74	161	70.3	35	L. Ankle
12	M	65	176	85.3	20	R. Hip
13	F	74	164	86.6	28	R. Knee
14	F	62	159	83.0	19	L. Knee
15	F	65	162	66.7	34	L. Ankle
16	F	59	167	89.8	34	L. Knee
17	F	51	163	54.9	6	R. Knee
18	M	72	182	114.8	45	R. Hip
Average		63.9	170.3	85.0	33.3	
STD**		8.4	10.2	17.1	14.5	
Minimum		49	159	54.9	6	
Maximum		75	199	120.5	58	

\*R – Right, L – Left

\*\*STD – standard deviation

### ANN Model

The ANN was able to accurately map the joint moments of subjects with OA. For the ankle, the mean correlation coefficients between the experimental joint moment and the estimated joint moment of the 12 cases were between 0.97 and > 0.99. For the knee, the values ranged between 0.89-0.97, and for the hip, the values were between 0.91 and 0.97.

A one-sample t-test was performed on each of the 12 cases for each joint, or 36 total tests, and a 95% confidence interval of the mean correlation coefficient was constructed (see t-test results for cases one through six in Table 4.2 and cases seven through twelve in Table 4.3). For the ankle, it was determined that with 95% confidence, the mean correlation coefficient for each model setting was above 0.95. This was also determined by examining the p-values for each training case for the ankle in which the p-values were smaller than the  $\alpha$  level of 0.05. However, for the knee and hip, only certain model settings produced results above 0.95. For the knee, the correlation coefficient of 0.95 was within the 95% CI for case two (model setting: MSE = 0.1, hidden units = 10), case nine (model setting: MSE = 0.01, hidden units = 15) and case ten (model setting: MSE = 0.01, hidden units = 20). However, each of these cases had p-values higher than the threshold of  $\alpha = 0.05$ . For the last two knee cases, case 11 (model setting: MSE = 0.01, hidden units = 25) and case 12 (model setting: MSE = 0.01, hidden units = 30), it was determined that with 95% confidence, the mean correlation coefficient was higher than 0.95. Again, the p-values for these two cases were smaller than  $\alpha = 0.05$ . Finally, for the hip, it was determined that with 95% confidence, the mean correlation coefficient was higher than 0.95 for cases nine through twelve (model settings: MSE = 0.01, hidden units = 15, 20, 25, and 30), and the p-values for these cases were less than  $\alpha = 0.05$ .

Table 4.2: T-test results for output correlation coefficients for cases 1-6 (MSE = 0.1).

		Ankle		Knee		Hip	
Case 1	p-value	<0.001		0.999		0.999	
	95% CI	0.9756	0.9866 *	0.8716	0.9035	0.9199	0.9293
Case 2	p-value	<0.001		0.070		0.999	
	95% CI	0.9759	0.9892 *	0.8870	0.9604 **	0.9380	0.9450
Case 3	p-value	<0.001		0.999		0.999	
	95% CI	0.9731	0.9892 *	0.9356	0.9433	0.9414	0.9437
Case 4	p-value	<0.001		0.999		0.999	
	95% CI	0.9645	0.9835 *	0.9378	0.9439	0.9399	0.9460
Case 5	p-value	<0.001		0.995		0.997	
	95% CI	0.9738	0.9855 *	0.9344	0.9453	0.9373	0.9457
Case 6	p-value	<0.001		0.967		0.996	
	95% CI	0.9659	0.9862 *	0.9232	0.9465	0.9405	0.9456

\* With 95% confidence, the correlation coefficient always reached 0.95

\*\* The correlation coefficient of 0.95 falls within the 95%CI

Table 4.3: T-test results for output correlation coefficients for cases 7-12 (MSE = 0.01).

		Ankle		Knee		Hip	
Case 7	p-value	<0.001		0.999		0.999	
	95% CI	0.9959	0.9973 *	0.8826	0.8997	0.9018	0.9212
Case 8	p-value	<0.001		0.981		0.990	
	95% CI	0.9973	0.9982 *	0.9329	0.9469	0.9411	0.9479
Case 9	p-value	<0.001		0.158		<0.001	
	95% CI	0.9975	0.9983 *	0.9456	0.9621 **	0.9515	0.9577 *
Case 10	p-value	<0.001		0.293		<0.001	
	95% CI	0.9968	0.9983 *	0.9079	0.9753 **	0.9525	0.9609 *
Case 11	p-value	<0.001		<0.001		<0.001	
	95% CI	0.9978	0.9984 *	0.9581	0.9744 *	0.9615	0.9665 *
Case 12	p-value	<0.001		<0.001		<0.001	
	95% CI	0.9971	0.9986 *	0.9588	0.9748 *	0.9625	0.9699 *

\* With 95% confidence, the correlation coefficient always reached 0.95

\*\* The correlation coefficient of 0.95 falls within the 95%CI

Experimental and estimated joint moment data were graphed together, and the predictive ability of the ANN was further analyzed by evaluating the accuracy of the

amplitude and timing of peaks on selected graphs for cases one and twelve. Joint moment graphs were chosen based on their coefficient of determination values such that good curve fitting examples had a high  $r^2$  value and poor curve fitting examples had a lower  $r^2$  value. The  $r^2$  values ranged from 0.96 to  $> 0.99$  for the ankle, 0.82 to 0.96 for the knee, and 0.86 to 0.99 for the hip (see Table 4.4 for  $r^2$  values).

Table 4.4: Coefficient of determination ( $r^2$ ) values for each curve-fitting example.

	Ankle		Knee		Hip	
	Case 1	Case 12	Case 1	Case 12	Case 1	Case 12
Good	$> 0.99$	$> 0.99$	0.91	0.96	0.99	0.99
Poor	0.96	0.98	0.82	0.82	0.86	0.87

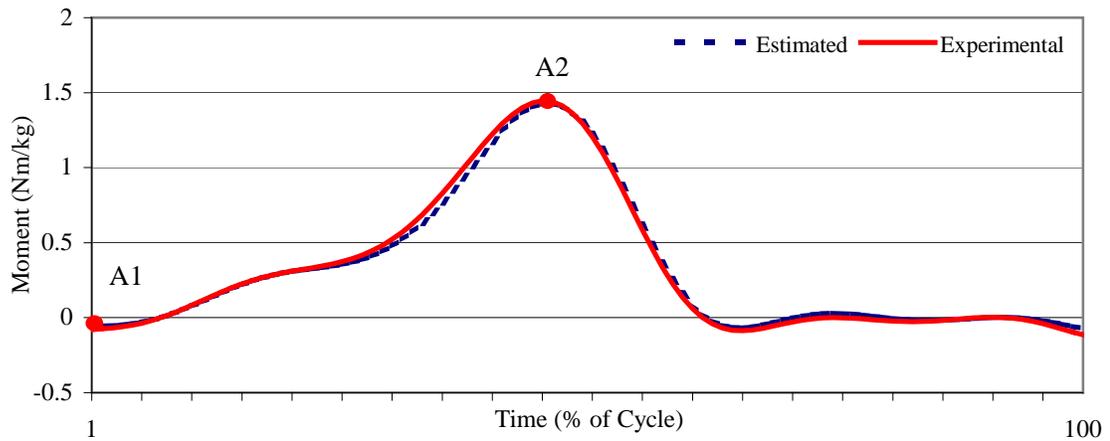
Table 4.5: Absolute estimation error for the amplitude and timing of peaks A1 and A2 from the selected ankle joint moment curves.

