

Fall 2007

Using wavelet and template analysis to classify hand postures in unsupervised daily activities

Soha Hassan Saleh

New Jersey Institute of Technology

Follow this and additional works at: <https://digitalcommons.njit.edu/theses>



Part of the [Biomedical Engineering and Bioengineering Commons](#)

Recommended Citation

Saleh, Soha Hassan, "Using wavelet and template analysis to classify hand postures in unsupervised daily activities" (2007). *Theses*. 345.

<https://digitalcommons.njit.edu/theses/345>

This Thesis is brought to you for free and open access by the Theses and Dissertations at Digital Commons @ NJIT. It has been accepted for inclusion in Theses by an authorized administrator of Digital Commons @ NJIT. For more information, please contact digitalcommons@njit.edu.

Copyright Warning & Restrictions

The copyright law of the United States (Title 17, United States Code) governs the making of photocopies or other reproductions of copyrighted material.

Under certain conditions specified in the law, libraries and archives are authorized to furnish a photocopy or other reproduction. One of these specified conditions is that the photocopy or reproduction is not to be “used for any purpose other than private study, scholarship, or research.” If a user makes a request for, or later uses, a photocopy or reproduction for purposes in excess of “fair use” that user may be liable for copyright infringement,

This institution reserves the right to refuse to accept a copying order if, in its judgment, fulfillment of the order would involve violation of copyright law.

Please Note: The author retains the copyright while the New Jersey Institute of Technology reserves the right to distribute this thesis or dissertation

Printing note: If you do not wish to print this page, then select “Pages from: first page # to: last page #” on the print dialog screen

The Van Houten library has removed some of the personal information and all signatures from the approval page and biographical sketches of theses and dissertations in order to protect the identity of NJIT graduates and faculty.

ABSTRACT

USING WAVELET AND TEMPLATE ANALYSIS TO CLASSIFY HAND POSTURES IN UNSUPERVISED DAILY ACTIVITIES

by
Soha Hassan Saleh

This project's goal was to identify determinants that characterize different types of activities an individual do in daily life, knowing the quality of hand function is essential to plan more effective rehabilitation therapies and treatments for upper limb movement disorders. The first part of the project was Jebsen-Taylor study where healthy individuals and individuals with brain injury performed seven activities classified as precision grasp, cylindrical grasp, and palmar grasp while metacarpal joint angles were measured in real time. The data from those seven activities was used to determine parameters that characterize each type of activity and which might be used as evaluation parameters after treatment. The determinants studied were the mean and variance of joints' angles, range of motion, flexion and extension speed, and range of motion. A glove was used to record hand activity of an individual for 24 hours. Characteristics of these hand activities produce signals that are localized in both time and frequency, thus wavelet transform was used to detect the instance of change in the type of activity. Three clusters built after analyzing the seven activities were used to scan the 24 hr data and summarize the types of activity that had been performed by the subject in addition to reporting multiple parameters of the hand as range of motion and speed. The result was that the subject did no activity for 8 hours, precision grasp activities for 2 hours, palmar grasp activities for 12 hours and cylindrical grasp activities for 1 hour.

**USING WAVELET AND TEMPLATE ANALYSIS TO CLASSIFY HAND
POSTURES IN UNSUPERVISED DAILY ACTIVITIES**

by
Soha Hassan Saleh

**A Thesis
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Biomedical Engineering**

Department of Biomedical Engineering

January 2008

Blank Page

APPROVAL PAGE

**USING WAVELET AND TEMPLATE ANALYSIS TO CLASSIFY HAND
POSTURES IN UNSUPERVISED DAILY ACTIVITIES**

Soha Hassan Saleh

Dr. Lisa K. Simone, Thesis Advisor Date
Associate Professor of Biomedical Engineering, NJIT

Dr. Richard Foulds, Committee Member Date
Professor of Biomedical Engineering, NJIT

Dr. Ali Akansu, Committee Member Date
Professor of Electrical and Computer Engineering, NJIT

BIOGRAPHICAL SKETCH

Author: Soha Hassan Saleh

Degree: Master of Science

Date: January 2008

Undergraduate and Graduate Education:

- Master of Science in Biomedical Engineering,
New Jersey Institute of Technology, Newark, NJ, 2008
- Bachelor of Science in Computer and Communication Engineering,
American University of Science and Technology, Beirut, Lebanon, 2006

Major: Biomedical Engineering

Presentations and Publications:

Soha H. Saleh and Lisa K. Simone,
“Identifying Determinants of Hand Posture of Individuals with and without
Movement Disorders,” Proceedings of the 2007 Biomedical Engineering Society
(BMES) Annual Meeting, Los Angeles, CA, USA.

Soha H. Saleh,
“Identifying Determinants of Hand Posture of Individuals with and without
Movement Disorders,” Graduate Student Association Research Day, NJIT,
Newark, NJ, USA.

To my beloved parents who trained me to be independent, ambitious, and
hard working

To my sisters and brothers who always trusted me

To my friends who are always in my heart even when they are far away

To the descendents of Phoenicians who spread the use of alphabets to the
world, and who build Damascus and Byblos, Tyre and Sidon, and Antioch.

To the Lebanese who have always been stronger than wars and destruction,
about who Gibran Khalil Gibran said:

“They are those who migrate with nothing but courage in their hearts and
strength in their arms but who return with wealth in their hands and a wreath
of glory upon their heads.

They are the victorious wherever they go and loved and respected wherever
they settle.

They are the ones born in huts but who died in palaces of learning.

These are the children of Lebanon; they are the lamps that cannot be snuffed
by the wind and the salt which remains unspoiled through the ages.”

To Lebanon, the land upon which God laid His gracious hand and raised His
messengers

ACKNOWLEDGMENT

I would like to express my deepest appreciation to Dr. Lisa Simone, who was more than a research advisor, she provided me with valuable and countless resources, insight, and intuition. I would like to thank her for trusting me to work on this project; she constantly gave me support, encouragement, and reassurance. Special thanks as well to Dr. Richard Foulds who supported me since the first day I came to United States and NJIT. His trust in me was a great source of encouragement. I would also like to thank Dr. Ali Akansu for actively participating in my committee and for giving me much of his time to discuss this study.

I would like to thank Brad Galego and Carlos Rosado, for being very special lab colleagues and very kind friends; I also appreciate their willingness to help during all stages of this work. Manish Raval was a special colleague and friend who inspired me with his attitude toward life and he deserves my recognition for his continuous support. Jonathon Groth was a friend who was always there to encourage and support, and who I would like to thank.

TABLE OF CONTENTS

Chapter	Page
1 INTRODUCTION.....	1
1.1 Statement of the Problem	1
1.2 Goal	3
2 BACKGROUND	5
2.1 Brain Injury.....	5
2.2 Therapy Evaluation Methods.....	8
2.3 Measurement Devices.....	10
2.4 Types of Grasps.....	14
2.5 Wavelet Analysis.....	18
2.5.1 Introduction to Wavelets.....	18
2.5.2 Wavelet Properties.....	20
2.5.3 Multiresolution Analysis (MRA).....	23
3 METHODS	26
3.1 Jebsen-Taylor Study.....	26
3.1.1 Data Collection.....	26
3.1.2 Jebsen Data Analysis.....	27
3.2 Long-Stream Data Study.....	39
4 RESULTS AND DISCUSSION.....	42
4.1 Jebsen-Taylor Study Results and Discussion.....	42

Chapter	Page
4.2 Long-stream Data Analysis Results and Discussions	51
5 RECOMMENDATIONS AND CONCLUSION.....	55
APPENDIX A SPEED COMPARISON.....	56
APPENDIX B DECOMPOSE.....	58
APPENDIX C CALCULATING MEANS OF JOINT ANGLES.....	59
APPENDIX D CALCULATING STANDARD DEVIATION.....	61
APPENDIX E SPEED ANALYSIS FUNCTION.....	63
APPENDIX F LONG-STREAM DATA ANALYSIS.....	65
APPENDIX G SEGMENTING FUNCTION.....	66
APPENDIX H DECISION.....	68
APPENDIX I ACTIVITY CLASSES.....	71
I.1 Class 1.....	71
I.2 Class 2.....	73
I.3 Class 3.....	76
I.4 Class 4.....	78
REFERENCES	79

LIST OF TABLES

Table	Page
3.1 Time Needed to Do a Jebsen Activity (HC Group).....	27
3.2 Time Needed to Do a Jebsen Activity (ABI Group).....	27
3.3 Summary of the Detailed Coefficients Maximum Amplitude for the Subjects in the Two Groups.....	31
4.1 The mean of Joint Angles' Ranges for each Activity.....	43
4.2 Distribution of Joint Angles during Writing Activity.....	44
4.3 Distribution of Joint Angles during Simulating Feeding Activity.....	44
4.4 Distribution of Joint Angles during Simple Page Turning Activity.....	45
4.5 Distribution of Joint Angles during Stacking Checkers Activity.....	45
4.6 Distribution of Joint Angles during Small Object Lift Activity.....	45
4.7 Distribution of Joint Angles during 'Holding Large Light Object' Activity.	46
4.8 Distribution of Joint Angles during 'Holding Large Heavy Object' Activity	46
4.9 Cluster Analysis of Jebsen Activities.....	50
4.10 Summary of the Four Classes of Activities.....	52

LIST OF FIGURES

Figure	Page
2.1 Causes of Brain Injury.....	8
2.2 Goniometer measuring the CP joint	12
2.3 Cyber-gloves first three to the (left) manufactured by Immersion Corporation [13] and the fourth manufactured by Humanware [14].....	14
2.4 Schlesinger’s classification of prehensile posture.....	15
2.5 Napier’s classification of prehensile postures. The first to right is “power grasp”, in the middle “precision grasp”, and to the left a special type of precision grasp called “coal hammer” [18].....	16
2.6 A. Pad Opposition that occurs along an axis that is parallel to the palm. B. Palm opposition that occurs perpendicular to the palm. C. Side opposition along an axis transverse to the palm [18].....	17
2.7 Oppositions described in terms of virtual fingers (VF1 and VF2). A. Pad opposition along an axis (x) parallel to the palm. B. Palm opposition along axis (z) perpendicular to the palm. C. Side opposition along an axis (y) transverse to the palm [18].....	17
2.8 Example of using wavelet analysis to identify discontinuity in the signal. The parameter “a” stands for approximate coefficients and “d” for detailed coefficients [23].....	20
2.9 Wavelet decomposition on the left and reconstruction on the right [23].....	24
2.3 Wavelet Decomposition and Reconstruction.....	26
3.1 Subject doing 7 different Jenson-Taylor activities.....	28
3.2 Different ways to hold a pen and write or hold a cylindrical object as a glass.....	34
3.3 Activity of pinkie during subject activity.....	36
3.4 Probability density estimate of pinkie activity.....	36
4.1 Distribution of variance for the 20 subjects (HC and ABI) while writing.....	47

Figure	Page
4.2 Distribution of variance for the 20 subjects (HC and ABI) during simulating feeding.....	47
4.3 Distribution of variance for the 20 subjects (HC and ABI) during simple page turning activity.....	48
4.4 Distribution of variance for the 20 subjects (HC and ABI) while stacking checkers.....	48
4.5 Distribution of variance for the 20 subjects (HC and ABI) while lifting small objects.....	49
4.6 Distribution of variance for the 20 subjects (HC and ABI) while holding large light object.....	49
4.7 Distribution of variance for the 20 subjects (HC and ABI) while holding large light object.....	49
4.8 Distribution of activities during the 24 hours and 40 minutes.....	51
4.9 Activities during the 24 hours and 40 minutes.....	52
4.10 The percentage of each of the four types of activities during daily activities..	53

CHAPTER 1

INTRODUCTION

1.1 Statement of the Problem

There are multiple neurological disorders, primarily brain injury that affect hand activity in terms of functional ability, ease and speed of movement, and range of motion. In the presence of a variety of rehabilitation therapies and treatments, the accuracy in studying hand function is a major concern as a post-treatment evaluation. Currently, several methods exist to study the function of the hand. Some assessment methods depend on measuring the time the subject requires to perform an action. Others include calculating range of motion of individual joints of the hand; however, a major drawback of the current hand function evaluation methods is that they do not give clear outcomes regarding the quality of hand function. Besides, they are restricted to evaluation in the clinic or research site. In addition to range of motion, quality of hand function can be more completely assessed by studying fingers' speed during daily life activities. A better assessment of hand function during normal daily activities is critical to plan for more effective rehabilitation therapy and treatments for upper limb movement disorders.

The goal behind this thesis project is to use measure joint angle activity for the five metacarpal (MCP) joints of the hand, and use the data to identify the types of activities the subject was doing at different instances of time, in addition to assessing the range of motion and the flexion and extension speed of the fingers during the activities.

The first challenge in this project is to find a measurement device to record hand activity while an individual is living life normally (driving, sleeping, cooking, typing, running, etc); therefore, there are multiple requirements needed to be present in a measurement device. These requirements include portability, ease in donning and doffing, low cost, low weight, and durability, because the device will be used for hours and maybe days.

Another concern besides the measurement device itself is the post-processing step of the data analysis. The challenge is to scan the data and to detect what types of activities the patients was doing while wearing the glove and for how long each activity was performed after a long stream of data (up to 24 hours) has been separated into activities, finger speed, and range of motion for each can be calculated. The need to identify types of activities require initial data from short known activities; however, these data will be used as the studied environment or training data. Important determinants or characteristics of these data will be used to scan and study the long streams of 24 hour raw data that include the unknown activities. The initial training data was recorded by capturing real-time finger posture during the performance of the standardized Jebsen-Taylor Hand Function Test (JTHFT).