ANKLE				
		Amplitude (Nm/kg)	Range (Nm/kg)	Timing (%)
Case 1 G	A1	0.04	1.54	0.00
	A2	0.05		0.00
Case 1 B	A1	0.03	1.38	5.00
	A2	0.03		3.00
Case 12 G	A1	0.01	1.69	0.00
	A2	$< 0.01$		0.00
Case 12 B	A1	0.01	1.80	0.00
	A2	0.03		1.00

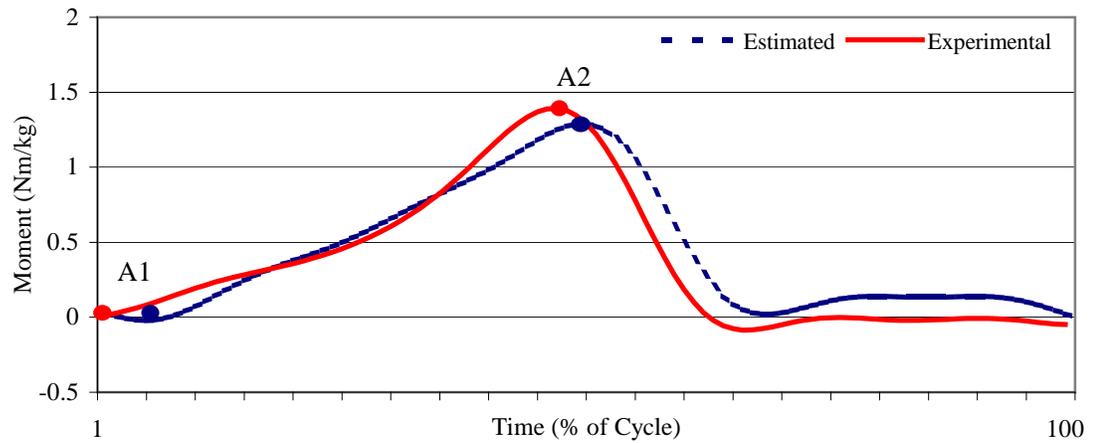
where G is the good curve-fitting

where B is the poor curve-fitting

Timing and amplitude errors for peaks A1 and A2 on the ankle joint moment curves were minor (see values in Table 4.5). Specifically, timing was exact for many of the peaks and only 3-5% off for the peaks of the poor curve-fitting example for case one.

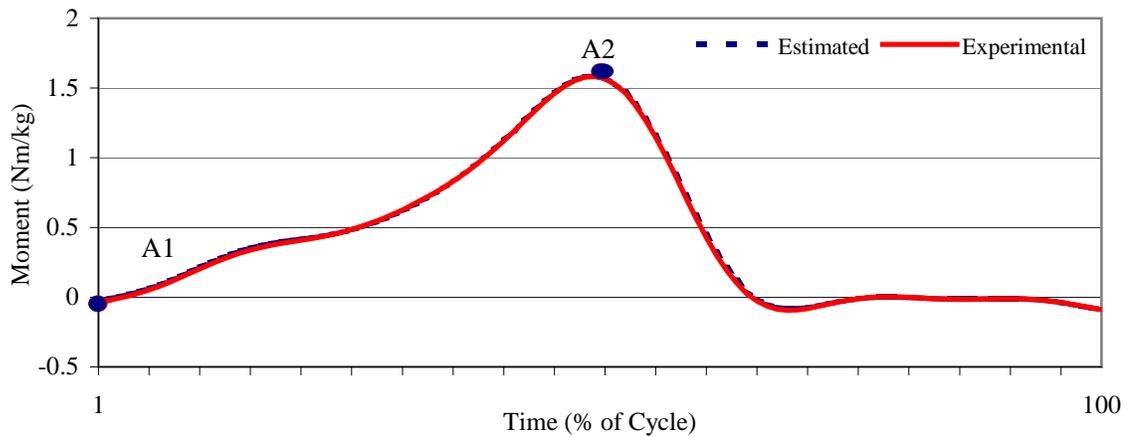


(a)

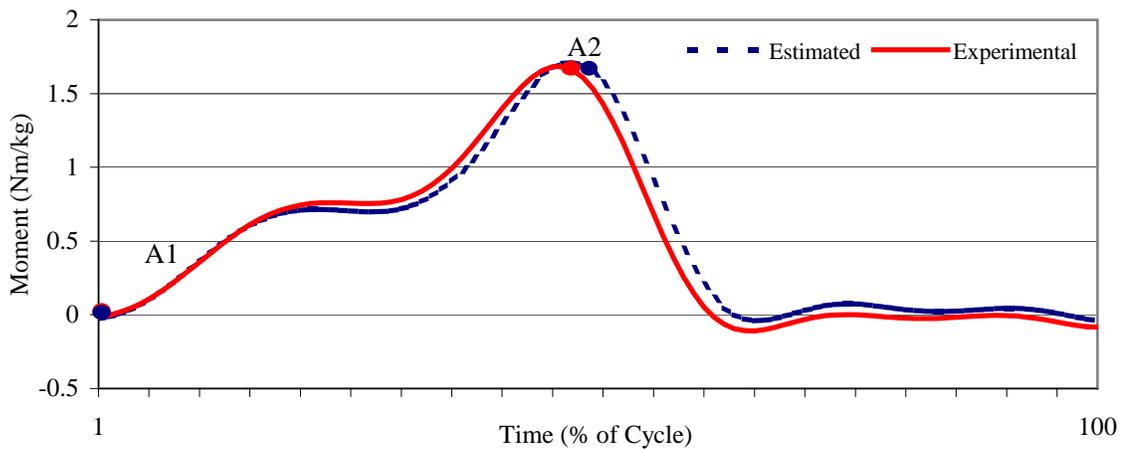


(b)

Figure 4.1: Ankle joint moment curves for case 1: (a) good curve-fitting example ( $r^2 > 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.96$ ).



(a)



(b)

Figure 4.2: Ankle joint moment curves for case 12: (a) good curve-fitting example ( $r^2 > 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.98$ ).

Amplitude shifts were also minor. For the good curve-fitting example for case one ( $r^2 > 0.99$ ), the absolute estimation error for A1 was 0.04 Nm/kg and for A2 was 0.05 Nm/kg. This was out of a possible range of 1.54 Nm/kg. For the poor example for case one ( $r^2 = 0.96$ ), the error of estimation for A1 and A2 was 0.03 Nm/kg with a possible range of 1.38 Nm/kg. The error of estimation for case twelve was smaller for both the poor curve-fitting example (A1 = 0.01 Nm/kg error and A2 = 0.03 Nm/kg error out of 1.80 Nm/kg)

and the good curve-fitting example ( $A1 = 0.01$  Nm/kg error and  $A2 < 0.01$  Nm/kg error out of 1.69 Nm/kg) in comparison to case one. This was expected since the model settings corresponding with case 12 were predicted to yield higher accuracies in modeling the joint moments. The graphs for each of these examples also show amplitude and timing errors to be minor (see Figures 4.1-4.2). The poor curve-fitting example for case one was the only example that presented a noticeable discrepancy in timing and amplitude. (see Figure 4.1b).

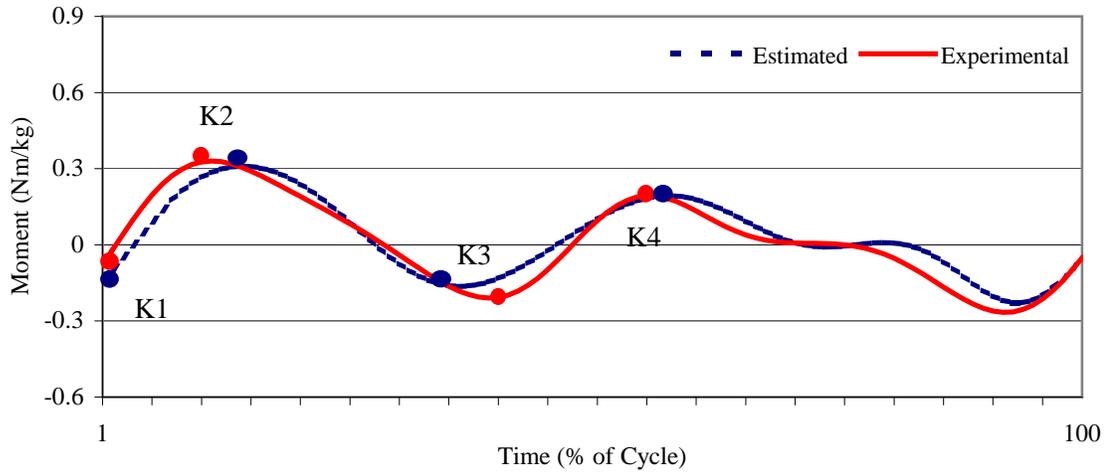
Table 4.6: Absolute estimation error for the amplitude and timing of peaks K1, K2, K3, and K4 from the selected knee joint moment curves.

		KNEE		
		Amplitude (Nm/kg)	Range (Nm/kg)	Timing (%)
Case 1 G	K1	0.06		0.00
	K2	0.02	0.59	3.00
	K3	0.05		3.00
	K4	< 0.00		2.00
Case 1 B	K1	0.08		
	K2	0.06	0.72	6.00
	K3	0.14		4.00
	K4	0.06		3.00
Case 12 G	K1	0.01		
	K2	0.07	0.92	1.00
	K3	0.11		3.00
	K4	< 0.01		2.00
Case 12 B	K1	0.12		
	K2	0.16	0.6	3.00
	K3	0.05		1.00
	K4	0.10		3.00

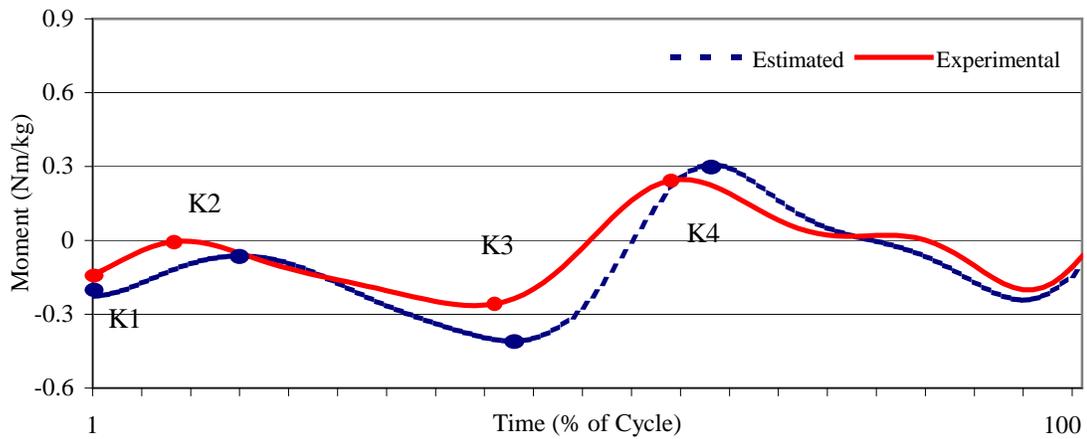
where G is the good curve-fitting

where B is the poor curve-fitting

Timing and amplitude errors were more noticeable for the peaks (K1-K4) of the knee joint moment curves (see Figures 4.3-4.4 for graphical representation and Table 4.6 for values). As expected, the good example for case 12 (model setting: MSE = 0.01, hidden units = 30) provided the best-fit curve with an  $r^2$  value of 0.96 (see Figure 4.4a).

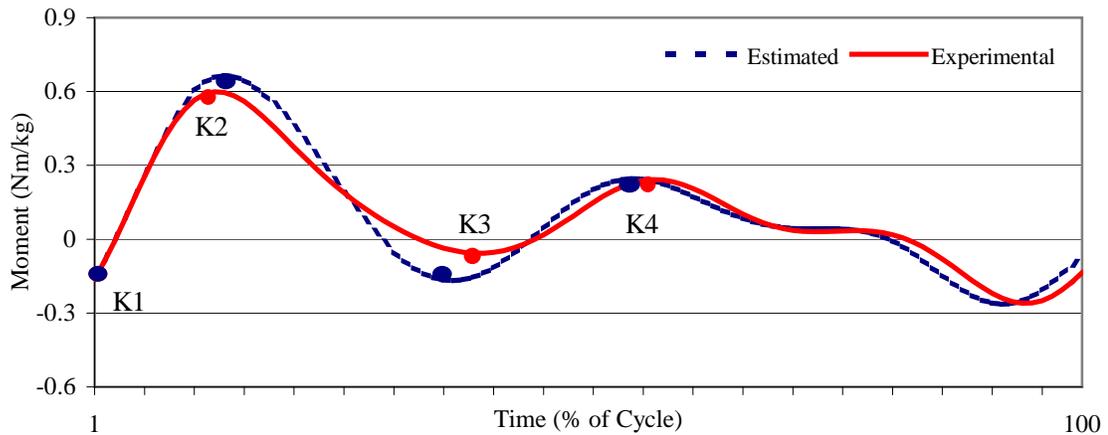


(a)