JTHFT include seven types of activities: writing, simulating page turning, simulating feeding by moving kidney beans using a spoon, lifting small objects, stacking checkers, lifting large heavy cans, and lifting large light cans. Ten healthy subjects (HC) and ten subjects with movement disorders (Acquired Brain Injury (ABI)) participated in the study. While doing the seven activities, MCP joint angles were measured; the next step was analyzing the data and identifying the trends. Identified determinants of hand

postures were used to scan long stream of data and give summary about the quality of hand function. The challenge in this step was to define the instance at which there is a change from one activity to the next. A hand activity characteristic is not regular or periodic, as a real time signal, it has no predictable time or frequency, and activities may be of different lengths of time. Therefore, simple Fourier analysis, which is most appropriate for periodic signal, may not yield useful results for long streams of changing data. The solution of this problem was found in wavelets; wavelet analysis is a signal processing technique that allows the study of signals localized in time and frequency, such as a series of hand activities that change characteristics unpredictably in time.

Different features were required in the measurement device of joint angles, those features include but are not limited to portability, low weight, low cost, and efficiency. The design of the Shadow Monitor glove was developed for such application. The glove's cost, wearability, light weight, and ease of use, are all advantages that permit using it with patients who have difficulty opening their fingers as a result of brain injury. In addition it is lower cost and can be used by patients without regard for major damage. For this project, the glove was used to measure bending angles for the 5 metacarpal (MCP) joints of the hand.

1.2 Goal

After data collection of the hand posture for the seven activities, the objective is to identify determinants in hand posture to define the type of activity. The first insight from the data suggested that mean, variance, and range of motion could be the primary parameters to identify the type of activity, and also the difference between posture of

healthy subjects and those with movement disorders. This hypothesis was studied by calculating those parameters; and comparing them within and between the two groups and the seven activities. The high frequency component of finger's activity has been compared between and within groups. Other parameters that were checked are average speed, flexion speed, and extension speed. The next step in this project was to define the parameters, put them into clusters, and then use that in scanning 24hr data and identify the types of activities performed over that time. The 24hr data was collected for a subject who used the shadow monitor glove for 24 hours, while doing different types of activities, writing, reading, eating, typing, sleeping, cooking, etc.

Assuming that the parameters defined in the first part are effective in defining the type of activity performed, a second challenge is how to determine the site of change of activity in the 24 hour data file. In the literature, Fourier analysis has been used to filter data and identify change in activity based in the change of absolute frequency components; however, hand posture is an activity that does not have predefined pattern for the change of frequency in the activity; instead, it is localized in both time and frequency. On the other hand, wavelet analysis has an advantage over Fourier analysis in extracting localized features in the data; therefore, it has been proposed in this project due to its ability to detect discontinuities in the signal, to define the site and the type of the change in terms of time and frequency, and to give the amplitude of the change. After defining the instance of the activity change, and segmenting the data, the parameters defined in the first part can be used to define the type of activities in the 24 hour streams of data.

CHAPTER 2

BACKGROUND

2.1 Brain Injury

Brain injury is a condition that affects millions of people. Acquired brain injury (ABI) is brain damage that happens after birth, ABI includes traumatic brain injury (TBI) and stroke, Whiplash is another type of ABI caused by injury to the neck. In the United States, approximately 5 million people are currently affected by some form of TBI disability which is also a leading cause of death for persons under age 45 [1]. In general, different types of brain injury are classified based on the cause of injury and severity level.

Traumatic Brain Injury (TBI) occurs after an outside force harshly moves the brain within the skull causing damage. TBI has also been called “silent epidemic” and it is associated with life-time emotional, behavioral, and cognitive impairments that could be temporary or permanent. TBI includes diffuse axonal injury, concussion, and contusion, in addition to coup-contrecoup injury, second impact syndrome, penetration injury, shaken body syndrome, and locked in syndrome. TBI comprises at least 14-20% of the surviving casualties in the time of combat. It is a significant health problem since it is not just a cause of death but also a reason of disability in US and in countries all over the world. Data from Center for Disease Control and Prevention (CDC) shows that about 50% of TBI cases are caused by transportation accidents (motor vehicles, car accidents, pedestrian accidents, etc). [1]

Acquired Brain Injury (ABI) is more associated with changing in neural activity and affecting the brain cells in terms of physical integrity, metabolic activity, and functional ability. The after effects of ABI include difficulties in cognition, speech-language communication, memory, attention, concentration, reasoning, abstract thinking, physical functions, psychological behavior, and information processing. The causes of ABI include but are not limited to anoxic and hypoxic brain injury after an inefficient supply of oxygen to the brain, heart attack, stroke, arterio-venous malformation, infectious disease, intracranial tumors, metabolic disorders, AIDS, meningitis, hypo/hyperglycemia, airway obstructions, electrical and lightning shocks. [1]

While TBI is associated with lethargy (sluggish, tires easily), numbness or tingling, ABI is more associated with general muscle movement disorders. In both cases, the condition directly affects the speed, fluency, quality, and ease of movement, which adds limitations to the ability to perform activities of daily living because individuals become unable to do certain activities, or do other simple actions with low speed and range of motion. [1]

There is a difficulty in assessing the impairments behind disability, basically due to the effects of spasticity and other impairments. Spasticity was seen as the major determinant of disability, clinically it is caused by abnormal reflex activity that increases resistance to passive movement to a relaxed muscle. The major impairments that show similar symptoms are spasticity, hypertonia, hyperflexia, and muscle overactivity. Physiologically, spasticity arises from disruption of certain descending pathways in the CNS that involves motor control, those pathways control proprioceptive, cutaneous, and nociceptive spinal reflexes. [2]

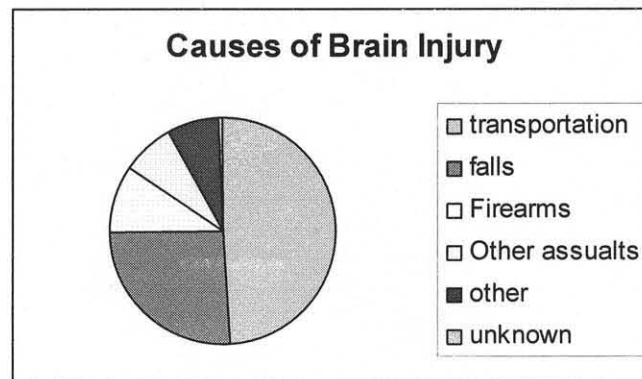


Figure 2.1 Causes of Brain Injury. [3]

The severity of brain injury is mainly classified as mild, moderate, or severe, based on three indexes: Glasgow Coma Scale (GCS) score, length of loss of consciousness (LOC), and length of post-traumatic amnesia (PTA) [1]. However, the evaluation of the case after initial treatment is not an accurate process, usually physicians depend on subjective methods to decide if the patient is improving, but there is no precise evaluation of the fluency and quality of motor movement.

The complexity of brain injury effect on hand posture is influenced by the complexity of hand posture itself. This is primarily because manipulation and coordination of hand fingers are extraordinary important for human and they require central and peripheral circuitry to control them. The brain injury could affect the central or peripheral circuitry in the cerebral cortex, or the pathways between central nervous system (CNS) and the upper limb. Regardless of the actual cause, the result is a loss of function that affects the ability to perform daily activities.

2.1 Therapy Evaluation Methods

Traditional evaluation methods of hand function, especially after treatment or therapy, often focus on measurement and treatment of specific impairments, such as range of motion (ROM) or perceived resistance to passive stretch; however, there is a need to use outcome measures that more closely reflect functional improvements [4]. Finch's group [5] suggested that assessment methods should focus on an individual's ability to be active and to do the general life activities. Rehabilitation clinicians, engineers, insurance companies, families and patients have different priorities on different outcome goals. For example, the insurance companies and families might not be satisfied by the subjective methods and experience of the clinician, they would desire more quantitative measures of the hand function to justify payment or to show clear progress.

One of the methods currently used to evaluate hand function is the Modified Ashworth Scale (MAS), it is a clinical measure of tone intensity that quantifies muscle tone on a scale of 0 (no increase in muscle tone) to, 1, 1+, 2, 3, and 4 (high degree of muscle tone). The Ashworth test depends on the assessment of the resistance to passive stretch by the clinician who applies the movement. A negative change in score signifies an improvement in muscle tone. This scale measure is useful for clinicians, but it is subjective and does not reflect function or individual's ability to do an activity at home. The reliability of the test is based on the ability of the observer both to control the rate of stretch and to assess the resistance [6]. Another scales used to measure functional activity is Tardieu scale. Tardieu scale include measuring velocity of stretch based on three scales V1 (as slow as possible), V2 (speed of the limb segment falling under gravity), and V3 (as fast as possible). The other parameters studied in Tardieu scale are

the quality of muscle reaction which is tested based on the resistance at 5 scales; 0 (no resistance), 1 (slight resistance throughout course of passive movement), 2 (clear catch at a precise angle), 3 (fatiguable clonus), and 4 (unfatiguable clonus) [6].

Elovic and Simone et al. [4] categorized outcome goals and assessments into 1 of 5 groups: physiological measurements, passive activity measures (e.g., Ashworth Scale and passive ROM), voluntary activity measures (i.e., Fugl-Meyer), functional measures, and quality of life (QOL) measures. The challenge is to focus on the functional and/or QOL assessment in addition to the physiological or motion assessment measures. An example of physiological measurement is measuring the excitability of the motor neuronal pool. Some passive activity measures include measuring changing of elasticity of connective tissues muscle tone, and deriving subjective measures such as the Ashworth scale, Tardieu scale, or more objective measures such as passive range of motion, torque, stiffness, and viscosity.

Measures of voluntary activity is a category that includes many assessments where the individual is asked to perform an activity, such as pedobarographs that provide information about foot position, movement, and center of pressure. Other tests include Fugl-Meyer test, the Box and Block test (BBT), and the 9-HPT. A Fugl-Meyer task does not include daily activities. BBT and 9-HPT are two tests that are commonly used in the assessment of the upper extremity. BBT includes testing how many boxes a patient can move from one container to another in one minute. BBT tests are commonly used in the literature to assess selected hand usage in the stroke population. The fourth category, functional measures, is used to assess daily activities as hygiene, standing, and ambulation in real life or under approximately real life situations. Examples of functional

measures are Disability Assessment Scale (DAS), used to evaluate efficacy of upper extremity, and 3D gait analysis. [4]

Finally, QOL measures are useful in assessing the satisfaction of a patient in life. Such measures include questionnaires or health surveys. It is important to create a new functional assessment method for assessing the performance of patient after treatment, based on the capability of living normal life, thus, the ultimate goal of this thesis is to introduce an objective method to measure the functional activity of an individual, specifically hand activity, and to help evaluate how well individuals can perform activities that are important in their daily lives.

2.3 Measurement Devices

Originally, joint angles and ROM were measured using a goniometer. The first goniometer device developed was mechanical, later electric, and optoelectronics goniometers were developed to improve the accuracy of the device and to allow for continuous data collection. A goniometer has two arms separated by a hinge. To measure MCP angle, one arm attaches along the back of the hand, and the other arm attaches on the segment after the joint. The length of the goniometer is aligned over the bones. In the alignment of the goniometer, several things can contribute to the inaccuracy of the results since placement is affected by the shape of the joints and bones, fat, and mass of muscles [7]. Besides, the goniometer does not stick to the site of contact with the joint and bones, it moves by the movement of joints, and this contributes to inaccuracy, and it decreases repeatability from one test to another at different time [8]. In addition, the manual goniometer is associated with Inter-tester error problems that are not

present in other approaches for measuring ROM as biomechanical or machine vision approaches [8]. The mechanical goniometer used to measure finger angles in the Functional Measurement lab is shown in Figure (2.2).

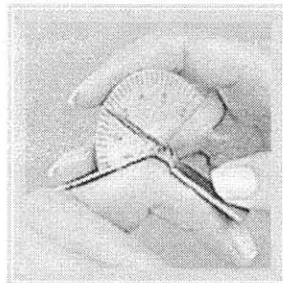


Figure 2.2 Goniometer measuring the CP joint. [9]

Although the goniometer measures joint angles, it can not be used to measure real time range of motion and hand function for multiple reasons. A meaningful hand function is formed by a sequence of hand actions and not by a static posture. Finally, the activity of a hand includes movement of multiple joints and not single one. Therefore, the need to measure multiple joint angles both automatically and continuously requires different methods.

There are different approaches to study hand activity by measuring joint angles in the hand in real time. The two main approaches are machine-vision and biomechanical or haptic approaches. The former analyzes the video and image data of a hand in motion while the basic idea of the haptic approach is to gather and analyze data from a glove [11]. The main disadvantage of the machine-vision approach is the need of a camera to continuously monitor the hand. One limitation is the need to locate the camera in a pre-defined position with respect to the hand all the time, and this is very cumbersome if the camera is to be worn by the individual, or a second person must follow the patient all day long. Another disadvantage is that post-processing of image data is complicated and time

consuming. In the Haptic approach, gloves can be used to capture quantified values of different properties of the hand, such as joint angles in real time; however, those devices should be portable, light weighted, cost-effective, and effectively functional over long period of time. Different gloves available in the market, each has different characteristics that make it suitable for specific application.