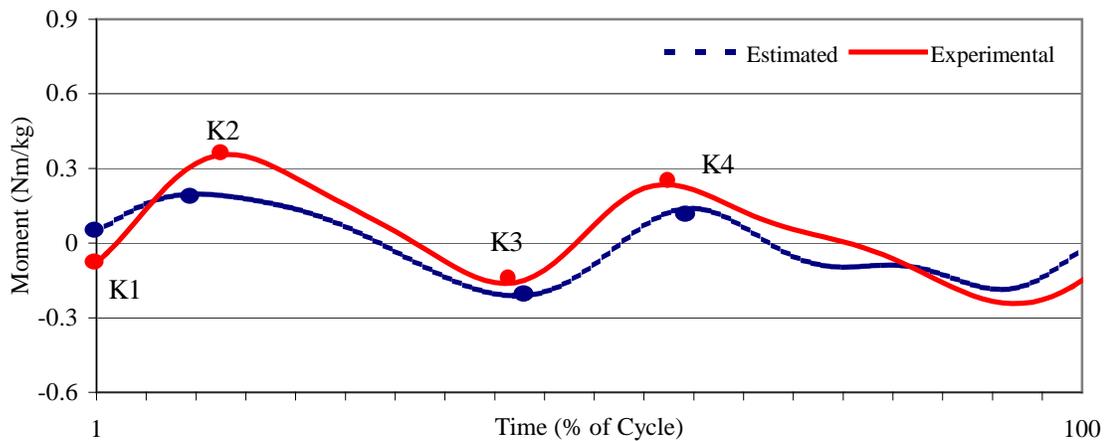


(b)

Figure 4.3: Knee joint moment curves for case 1: (a) good curve-fitting example ( $r^2 = 0.91$ ), (b) poor curve-fitting example ( $r^2 = 0.82$ ).



(a)



(b)

Figure 4.4: Knee joint moment curves for case 12: (a) good curve-fitting example ( $r^2 = 0.96$ ), (b) poor curve-fitting example ( $r^2 = 0.82$ ).

The absolute estimation errors for peaks K1 through K4 were  $< 0.01$  Nm/kg to 0.11

Nm/kg out of a range of 0.92 Nm/kg and the timing was off by at most 3%. Peak K3 had

the greatest amplitude and timing error for this case. The maximum timing offset was

6%, corresponding to peak K2 of the worst-case scenario (case 1 – poor example). Both

of the poor examples had higher absolute estimation errors (case 1: 0.06 Nm/kg to 0.14

Nm/kg out of 0.72 Nm/kg, case 12: 0.05 Nm/kg to 0.12 Nm/kg out of 0.60 Nm/kg) in

comparison to the good examples, and both poor examples had noticeable discrepancies between the estimated and experimental knee joint moment curves (see Figure 4.3 and Figure 4.4).

The hip joint moment curves were mapped fairly accurately with higher  $r^2$  values than the knee joint moment curves (see Table 4.4). Both of the good curve-fitting examples had high  $r^2$  values ( $r^2 = 0.99$  for both cases) and errors in timing and amplitude for the peaks H1 and H2 were small (see Table 4.7 for values and Figures 4.9 and 4.11 for graphical representation).

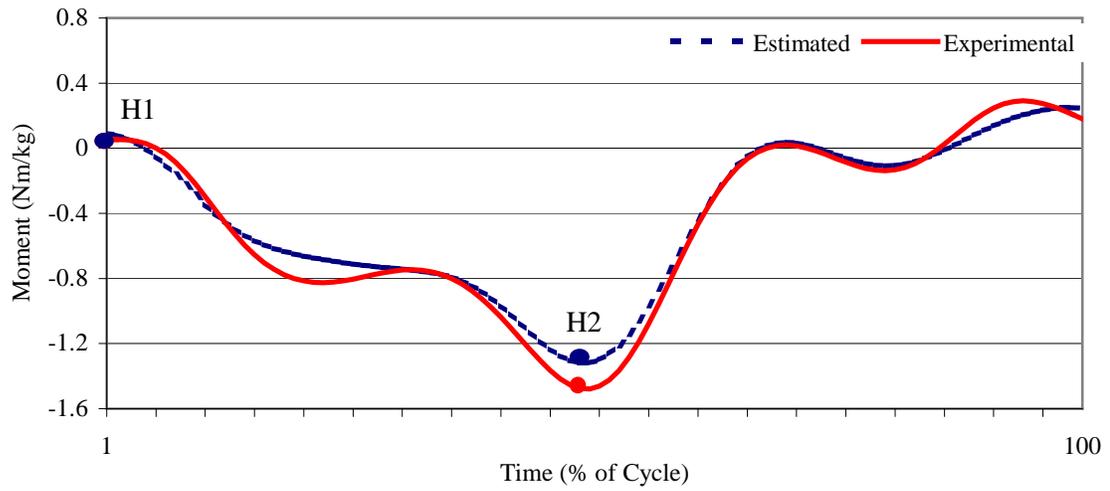
Table 4.7: Absolute estimation error for the amplitude and timing of peaks H1 and H2 from the selected hip joint moment curves.

		HIP		
		Amplitude (Nm/kg)	Range (Nm/kg)	Timing (%)
Case 1 G	H1	0.04	1.77	0.00
	H2	0.16		1.00
Case 1 B	H1	0.18	1.58	5.00
	H2	0.09		2.00
Case 12 G	H1	0.08	1.86	0.00
	H2	0.11		1.00
Case 12 B	H1	0.02	1.42	0.00
	H2	< 0.01		2.00

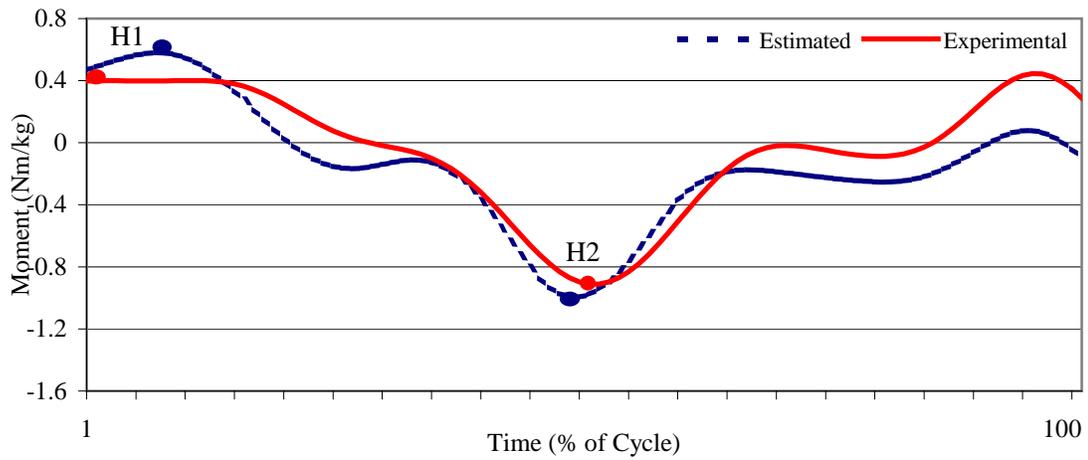
where G is the good curve-fitting

where B is the poor curve-fitting

For the good example for case one, the timing was exact for H1 and 1% off for H2 and the absolute estimation errors were 0.04 Nm/kg for H1 and 0.16 Nm/kg for H2 out of a range of 1.77 Nm/kg. Similarly, for the good curve-fitting example for case 12, the timing for H1 was accurate and off by 1% for H2. The error of estimation was 0.08 Nm/kg for H1 and 0.11 Nm/kg for H2 out of a range of 1.86 Nm/kg.

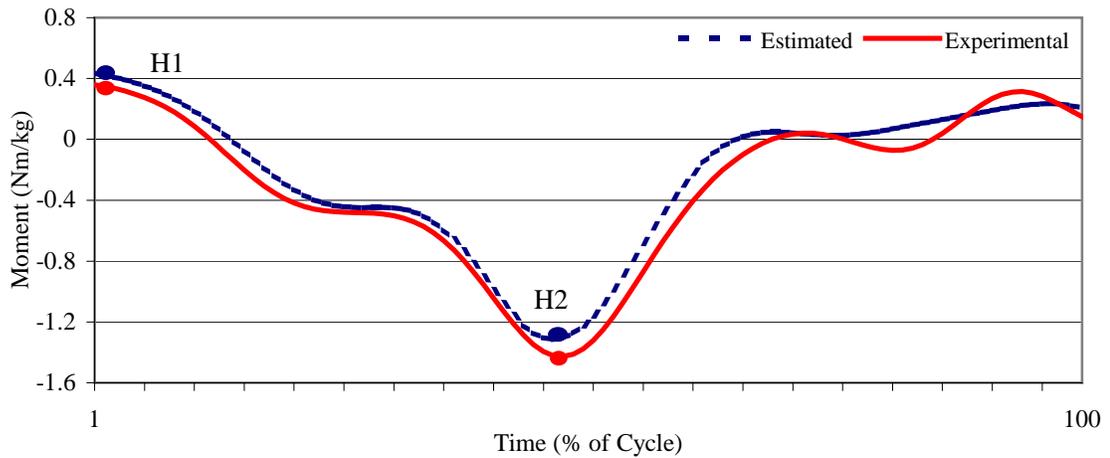


(a)

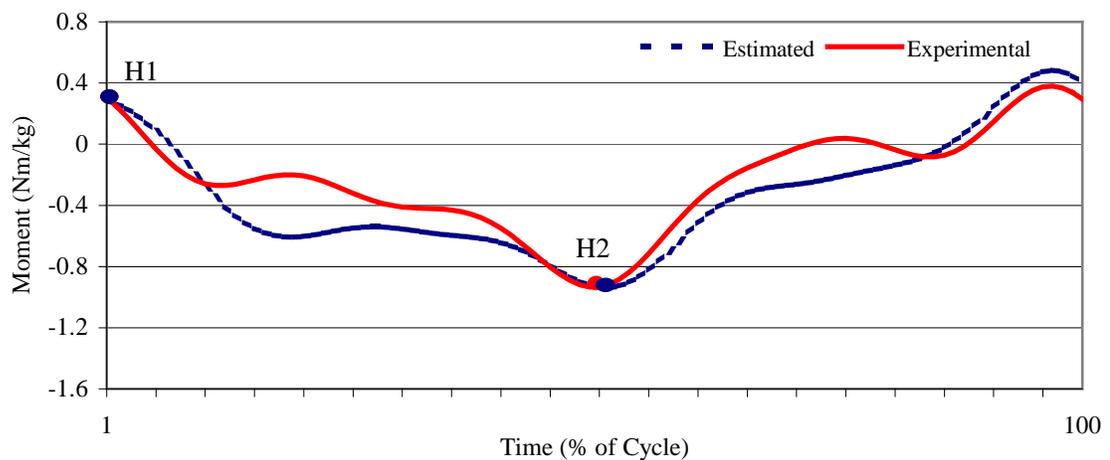


(b)

Figure 4.5: Hip joint moment curves for case 1: (a) good curve-fitting example ( $r^2 = 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.86$ ).



(a)



(b)

Figure 4.6: Hip joint moment curves for case 12: (a) good curve-fitting example ( $r^2 = 0.99$ ), (b) poor curve-fitting example ( $r^2 = 0.87$ ).

The poor curve-fitting example for case one had the greatest shifts in timing and amplitude (see Figure 4.5b). The timing for H1 was off by 5% and was 2% off for H2. The absolute estimation error was 0.18 Nm/kg for H1 and 0.09 Nm/kg for H2 out of a range of 1.58 Nm/kg. The difference between the peaks for the poor curve-fitting

example for case 12 were minor, however, this case had the most evident inconsistencies in magnitude between the experimental and estimated hip joint moment curves throughout the rest of the time-series (see Figure 4.6b).

## CHAPTER FIVE

### DISCUSSION

#### Introduction

The purpose of this study was to evaluate the performance of the previously developed ANN model at estimating ankle, knee and hip joint moments for subjects with OA. The broader purpose was to further validate the use of the ANN model as an alternative, less expensive method to traditional gait analysis. Results have been presented in this study to show that the ANN model is adaptive to a subject group with more diversity than the previously tested group of young, healthy subjects. These findings further support the supposition that the ANN model may provide an alternative to traditional gait analysis methods.

#### ANN Model

It was hypothesized that the ANN would be able to accurately predict the ankle, knee and hip joint moments for subjects with OA. For the ankle, the hypothesis was supported (p-value < 0.001) in all tested cases. For the knee and hip, the hypothesis was generally supported, but only cases 11 and 12 for the knee and cases 9-12 for the hip actually met the statistical threshold of a p-value less than the  $\alpha$  of 0.05. Cases 9-12 represent models with a higher number of hidden units and a lower allowable training error of MSE = 0.01. Models with these settings are expected to produce higher joint

moment estimation accuracy, based on findings from previous research by Hahn et al. (2006).

For the knee joint moment model, cases 2, 9 and 10 did not present strong evidence against the null hypothesis ( $p\text{-value} > 0.05$ ). While these cases were not in support of the alternative hypothesis statement, their mean correlation coefficients (0.92, 0.95 and 0.94, respectively) were comparable to values that have been considered acceptable by past researchers using ANN models for various biomechanical applications (Barton and Lees, 1997; Begg and Kamruzzaman, 2005; Holzreiter and Kohle, 1993; and Wu and Su, 2000). One possible explanation for failing to reject the null hypothesis may have been the greater range of correlation coefficients. Specifically, case 2 had a minimum correlation coefficient of 0.78 and a maximum of 0.95. Similarly, the values ranged from 0.81 to 0.97 for case 10. However, this was not true for case 9 which had a smaller range (0.92-0.96) similar to the range of correlation coefficients for cases 11 and 12 that were in support of the hypothesis.

The remaining knee cases (1, 3-8) and hip cases (1-8) did not support the hypothesis ( $p\text{-values} > 0.05$ ), and the CI for these cases was below the hypothesized value of 0.95. However, the performance of the ANN (mean correlation coefficients: 0.88-0.94 for the knee and 0.91-0.94 for the hip) was again comparable to that of previous ANN models used for biomechanical applications (Barton and Lees, 1997; Begg and Kamruzzaman, 2005; Holzreiter and Kohle, 1993; and Wu and Su, 2000) and is therefore considered functionally acceptable.