Example of commercial gloves include the Data-Glove family (Fifth Dimension Technologies (5DT), Irvine,CA), Cyberglove (Immersion Corporation, San Jose, CA), and the Humanglove™ (Humanware S.R.L., Pisa, Italy) [12]. Humanglove uses 20 Hall Effect sensors to measure data related to a degree of freedom (DOF) of the hand. The control unit of this glove is connected to the PC via RS-232, so it is not considered portable [11]. Its size makes it unsuitable for data collection while doing normal daily activities. CyberGlove® (Figure 2.3) uses piezoelectric sensors, it has been used in sign-language recognition applications, virtual technology, tele-robotics and video games; however, they have big size and mass, not portable, and expensive. In conclusion, they are not suitable for this application which is studying hand activity in the normal environment and not at a laboratory or clinic [12].

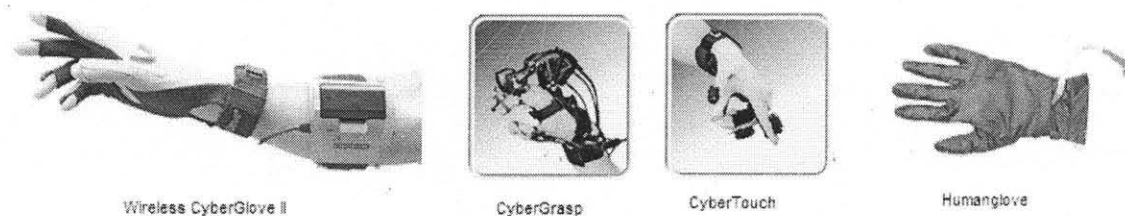


Figure 2.3 Cyber-gloves first three to the (left) manufactured by Immersion Corporation [13] and the fourth manufactured by Humanware [14].

Example of non commercial gloves is GRASSY (Grasp ASsessment System) glove; it is being used at the Computing Lab in Zurich for investigating human hand grasp function. The glove was implemented with Force Sensing Resistors (FRSs) to study finger tip forces, and sliding potentiometers mounted on the back of the hand have been used to quantify the flexion for each finger. Designers of this system report that the measurement data are very promising but no final assessment is available. [15]

Some companies as 5DT and Immersion offer wireless versions of their gloves using Bluetooth technology to transmit data to nearby computer; however, these wireless options can be expensive and do not give the wearer the freedom to move about the home and community settings while data is being collected [11].

In this application, there is a need to a glove that is easy to don and doff especially for individuals with reduced range of motion after brain injury, many cannot open the fingers to put on a traditional glove. The gloves must be lightweight and unobtrusive in order to be worn comfortably for more than 24 hours. Another concern is durability, and consistency, the results should remain consistent throughout the data collection period. The cost as well is a major concern since the glove will be used by many participants, and multiple gloves will be needed. In addition subjects are supposed to wear the glove while performing daily activities, so low cost allows easier replacement after possible damage.

Since existing measurement methods, especially commercial gloves, are not suitable for the assessment of functional capacity over time and in the community due to the broad range of hand function disorders, Shadow Monitor was developed to allow unobtrusive measurements of finger postures across all ability levels in this underserved population [16]. The shadow monitor glove is considered portable since it records

continuous streams of finger posture and transmit them wirelessly to the PC. The wearability property is due to the embedded flexion or bending sensors attached to the back of the hand over the 5 MCP joints, leaving the palm free of obstruction. Both the control unit and the sensors have light-weights. Conclusively, Shadow monitor gloves do defeat the obstacles of donning and doffing, sensor drift over joints, portability, low cost, and lightweight packaging [16], and they can be considered best suited for studying the functional measures of hand activity while doing daily activities. The function of the glove proved to be effective for this type of study in terms of repeatability.

2.4 Types of Grasps

The primary objective of this thesis study is trying to determine hand activity from the bending angle of the MCP joints. First, it is important to define the different types of grasping activities. Based on Webster's dictionary [17], grasp is to seize and hold by clasping or embracing with the fingers or arms. Prehension is the application of functionally effective forces by the hand to an object for a task, given numerous constraints. With activity, the joint angles change and hand muscles flex or extend in order for the hand to reach out and grasp an object, by opening or closing fingers into a shape suitable for a certain grasp. There have been several attempts to classify different hand postures from different perspectives including, medical, clinical, occupational, and industrial applications.

The first study on classifying hand posture was by Schlesinger in 1919. Schlesinger gave 12 classes for hand posture: open fist cylindrical grasp, close fist cylindrical grasp, spherical prehension, palmar prehension, tip prehension, lateral

prehension, hook prehension, cylindrical w/add thumb, flat and thin two finger pincer, three-jaw chuck, and nippers prehension. Schlesinger basic classifications are summarized in Figure (2.4). Some researchers classified different classes of hand posture based on anatomical features and others on the functional features of the hand. Napier classified power grip based on the anatomical position of the thumb, classifications are summarized in Figure (2.5). In a power grip, the thumb is located in the plane of the palm and the MCP and carpo-phalangeal (CP) joints are adducted. Precision element in the power grip depends on thumb placement which ranges from precision when the thumb is adducted and can contact the object to no precision when the thumb is abducted. Elliot and Connolly (1984) clarified that researchers should take care of the different features, anatomical and functional, when distinguishing hand posture. [18]

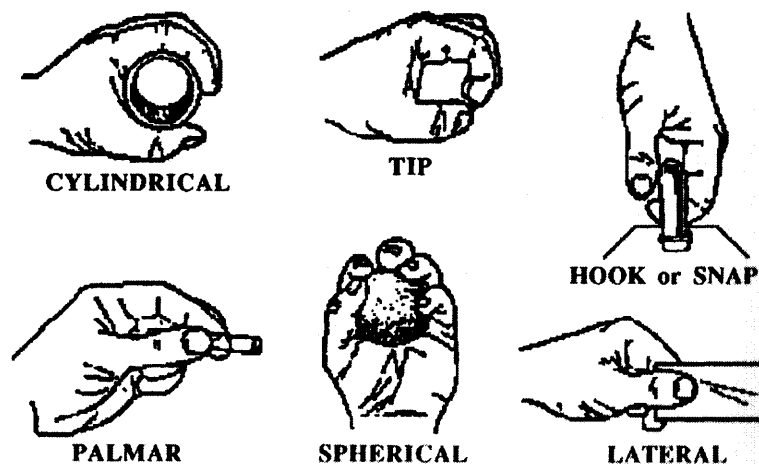


Figure 2.4 Schlesinger's classification of prehensile posture [18].

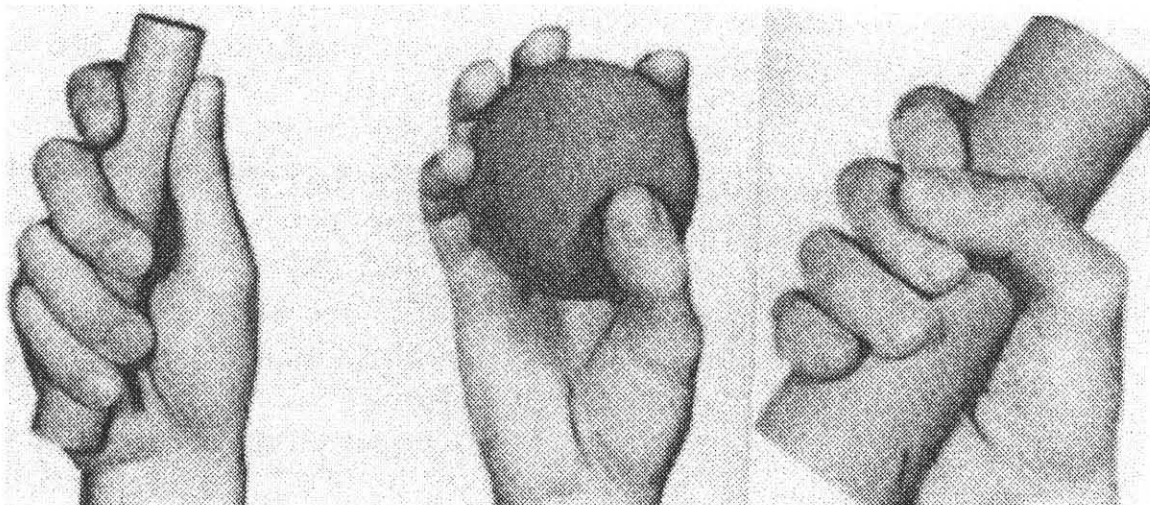


Figure 2.5 Napier's classification of prehensile postures. The first to right is "power grasp", in the middle "precision grasp", and to the left a special type of precision grasp called "coal hammer" [18].

An important way to look at hand prehension is to look at the forces being applied in opposition to each other against the surface of the object. Iberall, Bingham, and Arbib (1986) used for the first time the term opposition to define three classes: pad opposition, palm opposition, and side opposition. Pad opposition generally occurs along an axis parallel to the palm, as in the case of holding a small ball or a needle. On the contrary, palm opposition occurs along an axis perpendicular to the palm when holding for example a hammer. Lastly, side opposition occurs between hand surfaces along a direction generally transverse to the palm as when holding a cigarette. Figure (2.6) describes the different postures that consist of three basic ways the hand can provide opposition around objects. Figure (2.7) shows how something called virtual fingers (VF1 and VF2) define a specific grasp based on their orientation along x, y, and z axes. The literature shows that classifying a hand posture or hand prehension depends on MCP joints and CP joints and on the position of the hand surface with respect to the palm.

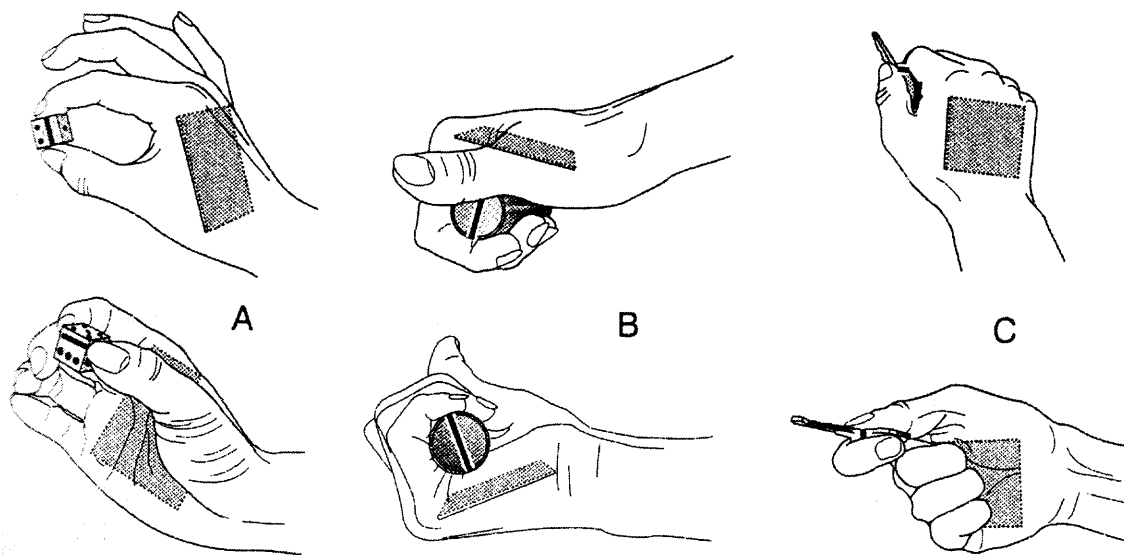


Figure 2.6 A. Pad Opposition that occurs along an axis that is parallel to the palm. B. Palm opposition that occurs perpendicular to the palm. C. Side opposition along an axis transverse to the palm [18].

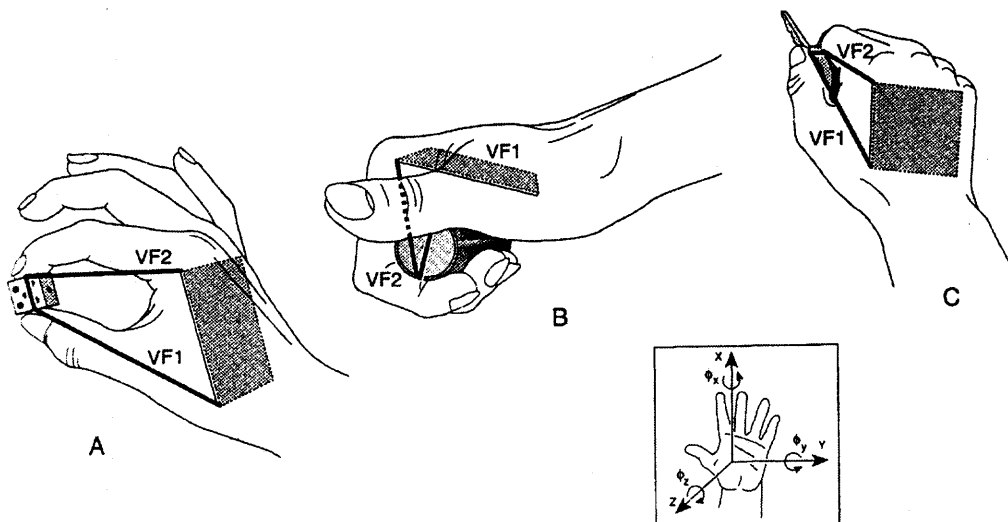


Figure 2.7 Oppositions described in terms of virtual fingers (VF1 and VF2). A. Pad opposition along an axis (x) parallel to the palm. B. Palm opposition along axis (z) perpendicular to the palm. C. Side opposition along an axis (y) transverse to the palm [18].