The correlation coefficients obtained during the current study were similar to those obtained from previous work by Hahn et al. (2006) in which the ANN was able to

estimate ankle, knee and hip joint moments for young, healthy subjects. Specifically, the highest mean correlation coefficient obtained for the ankle was above 0.99 in both studies, and for the knee and hip joint moment models, slightly higher values (0.97 compared to 0.96) were obtained during Hahn's prior research. Another research group utilizing an ANN to create EMG-muscle force models also reported similar successes (Liu et al., 1999). Specifically, they were able to estimate feline muscle forces from EMG during gait with correlation coefficients of 0.93 to 0.95.

Estimation accuracy of the present ANN model at estimating ankle, knee and hip joint moments from EMG data was also comparable to the prior work by Hahn et al. (2006). Previously, the error of estimation ranged from  $< 0.01$  Nm/kg for the case-specific knee estimate to 0.22 Nm/kg for the ankle whereas absolute estimation errors from the current study were  $< 0.01$  Nm/kg to 0.05 Nm/kg for the ankle and up to 0.18 Nm/kg for the hip estimate. This level of accuracy is also similar to the results from Sepulveda et al. (1993) in which errors of estimation were 0.03 Nm/kg for the hip and knee and 0.11 Nm/kg for the ankle.

### Future Work

The accuracy of the estimated joint moment curves was evaluated in the present study by examining the timing and amplitude of key peak values. Future researchers may wish to focus on the development of a better tool to analyze the accuracy of the estimated joint moment curve throughout an entire time series. Another avenue for future research may involve testing the ANN using a combined data set. Since modeling both groups independently with the ANN has yielded accurate joint moment estimations, it appears

likely that testing combined modeling routines will provide equally accurate results. This would allow more generalized application of the ANN model's predictive abilities.

Finally, the strength of any ANN model is directly related to the sample size and the generalizability is directly related to the diversity of the sample used for training.

Therefore, it is suggested that a larger, more diverse sample of data be collected to further validate the use of the ANN model as a less-expensive alternative to traditional gait analysis.

## CHAPTER SIX

### CONCLUSION

The purpose of this study was to evaluate the performance of the previously developed ANN model at estimating ankle, knee and hip joint moments for subjects with OA. The broader purpose was to further validate the use of the ANN model as an alternative, less expensive method to traditional gait analysis. In doing so, pathological locomotion data was used to train the ANN and the model's ability to estimate lower extremity joint moments was evaluated. Specifically, it was hypothesized that the ANN could predict the ankle, knee and hip joint moments for subjects with OA with a mean correlation coefficient of 0.95.

Overall, the model performed well, accurately estimating the joint moments of all three lower extremity joints of subjects with OA. Specifically, the mean correlation coefficients for the ankle estimations in all tested cases were determined to be above 0.95, supporting the hypothesis. For the knee, the last two cases (case 11 and case 12) supported the hypothesis, and the last four cases (cases 9-12) for the hip supported the hypothesis. The cases that did not support the hypothesis still resulted in good joint moment estimations (mean correlation coefficients ranging from 0.88 to 0.95) and were considered acceptable for functional application of model predictions. Additionally, the ANN's ability to accurately map the lower extremity joints was demonstrated through the evaluation of case-specific joint moment time-series curves.

It has been concluded from results presented in this study that the ANN model is adaptive to a more diverse sample than previously tested, supporting the supposition that the ANN may present an alternative to traditional gait analysis methods. Furthermore, the results from this study were encouraging enough to promote continued research. Specifically, the ANN model should be further validated by performing combined modeling routines in which the ANN is trained and tested on a combined data set with data from young, healthy subjects as well as subjects with OA. Additionally, the collection of more data from other subject groups would certainly strengthen the model's ability to generalize its estimates to a broader population of orthopedic and neuromuscular conditions.

REFERENCES CITED

- Amarantini, D., and Martin, L. (2004). A method to combine numerical optimization and EMG data for the estimation of joint moments under dynamic conditions. *Journal of Biomechanics*, 37, 1393-1404.
- Barton, J. G., and Lees, A. (1995). An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams. *Gait and Posture*, 5, 28-33.
- Begg, R., and Kamruzzaman, J. (2005). A machine learning approach for automated recognition of movement patters using basic, kinetic and kinematic gait data. *Journal of Biomechanics*, 38, 401-408.
- Bennett, D., Ogonda, L., Elliott, D., Humphreys, L., and Beverland, D.E. (2006). Comparison of gait kinematics in patients receiving minimally invasive and traditional hip replacement surgery: A prospective blinded study. *Gait and Posture*, 23, 374-382.
- Bogey, R. A., Perry, J., and Gitter, A. J. (2005). An EMG to force processing approach for determining ankle muscle forces during normal human gait. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13, 302-310.
- Chang, A., Hayes, K., Dunlop, D., Song, J., Hurwitz, D., Cahue, S. et al. (2005). Hip abduction moment and protection against medial tibiofemoral osteoarthritis progression. *Arthritis and Rheumatism*, 52, 3515-3519.
- Chau, T. (2001). A review of analytical techniques for gait data. Part 2: neural network and wavelet methods. *Gait and Posture*, 13, 102-120.
- Davis, R. B. (1997). Reflections on clinical gait analysis. *Journal of Electromyography and Kinesiology*, 7, 251-257.
- Hahn, M. E., Allen, J.R., and O'Keefe, K.B. (2006). Estimation of joint moments during gait using neural networks. *Proceedings of the 30<sup>th</sup> Annual Meeting of the American Society of Biomechanics*, Blacksburg, VA.
- Hahn, M. E. (2007). Feasibility of estimating isokinetic knee torque using a neural network model. *Journal of Biomechanics*, 40, 1107-1114.
- Haykin, S. (1994). *Neural networks: a comprehensive foundation*. New York: Macmillian College Publishing Company.
- Hof, A. L., Pronk, C. N., and Van Best, J. A. (1987). Comparison between emg to force processing and kinetic analysis for the calf muscle moment in walking and stepping. *Journal of Biomechanics*, 20, 167-178.