In this study, the Shadow Monitor was used to record angles from the MCP joints only. So, there is no information about the forces across the palm and about the CP joints. Therefore, it is impossible to imitate any of the classifications present in the literature; the

challenge was to create activity classifications specific to this study. In this application, there is a need to know the general type of activity and not strictly what was the type of grasps that is why it was suggested that using information just from MCP joints might be quite enough.

2.5 Wavelet Analysis

2.5.1 Introduction to Wavelets

As mentioned in the introduction, the hand posture activities include finger angles that vary in an unpredicted manner with changing time and frequency. Therefore, the data are localized in time and frequency. The concept behind Fourier analysis is to convolute the signal with a cutting window, knowing the exact frequency and the exact time of occurrence of this frequency in a signal. By other means, in Fourier analysis the Fourier transform of a waveform is to decompose or separate the waveform into a sum of sinusoids of different frequencies. However, joint angle in hand activity has no predefined pattern, and it was unrealistic to use Fourier analysis for analysis. Joint characteristics are non-stationary signals that involve a compromise between how well transitions between activities can be localized and how well long-term behavior can be identified. [19]

Wavelet analysis was the best alternative because of its scalable modulated window; in wavelet transform short windows are used at high frequencies and long windows at low frequencies, therefore, wavelet analysis help encounter many kinds of waves without favoring a set of particular functions [20]. Instead of fixing the time and the frequency resolutions (Δt and Δf) in Fourier transform, both resolutions vary in time-

frequency plane in order to obtain a multi-resolution wavelet analysis. Wavelet analysis is gaining popularity because of its power in giving chance for researchers to have good time and frequency resolution due to a shape that might be close to the signal and is not a sine wave.

The concept in wavelet analysis is to decompose the signal into a set of equal bandwidth frequency channels. A window with variable scaling factors is shifted along the signal and for every position the spectrum is calculated, this window is called mother wavelet. There are multiple wavelet families in the literature, wavelet families depend on different mother wavelets. The choice of a mother wavelet depends on multiple factors and it is very important since the application of wavelet transform is a correlation analysis between the input signal $s(t)$ and the basis function of the mother wavelet $\psi(t)$ [21]. The two variables that define wavelet matching are the width or scale “a” and the position or shift scale “b” (Equation 2.1). The wavelet is convolved with the original signal as defined in Equation (2.2).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right), \quad a, b \in \mathfrak{R}, \quad a \neq 0, \quad (2.1)$$

$$C(a,b) = \frac{1}{\sqrt{a}} \int s(t) \psi\left(\frac{t-b}{a}\right) dt \quad (2.2)$$

$C(a,b)$ are the coefficients produced after correlation between the signal and mother wavelet, it describes the quality of match between the signal and the wavelet. The integration of the signal multiplied by the wavelet shows that local maxima of C represents inflexion points in $s(t)*\psi$ and it defines initiation of signal [22] or it can be describes as a discontinuity or transition between inactive to active, Figure (2.8) describes how wavelet identify discontinuity in the signal.

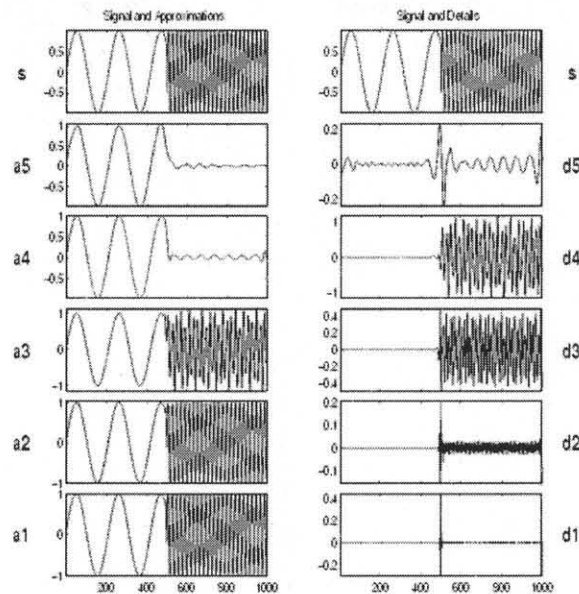


Figure 2.8 Example of using wavelet analysis to identify discontinuity in the signal. The parameter “a” stands for approximate coefficients and “d” for detailed coefficients [23].

The coefficients derived by Equation (2.1) can be used to reconstruct the original signal through “inverse coding”, however, faithful construction of a signal after decomposition, requires multiple conditions to exist in the wavelet primarily orthonormality. Before starting the discussion of reconstruct, there are two basic properties should present in the mother wavelet which are admissibility and regularity.

2.5.2 Wavelet Properties

The admissibility condition in the wavelet makes it oscillate about a mean of zero (Equations 2.3 and 2.4). This conditions implies that frequencies at or near 0 are very slow waves with infinity wavelength, and then the wavelet vanishes at a definite point in time. This concludes that the wavelet is localized in time domain, and compactly supported in the frequency domain. The localization in time and compact support in

frequency properties cannot both be exact at the same time; the condition depends on the position of time (t) and frequency (ω) in the Heisenberg box. Heisenberg box (Figure (2.7)) is a rectangle R with area 2π in the time-frequency plane. The position of t and ω in the box defines the Heisenberg uncertainty plane (Equation 2.4) where the Heisenberg uncertainty principle insures that the time (Δt) and ($\Delta\omega$) are inversely proportional and cannot both be solved for at the same time [20].

$$\int \psi(t) dt = 0 \quad (2.3)$$

$$|\psi(\omega)|^2 |_{\omega=0} = 0 \quad (2.4)$$

$$\Delta t \Delta f \geq \frac{1}{4} \pi \quad (2.5)$$

When the energy of the signal is finite, admissibility function permits exact reconstruction of the original signal without need for all values of decomposition, or for all coefficients. Known wavelets generally satisfy the admissibility condition. The effect of admissibility condition is to make it possible to characterize a continuous-time signal $s(t)$ by the knowledge of the discrete transform. Discrete analysis is sufficient in such case while continuous analysis is redundant. When the signal is recorded in continuous time or on a very fine time grid, both analyses are possible. Discrete analysis ensures space-saving coding and is sufficient for exact reconstruction. The major advantage of continuous analysis is that it is easy to interpret, since its redundancy tends to reinforce the traits and makes all information more visible. This is especially true for very subtle information.

Regularity property insures that the product of time and frequency (Δt and Δf) as low as possible. This could be accomplished by eliminating low frequency components

from high scales, so at very small scales approach zero, the wavelet decay to amplitude zero. Therefore, the coefficients of the signal decay as the scale converges to zero. As discussed at Matlab[®] Wavelet toolbox, the regularity criterion is useful for getting nice features, like smoothness of the reconstructed signal. Both the smoothness and localization of wavelet ψ combined with the admissibility condition suggest that [24]:

- i) Wavelets are bandpass filters such that the frequency response decays sufficiently rapidly as $\omega \rightarrow \infty$ and is zero as $\omega \rightarrow 0$.
- ii) $\Psi(t)$ is impulse response of the filter which decays rapidly as t increases. It is an oscillatory function with mean zero and assumed to be absolutely integrable functions.

Wavelet analysis depends on convoluting a section of the signal $s(t)$ and a wavelet. The scaling factor “a” is the frequency parameter, if “a” is large, the basis function will be a stretched version of the original mother wavelet, and this basis function is useful for isolating low frequency components of the signal. If “a” is small, the basis function will be a compressed version of the mother wavelet and it will be used in isolating high-frequency components of the signal. The convolution of the signal with a basis function of mother wavelet that has a “large” and “small” scaling factor lead to decomposing the signal into “approximate” and “detailed” coefficients of the signal respectively. The translation factor “b” is the time parameter that helps scan the signal with the basis functions with all possible scaling factors. The result of wavelet decomposition is a list of time-frequency representations of the signal known as decomposition coefficients. Each of the different scales in the decomposition process pertains to a specific frequency channel so that various scales will bring out details that are not apparent in the original signal.

2.5.3 Multi-resolution Analysis (MRA)

The simultaneous existence of multi-scale of the original signal is also referred as multi-resolution. Based on different applications, MRA is an effective framework for hierarchical decomposition of a signal into component of different scales [24]. MRA is completely determined by the scaling function $\varphi(t)$. The concept behind MRA is to represent a signal as a formal approach to construct orthogonal wavelet. The theory of MRA is to start from a single wavelet ψ , and a family of functions $\psi_{m,n}$ that is generated from ψ by the operation of binary dilations by 2^m and dyadic translation $n2^{-m}$, the factor $2^{m/2}$ is introduced to ensure orthonormality (Equation 2.6). The orthogonality property insures simpler reconstruction of the signal and Orthonormality is the condition where both orthogonality and normality properties exist.

$$\psi_{m,n}(x) = 2^{m/2} \psi \left(2^m \left(x - \frac{n}{2^m} \right) \right) = 2^{m/2} \psi(2^m(x-n)), \quad m, n \in \mathbb{Z} \quad (2.6)$$

A wavelet of ψ is said to be orthonormal if the family functions $\psi_{m,n}$ is orthonormal. The wavelet series of a function f is described in Equation 2.7, where $c_{m,n}$ defines the wavelet coefficients (Equation 2.8).

$$f(x) = \sum_{m,n=-\infty}^{\infty} c_{m,n} \psi_{m,n}(x) \quad (2.7)$$

$$c_{m,n} = (f, \psi_{m,n}) \quad (2.8)$$

Exact reconstruction of the signal requires bi-orthogonal two pairs of filters. The concept behind signal decomposition in wavelet analysis is to multiply the signal by low pass filter H to get approximate coefficients, and high pass filter G to get detailed

coefficients. Those filters must be orthogonal to ensure faithful construction of the signal, so the following conditions should apply [25]:

- 1) Self duality $H * H = G * G = 1$
- 2) Independence $G * H = H * G = 0$
- 3) Exact Reconstruction $H \times H + G \times G = I$
- 4) Normalization $Hl = \sqrt{2}l$ where $l = \{\dots, 1, 1, 1, \dots\}$

These four conditions lead to orthogonal property, in case of Quadrature filters ($H = H'$ and $G = G'$) Bi-orthogonality is insured.

Figure (2.9) shows the wavelet analysis for three decomposition levels on the left, signal reconstruction or synthesis from coefficients is represented on the right [26]. HPF and LPF stands for high pass and low pass filters respectively, IHPF and ILPF stands for inverse HPF and LPF respectively.

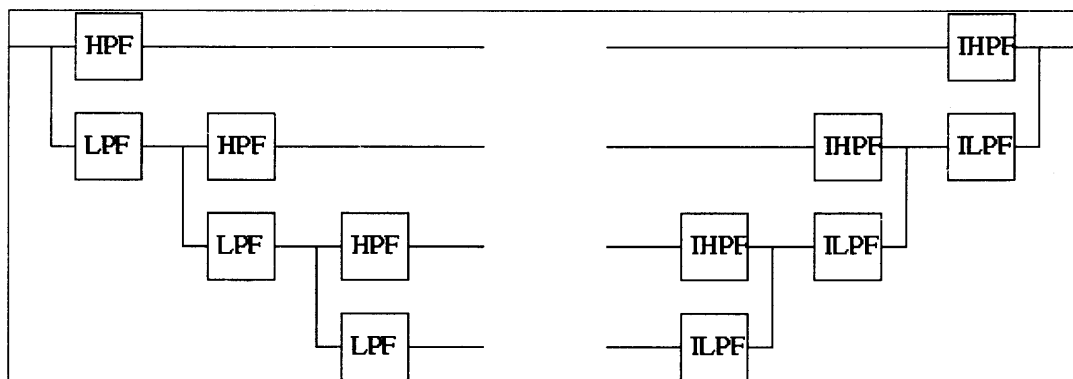


Figure 2.9 Wavelet decomposition on the left and reconstruction on the right [23].

The presence of admissibility, regularity, and orthogonality could lead to good analysis of a signal and faithful reconstruction however there is still one factor should be taken into consideration when choosing a mother wavelet. This factor is the resemblance between the wavelet and the studied signal is important, for example Wilen [27] used

“db6” mother wavelet because of the similarity between the wavelet and the studied motor unit action potential (MUAP). Ismail and Asfour [28] used “db4” in their study since it resembles the triphasic pattern of the studied MUAP.

There exist two types of wavelet analysis, Discrete and Continuous wavelet analysis. As a brief summary, continuous analysis is easy to interpret, and its redundancy reinforces the traits and makes all information more visible. On the other hand, discrete analysis has an advantage by ensuring space-saving coding and by being sufficient for exact reconstruction; therefore what the continuous analysis gains in "readability" and ease of interpretation, it loses in terms of saving space [23]. In this application, the discrete wavelet analysis approach was taken simply because discrete decomposition of the signal is enough in this application, besides it saves time of processing.

After decomposition, coefficients can be used to faithfully reconstruct the original signal without loss of important information in the signal. However, decomposition of the signal in this study was useful to define the site of change of activity by separating high and low frequency components of the data, but reconstruction of the signal after decomposition was not an objective. Temporal analysis is performed with a contracted, high-frequency version of the wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. The site of change in activity is temporal information, thus, it was defined at the instance of high amplitude or peak in the detailed coefficients.