- Holzreiter, S. H., and Kohle, M. E. (1993). Assessment of gait patterns using neural networks. *Journal of Biomechanics*, 26, 645-651.
- Kellgren, J. H., and Lawrence, J. S. (1957). Radiological assessment of osteoarthritis. *Annals of the Rheumatic Diseases*, 16, 485-493.
- Lafuente, R., Belda, J. M., Sanchez-Lacuesta, J., Soler, C., and Prat, J. (1997). Design and test of neural networks and statistical classifiers in computer-aided movement analysis: a case study on gait analysis. *Clinical Biomechanics*, 13, 216-229.
- Lethbridge-Ceiku, M., Schiller, J. S., and Bernadel, L. (2004). Summary of health statistics for U.S. Adults: National Health Interview Survey, 2002. National Center for Health Statistics. *Vital Health Statistics*, 10(222).
- Levenberg, K., 1944. A method for the solution of certain non-linear problems in least squares. *Quarterly of Applied Mathematics*, 2, 164-168.
- Liu, M. M., Herzog, W., and Savelberg, H. (1999). Dynamic muscle force prediction from EMG: an artificial neural network approach. *Journal of Electromyography and Kinesiology*, 9, 391-400.
- Luh, J.J., Chang, G.C., Cheng, C.K., Lai, J.S., Kuo, T.S., 1999. Isokinetic elbow joint torques estimation from surface emg and joint kinematic data: Using an artificial neural network model. *Journal of Electromyography and Kinesiology*, 9, 173-183.
- Manal, K., and Buchanan, T. S. (2003). A one-parameter neural activation to muscle activation model: estimating isometric joint moments from electromyograms. *Journal of Biomechanics*, 36, 1197-1202.
- Marquardt, D.W., 1963. An algorithm for least squares estimation of nonlinear parameters. *Journal of the Society of Industrial and Applied Mathematics*, 11, 431-441.
- National Institutes of Health. (2001). Questions and Answers about Hip Replacement. Retrieved March 23, 2006, from <http://www.niams.nih.gov/hi/topics/hip/hiprepqa.htm>
- National Institutes of Health. (2002). Handout on Health, Osteoarthritis. Retrieved September 23, 2006 from <http://www.niams.nih.gov/hi/topics/arthritis/oahandout.htm>
- National Institutes of Health. (2003). National Institutes of Health Consensus Development Conference Statement. NIH Consensus Development Conference on Total Knee Replacement. Retrieved March 23, 2006, from <http://consensus.nih.gov/2003/2003TotalKneeReplacement117html.htm>

- Olney, S. J. and Winter, D. A. (1985). Predictions of knee and ankle moments of force in walking from EMG and kinematic data. *Journal of Biomechanics*, 18, 9-20.
- Schollhorn, W. I. (2004). Applications of artificial neural nets in clinical biomechanics. *Clinical Biomechanics*, 19, 876-898.
- Sepulveda, F., Wells, D. M., and Vaughn, C. L. (1993). A neural network representation of electromyography and joint dynamics in human gait. *Journal of Biomechanics*, 26, 101-109.
- Wang, L., and Buchanan, T. S. (2002). Prediction of joint moments using a neural network model of muscle activations from EMG signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 10, 30-37.
- Wu, W.-L., and Su, F.-C. (2000). Potential of the back propagation neural network in the assessment of gait patterns in ankle arthrodesis. *Clinical Biomechanics*, 15, 143-145.

APPENDICES

APPENDIX A  
SUBJECT CONSENT FORM

**SUBJECT CONSENT FORM**  
**FOR PARTICIPATION IN HUMAN RESEARCH**  
**MONTANA STATE UNIVERSITY**

---

**PROJECT TITLE:** JOINT MOMENT ESTIMATION FROM EMG SIGNALS OF OSTEOARTHRITIS PATIENTS DURING GAIT USING AN ARTIFICIAL NEURAL NETWORK

**PROJECT DIRECTOR:** Katie O’Keefe, Graduate Student, Biomechanics  
Dept. of Health and Human Development  
Movement Science / Human Performance Laboratory  
Montana State University, Bozeman, MT 59717-3540  
Phone: (406) 570-3490; FAX: (406) 994-6314;  
E-mail: [kathryn.okeefe@myportal.montana.edu](mailto:kathryn.okeefe@myportal.montana.edu)

**FUNDING:** This project is not currently funded.

---

**PURPOSE OF THE STUDY:**

The purpose of this project is to develop a mathematical model for estimating joint moments in osteoarthritis patients. Involvement in this project includes one visit to the Movement Science/Human Performance Laboratory at Montana State University. The time commitment will be approximately two hours.

**STUDY PROCEDURES:**

The study will consist of one laboratory session that entails muscle activation analysis and a full three-dimensional gait analysis. After reading and signing the Informed Consent Document, you will be asked to change into athletic shorts, tank top shirt, socks and athletic shoes. You will then have your body weight and body height determined using a standard physician’s beam-scale.

**Electromyographic (EMG) Measurements:**

Muscle activation will be recorded during gait analysis. EMG signals will be collected using passive surface electrodes. Electrodes will be placed over seven muscles (see Figure A.1 on next page) to detect the electrical signals of muscle activation. The seven muscles are located on: the shin, the calf, the middle and outer quads, the hamstrings, the buttocks and the hip. The muscles will be located by the project director. Placement of the EMG electrodes over the shin and calf will be over the mid-portions of the front and back of the lower leg, respectively. Electrode placement over the outer quads and hamstrings will be over the lower third of the front and back of the thigh, respectively. Electrode placement over the middle quads will be over the mid-section of the front surface of the thigh and the hip electrode will be placed just under the outer edge of the bony portion of the hip. Electrode placement over the buttocks will be just superior of the upper thigh. Placement of this electrode will require indirect exposure of the lower buttocks while the electrode is fixed with tape.

### 3-Dimensional Motion Measurements:

Joint dynamics will be assessed during level walking conditions. A set of 16 reflective markers will be placed on bony landmarks of your lower body to allow reconstruction of the lower body's musculoskeletal system. These markers will be placed using double-sided tape.