CHAPTER 3

METHODS

3.1 Jebsen-Taylor Study

3.1.1 Data Collection

Previous to studying the hand activity for individuals with movement disorders, it was required to identify determinants of hand posture. What meant by determinants are the quantitative parameters that characterize different activities and different functional performance between healthy and ABI subjects. Those determinants are proposed to scan and divide long-stream data into different segments which have similar properties which roughly correspond to the different activities. The Jebsen-Taylor Hand Function Test includes different types of activities that people do in their daily life, and performance is normally determined by time to complete the tasks. The two groups enrolled in the study are: healthy subjects used as control, and subjects suffering from movement disorders caused by stroke and other types of brain injury. Each group included ten subjects. The seven types of activities are: writing using a pen (J1), simulating turning papers(J2), lifting small objects as a small spherical object (J3), simulate feeding by using a spoon to hold a bean(J4), stacking checkers(J5) , holding a large light can (J6), and holding a large heavy can(J7). The mean age of the 20 subjects was 50.3 (41.0 for HC and 59.5 for ABI). Tables (3.1) and (3.2) summarizes the time that was needed by the subjects to accomplish

the defined activities for the HC and ABI groups respectively. The average time for HC group is 9.935 seconds and 57.315 seconds for the ABI group.

Table 3.1 Time Needed to Do a Jebsen Activity (HC group)

subject\ activity	J1	J2	J3	J4	J5	J6	J7	average
2	10.84	7.88	6.16	5.08	7.92	5.48	5.48	8.140
3	27.86	21.24	27.08	10.2	9.52	7.52	6.86	18.380
4	42.84	3.64	13.04	6.4	11.08	3.2	2.36	13.760
5	22.6	5.8	5.84	5.68	5.56	4.2	4.24	8.987
6	9.72	4.6	6.6	4.2	6.92	4.32	4.84	6.8677
7	25	7.32	8.24	5.32	8.68	5.48	5.36	10.900
8	11.68	4.04	4.08	5.4	6.56	3.4	3.36	6.42
9	14.44	5.24	6.44	6.52	7.56	4.6	4.6	8.233
13	20.32	5.52	10	8.8	11.52	5.32	5.4	11.147
19	9	3.52	6.2	5.12	6.04	4.32	4.92	6.52
average	19.43	6.88	9.368	6.27	8.136	4.78	4.742	9.935

Table 3.2 Time Needed to Do a Jebsen Activity (ABI Group)

Subject activity	J1	J2	J3	J4	J5	J6	J7	average
10	48.64	21.2	23.36	44.84	32.64	16.1	9.36	32.687
11	38.7	217	67.52	34.6	298.1	30	71.8	126.373
12	52.5	69.6	200	28.2	40.2	22.2	21.32	72.347
14	29.9	12.6	26.68	13.4	14	11.8	11.6	20.00
15	42.1	16.2	29.8	21.9	89.76	21.1	13.2	39.027
16	23.8	12.2	19.12	14.0	16.48	10.2	8.32	17.360
18	303	27.9	34.24	148.	24.64	15.3	15.4	94.820
21	16	6.48	10.16	11.9	7.28	7.32	6.96	11.027
22	67.6	110	213.2	191	39.48	19.1	58.96	116.767
23	134	17.3	39.56	19.6	30.84	7.6	7.12	42.740
average	75.7	51.2	66.4	52.9	59.3	16.1	22.4	57.315

3.1.2 Jebsen Data Analysis

Hand posture is not normally evaluated during the test, although MCP joint angle was collected to explore hand posture as well. First, general data pre-analysis was done using Microsoft Excel and it showed that frequency, mean, and standard deviation are

parameters that might characterize different types of activities and differentiate between the two groups. There is no pre-defined frequency to any activity; subjects perform activities at different speed, which is why it was impossible to compare activities based on absolute frequencies although some activities such as writing were characterized by higher frequencies than other activities.

In this study, 20 subjects participated and each subject did 7 activities, therefore, there are 140 files to be analyzed. Microsoft Excel was useful for primary manual analysis; however, it was decided to use Matlab[®] for fast and more efficient automated analysis. For each activity, there are two Matlab[®] files to load data, one for each group, HC and ABI. In the same file, after reading data from the comma-separated (.csv) files, the mean and standard deviation of the data were calculated.

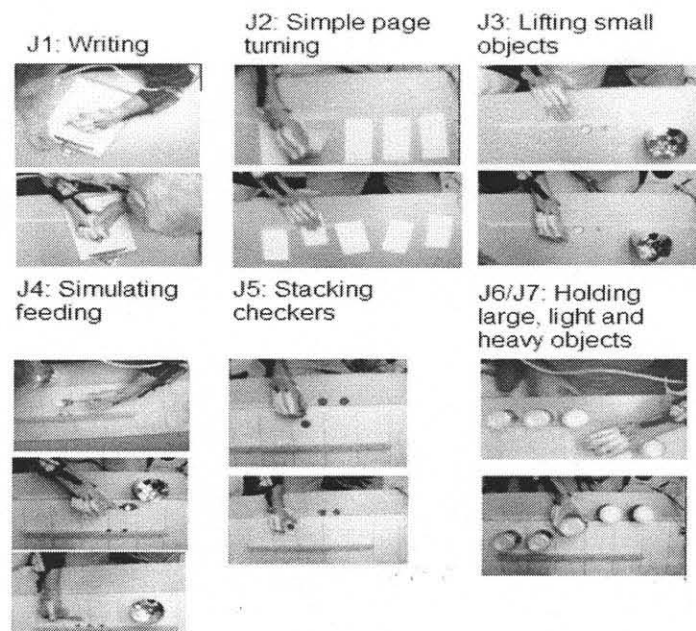


Figure 3.1 Subject doing 7 different Jenson-Taylor activities.

As discussed previously, Wavelet transforms were proposed to detect the instance when the individual changes activity. Wavelet analysis include decomposing the signal into detailed and approximate coefficients, it was suggested that those coefficients could be useful not just to detect instance of change but to differentiate between activities and between the normal and abnormal hand posture. It is important to state here that data analysis was done on digitized data and not continuous signal; however, the theory behind wavelet transform is to decompose continuous signal therefore, wavelet transform on Matlab[®] could also be called Sub-band transform.

The choice of mother wavelet was based on the presence of general properties, admissibility, regularity, and orthogonality, due to their advantages discussed in section (2.5). However, it has been found that there are multiple wavelets in Matlab[®] that supplies these properties. Different wavelets were explored to decompose and analyze the joint activity characteristics; it has been found that different wavelets (including, Haar, Coiflet, Symlet (Sym), Mexican hat (mexh), and Daubechies (db)) give similar results with respect to this application. This similarity includes showing same trend of the signal when using different wavelets. The difference was in the shape of the signal, some wavelets show more resemblance with the studied signal with respect to others. Often, the wavelet selected bears a resemblance to the signal being studied; therefore, based on resemblance with the signal, the Daubechies wavelet was used.

Daubechies wavelet exists with multiple levels. The level of the wavelet is associated with the distance between consecutive filters in the signal. Higher level means closer scaling functions and reading more details in the signal, which increases the result number of coefficients. Given that the wavelet family level is $2*N$, the scaling and

wavelet functions are defined in equations (3.1) and (3.2). The parameters c_k and d_k are wavelet and scaling functions respectively.

$${}_N\phi(x) = \sqrt{2} \sum_{k=0}^{2N-1} c_k \phi(2x - k) \quad (3.1)$$

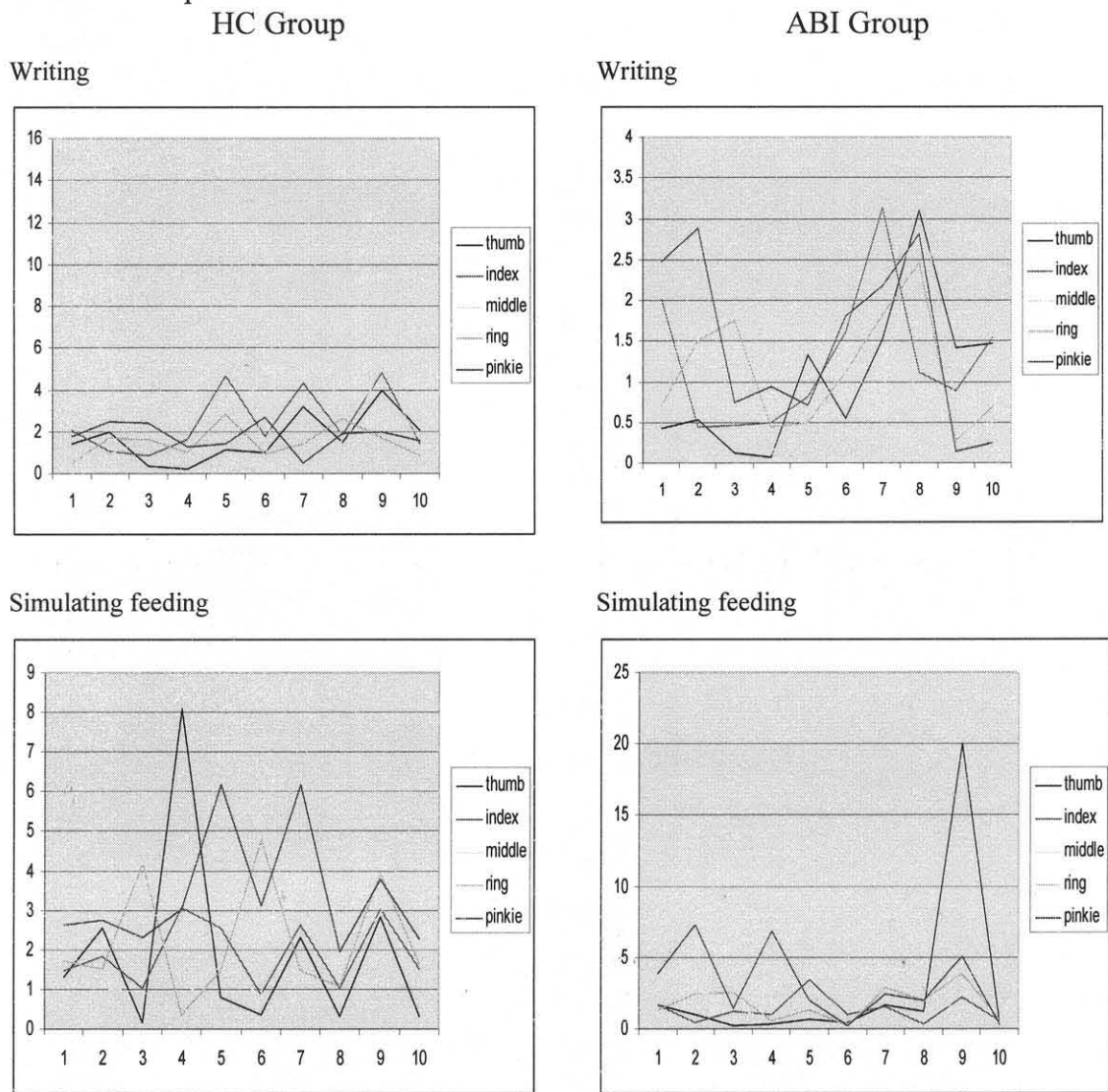
$${}_N\psi(x) = \sqrt{2} \sum_{k=0}^{2N-1} d_k \phi(2x - k) \quad (3.2)$$

The Daubechies wavelet family with level eight was used to study the joint angle's characteristics, since it has been found enough to represent the signals. The result of decomposing the signal leads to a set of approximate "a" and detailed coefficients "d". Those coefficients can be used to reconstruct the signal; however, signal reconstruction was not an objective.

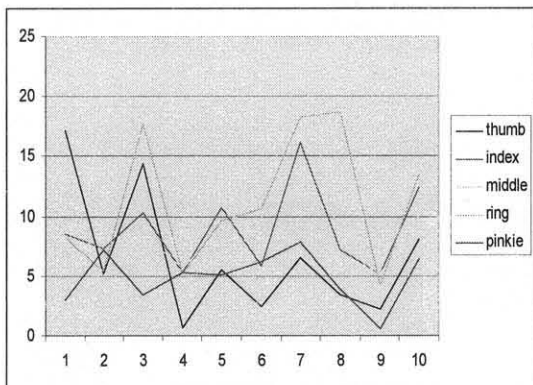
The detailed and approximate coefficients between the two groups were compared. It has been found that the coefficients, specifically detailed coefficients, are generally lower in amplitude and bandwidth in the ABI group than the HC group. This could be due to abnormal motor control (caused by the spasticity in the muscles or low tone), which lessens the ability to do higher frequency (faster) actions with high amplitude by opening and closing joints more fully. With respect to the approximate coefficients, they faithfully represent the original signal; they can be used for mean, standard deviation, and range of motion testing instead of the original signal. Conclusively, approximate coefficients were found useful to study the activity while detailed coefficients show difference between groups. Unfortunately, the difference in detailed coefficients between the two conditions, HC and ABI, could not be quantified. The detailed coefficients were derived for the 20 subjects in the two groups. Table (3.3)

summarizes the plots for those peaks. Although the detailed coefficients' are of lower amplitude in case of ABI group, it is clear that the values are variable so that the difference can not be quantified. The basic reason is that the subjects participated in the study are of different severity levels, besides different people have different ways in writing, holding objects, etc.