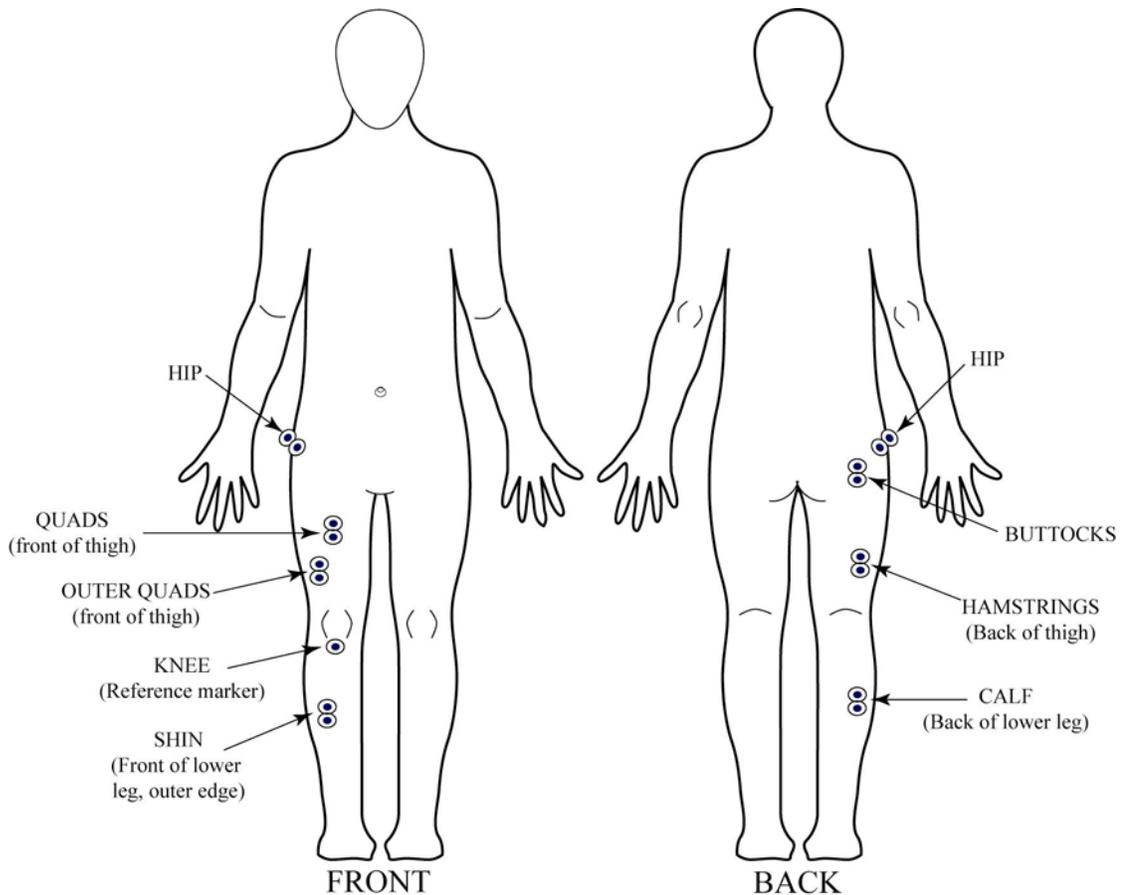


Figure A.1: Surface electrode placement on seven muscles of the leg.

### POTENTIAL RISKS:

Removal of double-sided tape may involve discomfort.

### BENEFITS:

The direct benefit will be feedback regarding the results of your gait analysis. The results of the gait analysis may lead to more effective treatments or rehabilitation programs. Additionally, the gait analysis may be used later to compare pre- and post-operative gait. You may request a summary of the study findings by contacting the Project Director, Katie O'Keefe, by phone (406-570-3490) or by E-mail ([kathryn.okeefe@myportal.montana.edu](mailto:kathryn.okeefe@myportal.montana.edu)).

**CONFIDENTIALITY:**

Personal information and all recorded data will be regarded as privileged and confidential materials. Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission. Subject identities will be kept confidential by coding the data using subject pseudonyms. The code list will be kept separate and secure from the actual data files.

**FREEDOM OF CONSENT:**

*Participation in this project is completely voluntary.*

You may withdraw consent for participation in writing, by telephone, or in person without prejudice or loss of benefits (as described above). Please contact the Project Director, Katie O'Keefe, by phone (406-570-3490) or by E-mail ([kathryn.okeefe@myportal.montana.edu](mailto:kathryn.okeefe@myportal.montana.edu)) to discontinue participation.

In the UNLIKELY event that your participation in the project results in physical injury to you, the Project Director will advise and assist you in receiving medical treatment. No compensation is available from Montana State University for injury, accidents, or expenses that may occur as a result of your participation in this project. *Further information regarding medical treatment may be obtained by calling the Project Director, Katie O'Keefe, at 406-570-3490.* You are encouraged to express any questions, doubts or concerns regarding this project. The Project Director will attempt to answer all questions to the best of their ability prior to any testing. The Project Director fully intends to conduct the study with your best interest, safety and comfort in mind. *Additional questions about the rights of human subjects can be answered by the Chairman of the Institutional Review Board, Mark Quinn, at 406-994-5721.*

**PROJECT TITLE:**

**JOINT MOMENT ESTIMATION FROM EMG SIGNALS OF  
OSTEOARTHRITIS PATIENTS DURING GAIT USING AN ARTIFICIAL  
NEURAL NETWORK**

**STATEMENT OF AUTHORIZATION**

I, *the participant*, have read the Informed Consent Document and understand the discomforts, inconvenience, risks, and benefits of this project. I, \_\_\_\_\_  
(*print your name*), agree to participate in the project described in the preceding pages. I understand that I may later refuse to participate, and that I may withdraw from the study at any time. I have received a copy of this consent form for my own records.

**Signed:** \_\_\_\_\_ **Age** \_\_\_\_\_  
**Date** \_\_\_\_\_

*Subject's Signature*

APPENDIX B

VIDEO CONSENT FORM

**VIDEO CONSENT FORM  
MONTANA STATE UNIVERSITY**

---

**PROJECT TITLE:** JOINT MOMENT ESTIMATION FROM EMG SIGNALS OF OSTEOARTHRITIS PATIENTS DURING GAIT USING AN ARTIFICIAL NEURAL NETWORK

**PROJECT DIRECTOR:** Katie O’Keefe, Graduate Student, Biomechanics  
Dept. of Health and Human Development  
Movement Science / Human Performance Laboratory  
Montana State University, Bozeman, MT 59717-3540  
Phone: (406) 570-3490; FAX: (406) 994-6314;  
E-mail: [kathryn.okeefe@myportal.montana.edu](mailto:kathryn.okeefe@myportal.montana.edu)

**FUNDING:** This project is not funded.

---

**PERMISSION TO RECORD VIDEO INFORMATION:**

During the functional testing sessions in the laboratory, your image may be recorded using a standard digital video recorder. The purpose of this recording is to provide information for the research staff to enhance the functional mobility measures taken in the physical therapy clinic. This footage will be regarded as privileged and confidential, and will not be used beyond the research project without obtaining your express written permission.

---

**STATEMENT OF AUTHORIZATION**

I, *the participant*, have read the Informed Consent Document and understand the discomforts, inconvenience, risks, and benefits of this project. I, \_\_\_\_\_  
(*print your name*), agree to participate in the project described in the preceding pages. I understand that I may later refuse to participate, and that I may withdraw from the study at any time. I have received a copy of this consent form for my own records.

**Signed:** \_\_\_\_\_ **Age** \_\_\_\_\_ **Date** \_\_\_\_\_  
*Subject’s Signature*

APPENDIX C

WOMAC INDEX

58  
WOMAC 3.1 Index

The Western Ontario and McMaster Universities (WOMAC) Index for Osteoarthritis  
Rating: 0 - None, 1 - Slight, 2 - Moderate, 3 - Severe, 4 - Extreme

Pain

1. Walking
2. Stair climbing
3. Nocturnal
4. Rest
5. Weight bearing

Stiffness

1. Morning stiffness
2. Stiffness occurring later in the day

Physical Function

1. Descending stairs
2. Ascending stairs
3. Rising from sitting
4. Standing
5. Bending to the floor
6. Walking on a flat surface
7. Getting in or out of a car
8. Going shopping
9. Putting on socks
10. Rising from bed
11. Taking off socks
12. Lying in bed
13. Sitting
14. Getting in or out of bath
15. Getting on or off the toilet
16. Heavy domestic duties
17. Light domestic duties