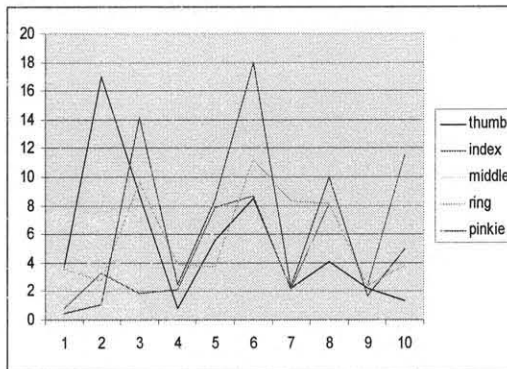
Table 3.3 Summary of the Detailed Coefficients Maximum Amplitude for the Subjects in the Two Groups



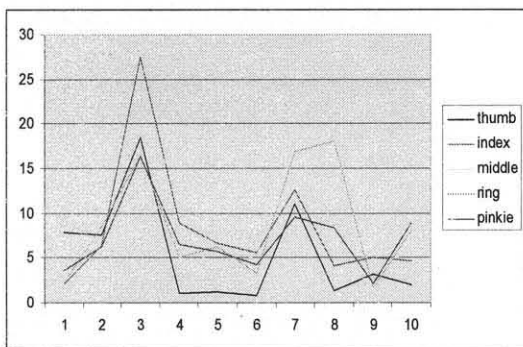
Simple page turning



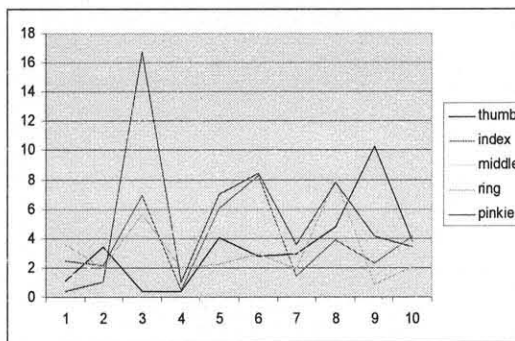
Simple page turning



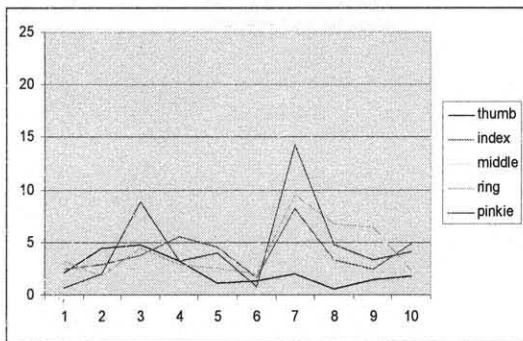
Lifting small object



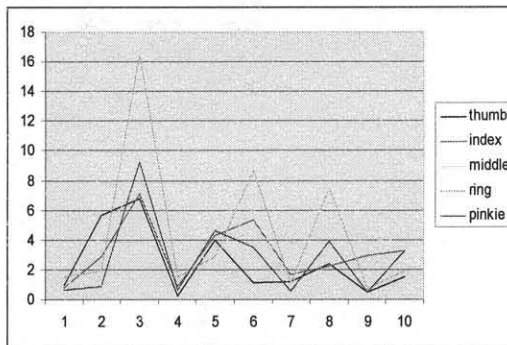
Lifting small object



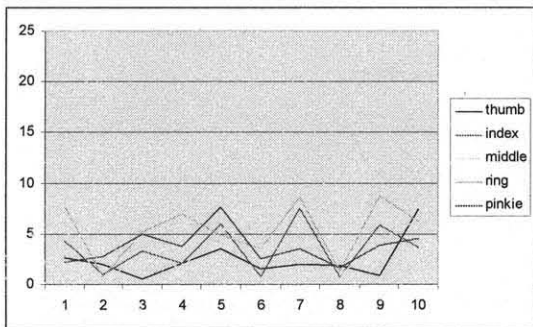
Stacking checkers



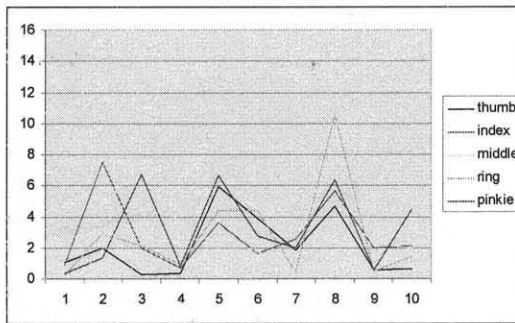
Stacking checkers



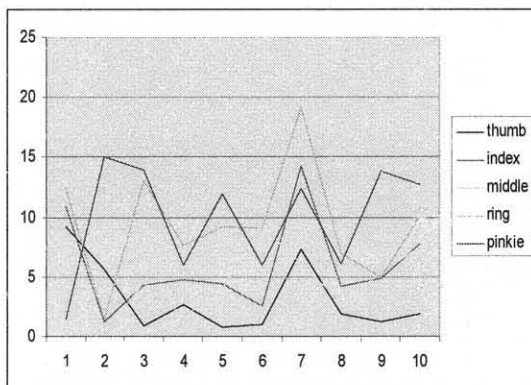
Holding large light object



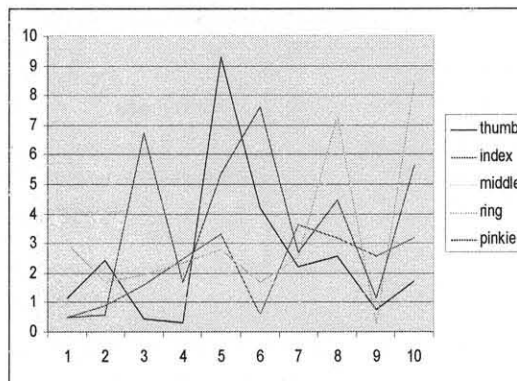
Holding large light object



Holding large heavy object



Holding large heavy object



Analysis was made more difficult because subjects perform the same activities in different ways. Examples of different ways to do an activity are the different ways to hold a pen while writing or different ways to grasp a can, it has been noticed that some subjects hold a can in a cylindrical way where the palm is parallel to the central axis of the cylindrical can while others hold it by putting the palm tangential to the top of the can Figure (3.2). The inability to quantify the difference between detailed coefficients of the ABI and HC group made it impossible to make conclusion about the relation between the detailed coefficient and the level of disease; however, it is important to study this factor in a study where the conditions of the participating subjects are known and quantified based on certain scale, this could help define correlation between detailed coefficient and severity of disease.

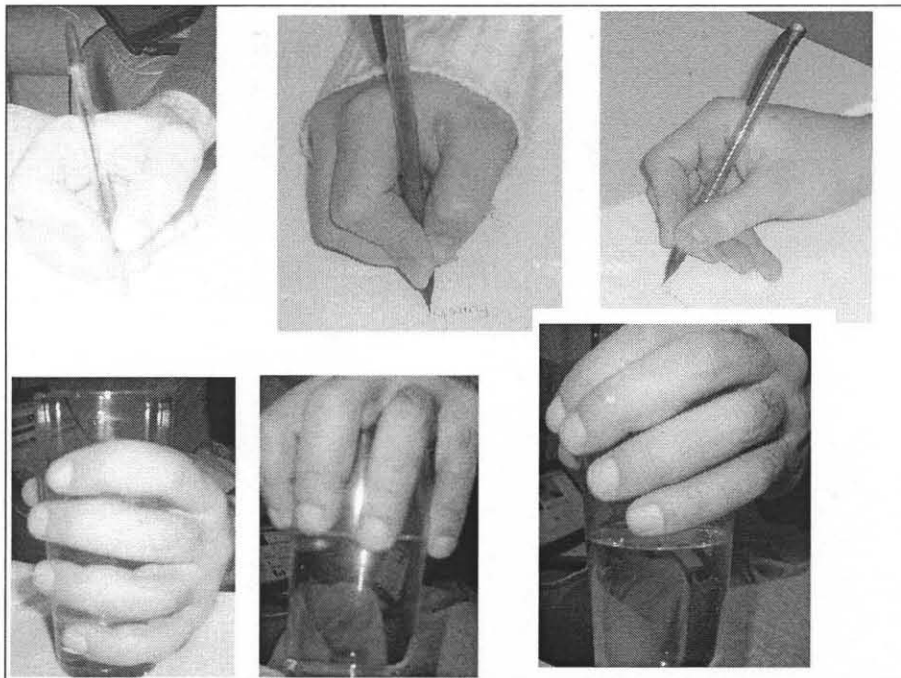


Figure 3.2 Different ways to hold a pen and write or hold a cylindrical object as a glass.

During object grasp, the activation of distal muscles must be coordinated in a way to shape the hand in relative to the physical properties of the object; those physical properties include mass, shape, and size of the object, in addition to the material in contact with the hand. The type of activity limits the range of motion of fingers, thus limits the range of the degree at the MCP joint. Therefore, the range of angle at each of the five MCP joints could help identify the type of activity; this hypothesis was studied by quantifying the range of motion and comparing it between activities and groups.

Conventional method to calculate range of motion is to subtract the minimum angle from the maximum one. However, it is possible that the data include outliers that do not contribute to the activity. Those outliers would affect calculation of ROM. A better method to calculate ROM of an activity is proposed by using the probability density estimate (PDE) of the approximate coefficients. PDE is useful to define

distribution of joints' angles around the peak of PDE, while ignoring any spikes or noise that could appear in the signal. Figure (3.3) shows the joint angles of pinkie, the maximum angle is 75 degrees, and the minimum angle is 19. The 75 degree peak is likely caused when the subject banged his hand on the table; these spikes are not related to the writing activity. If the range was calculated by the difference between minimum and maximum, the result is range of 51 degrees, however the probability density in Figure (3.4) suggests that the 75 degree peak does not contribute to the activity, and that the more realistic range is between 25 and 40.

To perform this analysis, the Matlab[®] function used is `ksdensity`, which depends on the kernel smoothing method to calculate PDE. The range of angles in addition to the difference between upper and lower limit in the range were calculated for the seven activities in the two groups. As an example, in case of writing one of the subjects had the range of angles at the thumb between 62 and 82, index between 53 and 64, middle between 74 and 79, ring 45 and 50, and pinkie between 35 and 43, The difference between upper and lower limit was found maximally 20 or for writing. The ranges for all the subjects were calculated in the same way, their averages are summarized in Table (4.1) in Chapter 4. In the table, the Lower Angle is the minimum joint angle during an activity and the higher angle is the maximum one, 'diff' is the difference between the maximum and minimum angle in each activity for the five joints. The table shows clearly how the ranges are much similar within three groups of activities (J1&J4), (J2, J3, & J5), and (J6&J7). This conclusion introduced to the fact that the seven activities can be classified into clusters.

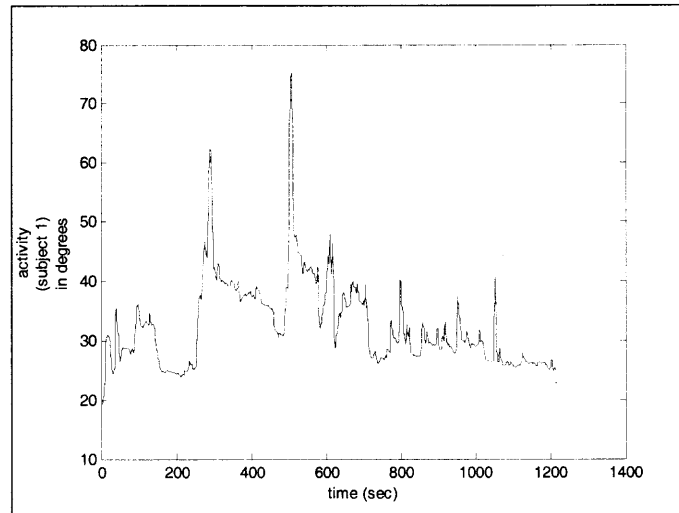


Figure 3.3 activity of pinkie when the subject was writing with a pen (ABI group).

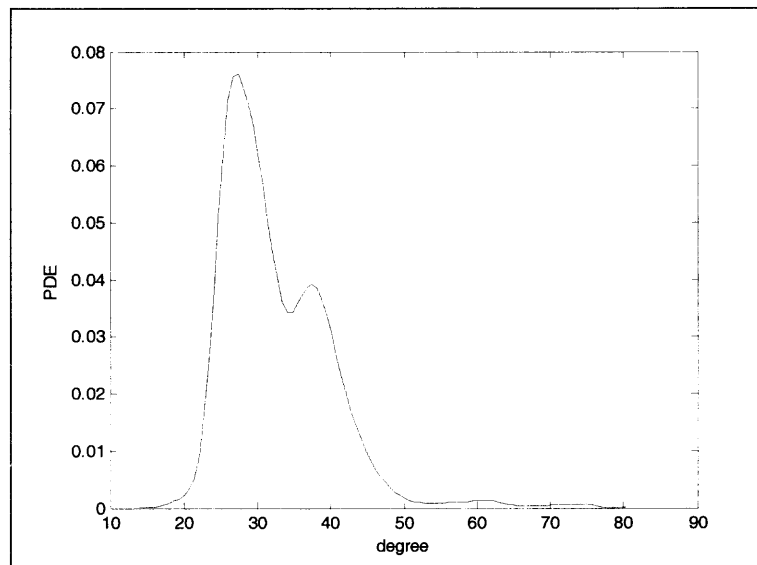


Figure 3.4 probability density estimate of pinkie activity shown in figure (3.3)

After analyzing range of motion, the mean and variance of joint angles were calculated and saved in excel (.xls) files. Later those files were studied to quantify the difference between activities. The joint angles' means were compared for each activity, between and within the two groups (HC and ABI). It was concluded that despite the change between mean average between HC and ABI groups, this difference exists as well within the same group between subjects doing the same activity, this is due to the fact

that hand activity is a very complex action where multiple factors contribute in changing it from a person to another.

With respect to variance, there were no significant difference between HC and ABI group, since similar difference existed between healthy subjects doing same activity. In general, variance of ABI group is lower. The joint angles' mean and variance were used to characterize an activity. For each activity, it has been found that an activity lies more likely in a specified range of means more than another one, this lead to define three ranges for each activity giving each range a power. Besides, it has been found that for each group of activities there is a maximum variance. Similarities and difference in the mean of joint angles and maximum variance is discussed in chapter four. It can be stated here that those similarities and difference lead to classify the seven activities into three clusters, precision, palmar, and cylindrical grasp.

Next study was speed analysis. Speed of activity is a parameter used to study the condition of hand activity, so the speed of flexion and extension of fingers were calculated and compared between and within groups. Speed analysis Matlab[®] function was built to calculate joint speed as the difference between current and previous sample divided by the difference of time (3.1).

$$speed(n) = \frac{data(n) - data(n-1)}{time(n) - time(n-1)} \text{ deg/sec} \quad (3.1)$$

Minimum flexion and maximum flexion are the minimum and maximum positive speed respectively, and minimum and maximum extension speeds are the minimum and maximum negative speed respectively. The output of the speed analysis function is the flexion average speed, extension average speed, maximum and minimum extension, maximum and minimum flexion, and range of motion which is the difference between

maximum flexion and minimum flexion. Speed is used to provide information about the condition of the activity in terms of fluency and quality; but it is not used to differentiate between activities, simply because different individuals performed same activity with different patterns and speeds, tables in Appendix A summarizes the average speed for the 20 subjects while doing the seven activities. Although, for the same subject, flexion and extension speed differs between from one activity to another. This could not be extrapolated to conclude range of speed to different activities although it is taken into consideration in the study due to its correlation with standard deviation.

The seven activities were classified into three clusters based on the similarity in the mean and variance ranges. Three Matlab programs were built for each cluster. In each cluster, the mean and variance of the joint angles were compared by the ranges predefined by the results of Jebsen study; each range was given a power of 60, 40, or 20. This power is defined by the statistical analysis of Jebsen study. For each activity in a cluster, the powers for the four fingers, index, middle, ring, and pinkie are calculated. The power of the thumb was not calculated since the range of mean did not vary much between activities. The sum of powers are calculated, it varies between 0 and 240. Class one include calculating powers of the writing and simulating feeding activities, class two for palmar group that include simple page turning, stacking checkers, and lifting small objects. Class three works for the cylindrical group that includes holding large heavy and light cans. Class one define precision activities, class two more include activities done across the palm (palmar grasp), and class three include cylindrical grasp activities. Class four was added to match with durations when the subject is not active, a minimum standard deviation was defined (6 degrees), if the five joints have joint angles with

standard deviation less than 6 degrees, and the activity is classified as class four which means no activity. In each class, class power is the maximum of the individual activity powers.

3.2 Long-stream Data Study

Data of hand activity was collected from a subject who used the Shadow Monitor glove for about 25 hours. The subject is a healthy person who performed normal daily activities as office work, cooking, typing, driving, and sleeping while wearing the glove. The primary goal was to define the instance of transition from one activity to the next in order to classify types of activities performed, and the durations of these activities. As mentioned previously, wavelet analysis was used to define the site of change by tracking peaks in the detailed coefficient. The Daubechies wavelet ($2N=8$) was used. Analysis was done at the second level, the position of peaks along the time span of the signal does not change much from the first to 8th level

In order to define a peak in the detailed coefficient that represents the instance of activity change, a minimum threshold for peak should be defined. The choice of threshold needs to be done carefully in order to avoid missing an instance of activity change if it is very high, or having very short segments if the threshold is low. Visual feedback from the detailed coefficients of the signal showed that threshold could be defined at amplitude of 3 degrees in the detailed coefficients. This threshold could be different for another subject; during Jebson study the amplitude of detailed coefficients was variable between subjects.

For different types of activities, the index is the finger that mostly changes between different types of activities, so it was suggested to use the index to determine the instance of activity change, instead of tracking the peaks at the five joints. The validity of this choice was studied by comparing the instance of peaks at the five fingers; it was found that those peaks occurred at nearly the same time for the five joints. Therefore, choosing one joint is better for reducing duration of data analysis.

After decomposing the index, and detecting the peaks, the data is segmented between one peak and the next one. The length of this segment is calculated, if the length is shorter than 500 samples which is approximately 20 seconds, the segment is ignored because it might be short to describe a complete activity. Data segmenting continues to the second peak ignoring the previous one. After cropping every segment, a function decision is called. This function includes running the programs for the four clusters and comparing the power for each class.

In the decision function, the power of each class is calculated; the powers are then compared to define the maximum one, and the confidence proportion for each class was calculated by dividing the class power over the maximum power which is 240. The decision of activity depends on which class has the highest power. Presenting the confidence proportions next to the activity will show how close an activity is to each class, this is important since there is overlap in the mean ranges and variances in the three classes so that any activity can not be absolutely classified. After defining the segment activity, the function "speed analysis" is called to calculate; flexion and extension speed averages, in addition to maximum and minimum flexion and extension speed. The

averages of ROM for the five joints are also calculated, in addition to standard deviation average.

Finally, a Matlab[®] file (`longstream_data_analysis.m`) was built to do data analysis of the whole long stream data. The long-stream data was saved in 35 spreadsheet files because of the limitation to save the whole data in one file. In this file, each of the 35 spreadsheet files are loaded, then “`decompose.m`” function is called given index data as input. After decomposition step, the “`Segment.m`” file is called. The result of the last function is an array “`R`” that include: duration of segments, activity during each segment, confidence proportion for three classes, flexion speed average, extension speed average, maximum flexion, maximum extension, average of ROM, and finally average of standard deviation. The final step after analyzing each file is to summarize the results. After analyzing the first data file an array “`T`” that include titles of data in the R files is saved to spreadsheet file named “`result.csv`”, then the transpose of array “`R`” is appended. After analysis of every data file, the transpose of array “`R`” is appended to the result file. The final result will be a spreadsheet file (`result.csv`) that summarizes information about hand activity during 25 hours.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Jebsen-Taylor Study Results and Discussion

The main objective behind doing the Jebsen-Taylor study was to identify determinants in hand activity and extrapolate the results to analyze data of unknown activity. The result was classifying the seven Jebsen activities into three groups: precision grasp, palmar grasp, and cylindrical grasp. This classification was based on the similarity of parameters whether range of angle, mean, and variance within each group.

The range of angle analysis implied that the seven groups could be defined in three clusters. In case of writing and simulating feeding data, the difference between upper and lower borders of the angle is low, it is also low in case for holding cans however, the ranges of joint's angles were lower than in case of writing and simulating feeding simply because the fingers are widely open when holding can while they are bent to hold a small object or to do precise activity. In case of simple page turning, lifting small objects, and stacking checkers, the range borders changed between low and high, but the difference between the lower and upper borders of the range was found to be higher than the other activities. These conclusions introduced to the possibility that the seven activities could be put into clusters. The next parameters to be studied were mean and standard deviation, the mean and standard deviation of joint angles represent the distribution or range of joint angles during an activity.

Table 4.1 The Means of Joint Angles' Ranges for each Activity.

Activity	thumb			index			middle			
	lower angle	higher angle	diff	lower angle	higher angle	diff	lower angle	higher angle	diff	
J1	12.50	26.38	13	30.6	46.47	15.5	42.82	60.7	19	
J4	11.52	28.62	17	23	44.35	21.1	29.54	53.3	24	
J2	3.05	29.35	26	7.9	47.33	39.4	2.202	57.17	55	
J3	3.57	25.48	22	13.6	54.45	40.8	10.76	53.44	43	
J5	3.45	30.52	27	14.9	52.27	37.4	9.388	48.35	39	
J6	2.55	19.8	12	3.94	27.64	25.2	3.31	30.85	28	
J7	2.611	22.78	20	3.62	29.67	26.1	3.33	32.41	29	
ring				pinkie						
Activity	lower angle	higher angle	diff	lower angle	higher angle	diff				
J1	26.06	14.47	28	44.1 2	18.31	41.1				
J4	25.06	55.49	30	22.4	55.12	32.6				
J2	1.385	43.25	41	2.37	41.83	33.3				
J3	10.16	49.61	39	5.26 7	46.51	41.2				
J5	7.98	51.89	44	3.99	49.67	45.7				
J6	2.69	34.38	31	3.33	35.9	32.6				
J7	2.61	34.67	32	3.31	36.35	33.1				

The mean of each activity for the five joints were calculated and the distribution of the angles in a range was summarized in the tables (4.2) through (4.8). Three intensity levels, black, dark grey, and grey, were used to illustrate higher, medium, and lower number of subject have activity in a specific range. For the writing and simulating feeding activities, the angles were distributed along high angles. The distribution is more clear and localized in the writing activity than the simulating feeding activity. Since in the both cases the joint angles are high, then those two activities were located in a cluster defined as the precision grasp class.

Table 4.2 Distribution of Joint Angles during Writing Activity

Writing	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Thumb	■									
Index			■	■	■	■				
Middle				■	■	■	■	■		
Ring	■				■	■	■	■	■	
Pinkie	■	■					■	■	■	

Table 4.3 Distribution of Joint Angles during Simulating Feeding Activity

Simulate feeding	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Thumb	■									
Index		■	■	■	■	■	■	■		
Middle			■	■	■	■	■	■		
Ring	■			■	■	■	■	■	■	
Pinkie		■	■	■	■	■	■	■	■	■

The distribution of the joint angles for the simple page turning activity was found to be around 10 to 30 degrees. Its distribution is considered to be low with respect to the writing and feeding activities. In the case of stacking checkers, the joint angles were distributed highly between 20 and 40 degrees and to a lesser degree around that range. In case of lifting small object, the ranges of joint angles are more distributed, the ranges are said to be low or medium. Tables (4.7) and (4.8) show the distribution of the average joint angles when the subject used to hold light and heavy cans respectively. The angles were found to be low.

Table 4.4 Distribution of Joint Angles during Simple Page Turning Activity

Simple Page Turning	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Thumb	████████████████████									
Index		██	██	██	██					
Middle		██	██	██						
Ring	██	██	██	██						
Pinkie	██	██	██							

Table 4.5 Distribution of Joint Angles during Stacking Checkers Activity

Stacking Checkers	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Thumb	████████████████									
Index		██	██	██	██	██				
Middle	██	██	██	██	██	██				
Ring	██	██	██	██						
Pinkie	██	██	██	██	██	██	██			

Table 4.6 Distribution of Joint Angles during Small Object Lift Activity

Small Object Lift	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Thumb	████████████████									
Index		██	██	██	██	██	██			
Middle	██	██		██	██		██	██		
Ring	██	██	██	██	██	██	██			
Pinkie	██	██	██	██	██					

Table 4.7 Distribution of Joint Angles during 'Holding Large Light Object' Activity

Large Light Object	-10 - 0	0- 10	10 - 20	20- 30	30- 40	40- 50	50- 60	60- 70	70- 80	80- 90	90- 100
Thumb											
Index											
Middle											
Ring											
Pinkie											

Table 4.8 Distribution of Joint Angles during 'Holding Large Heavy Object' Activity

Large Heavy Object	- 10- 0	0- 10	10- 20	20- 30	30- 40	40- 50	50- 60	60- 70	70- 80	80- 90	90- 100
Thumb											
Index											
Middle											
Ring											
Pinkie											

The variances for different activities were also studied. The Figures (4.1) through (4.6) show that variance values vary between subjects whether in the HC (1 through 10) or ABI (11 through 20). With respect to writing and simulating feeding activities, the variance values were found low with respect to other activities. For simple page turning, stacking checkers, and lifting small objects activities, the variance was variable between low and medium, and a big difference was found between the different joints. The same case was in the case of holding large and light cans. The variance values were found mainly low for thumb, index, and middle and higher for ring and pinkie. Conclusively, the maximum variance for each joint in each activity was calculated and the activities were classified into three groups.

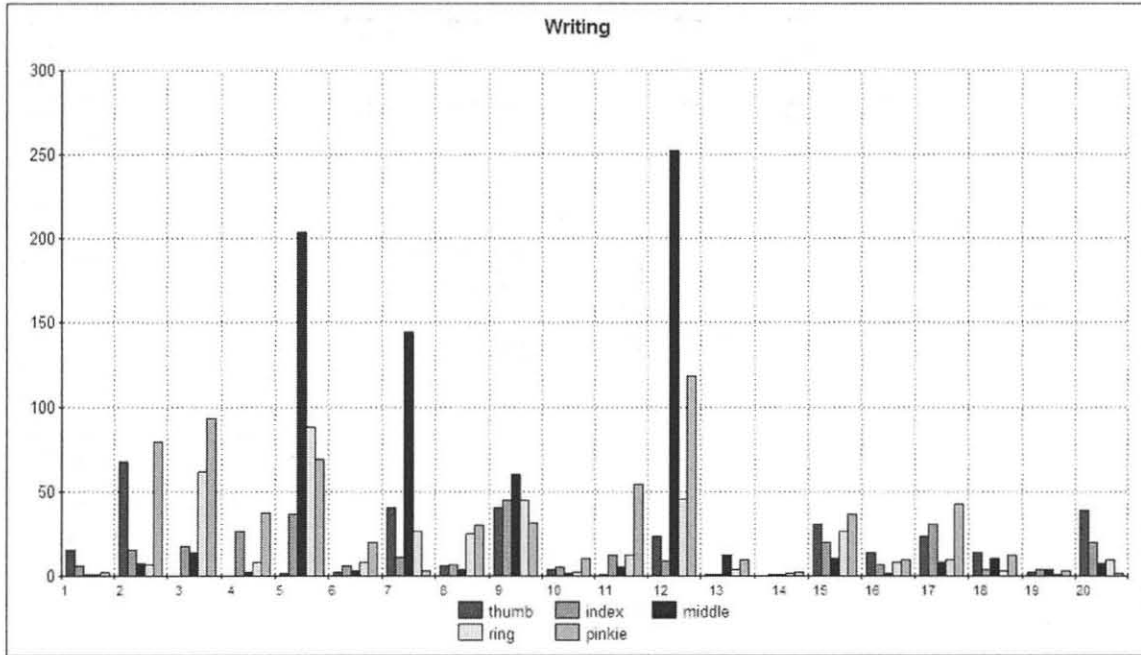


Figure 4.1 distribution of variance for the 20 subjects (HC and ABI) while writing.

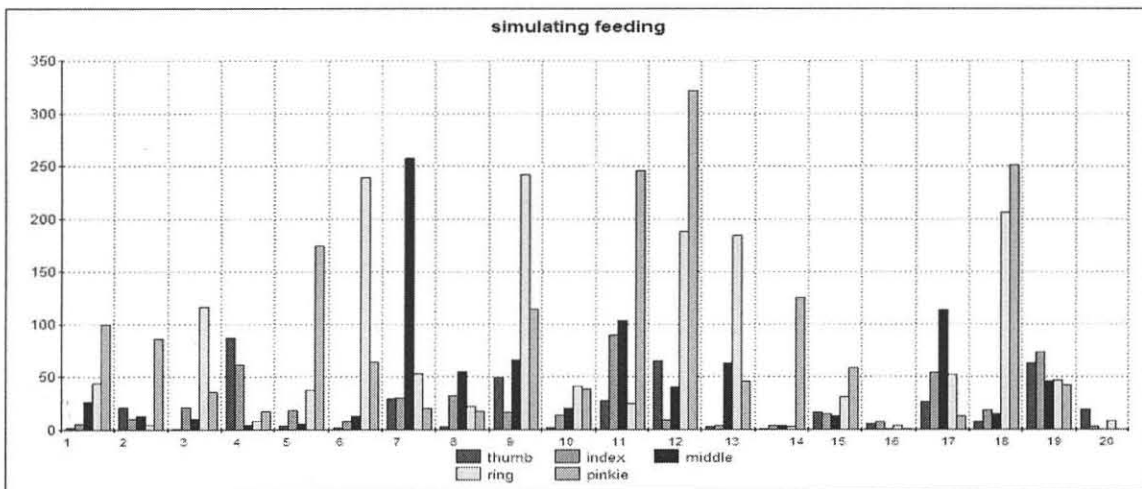


Figure 4.2 distribution of variance for the 20 subjects (HC and ABI) while simulating feeding.

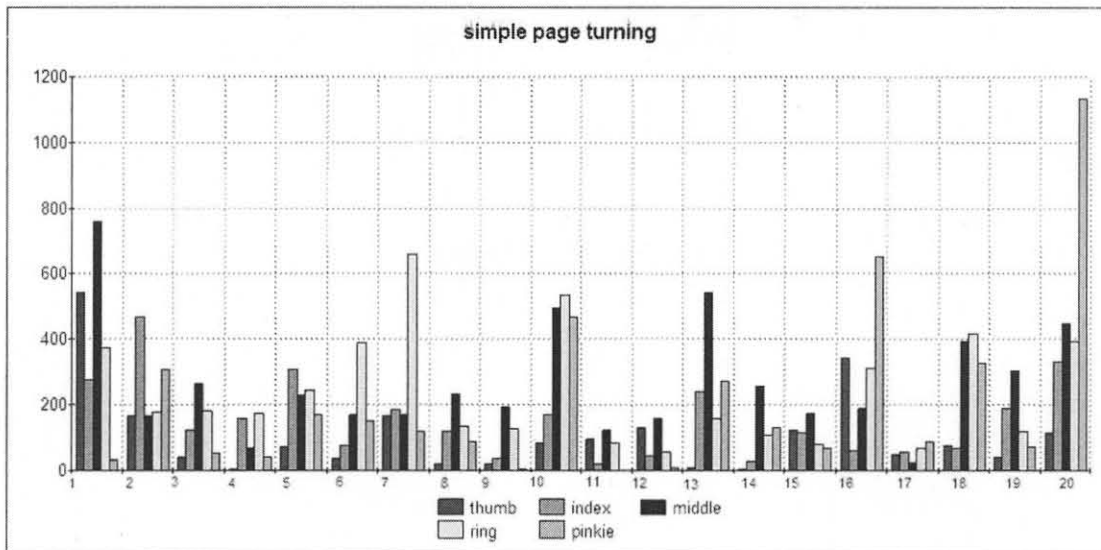


Figure 4.3 distribution of variance for the 20 subjects (HC and ABI) during simple page turning activity.

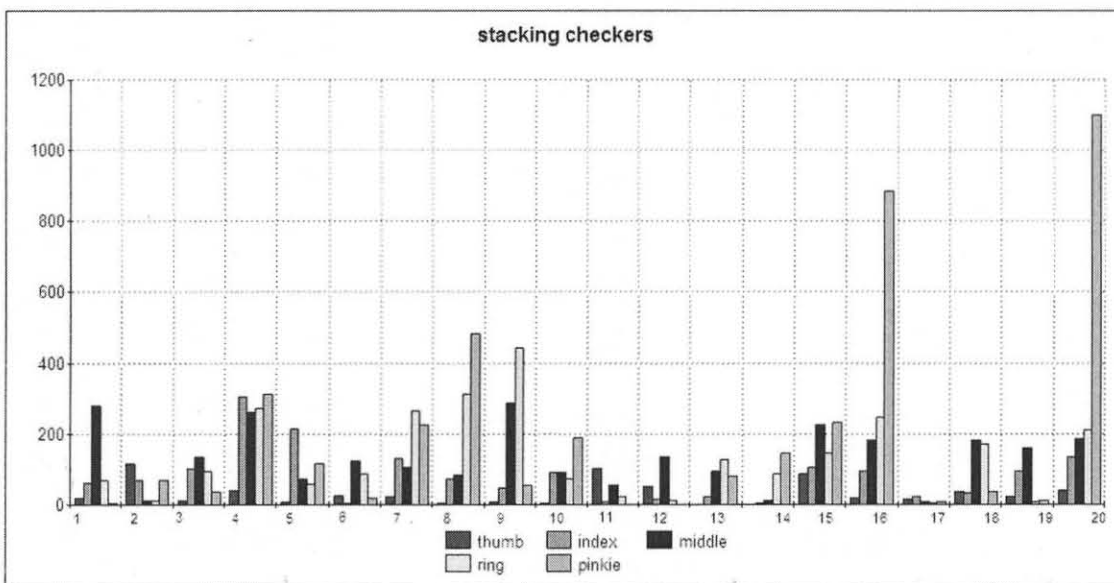


Figure 4.4 distribution of variance for the 20 subjects (HC and ABI) while stacking checkers.

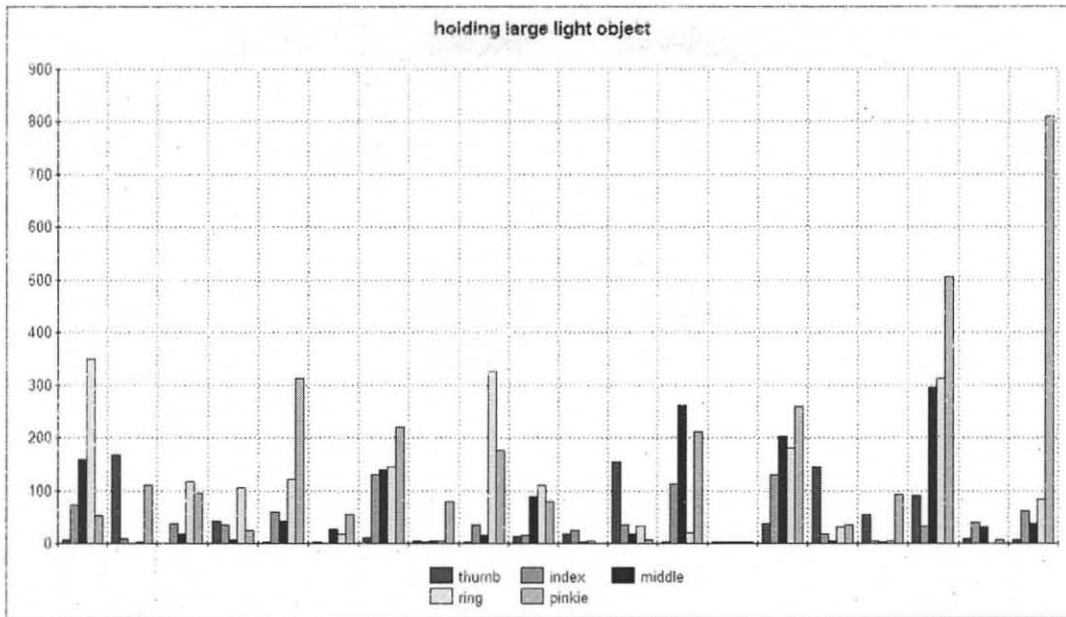


Figure 4.5 distribution of variance for the 20 subjects (HC and ABI) while holding large light object.

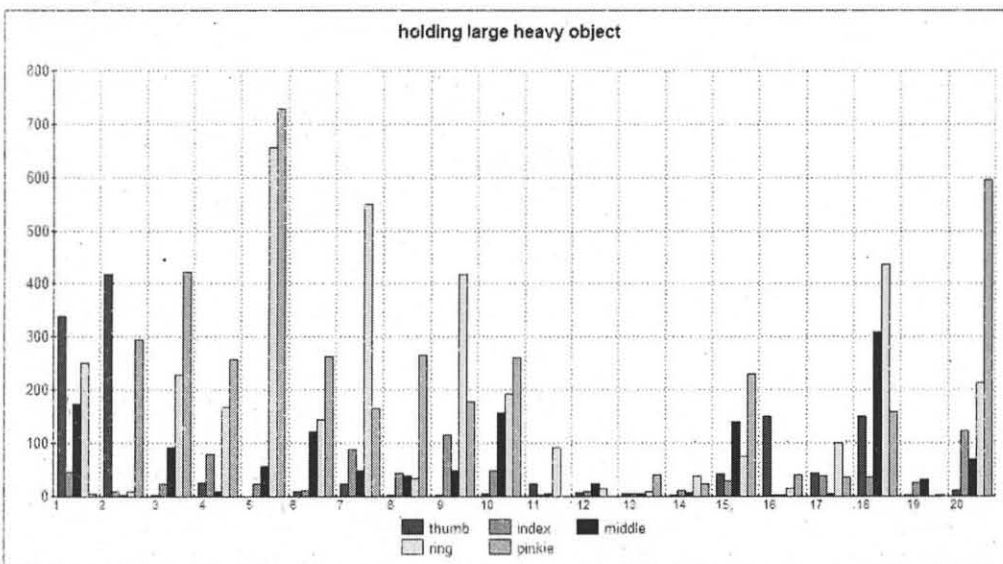


Figure 4.6 distribution of variance for the 20 subjects (HC and ABI) while holding large heavy cans.

Conclusions about range of motion, average means, and variance were used to classify the seven Jebsen activities into three groups:

- i) Precision Grasp includes writing and simulated feeding activities.
- ii) Palmar Grasp includes simple page turning, stacking checkers, and lifting small objects activities.
- iii) Cylindrical Grasp includes holding large light objects and holding heavy objects.

Those classifications were found consistent with the k-means cluster analysis done by Dr. Lisa Simone for the same data. Dr. Simone chose to use speed, average angle, and average standard deviation to put the seven activities into clusters. It has been found that J1(writing) and J4 (simulating feeding) come into one group whether studying each group, HC or ABI, or both groups together. J2 (simple page turning) and J5(lifting small objects) were clearly concluded to be in one group, (J7)holding large heavy objects has been found close to this group in the HC group.

Table 4.9 Cluster Analysis of Jebsen Activities

	J 1	J2	J3	J 4	J5	J6	J7	Su m	
Cluster 1	0	10	9	1	10	6	8	44	L/M angle, L/Mspeed, H SD
Cluster 2	1 6	0	3	1 7	2	0	0	38	H angle, L speed, M SD
Cluster 3	0	6	3	0	0	0	4	13	M angle, M/H speed, M/H SD
Cluster 4	4	4	5	2	8	14	8	45	L angle, L speed, L/M SD

HC	J 1	J2	J3	J 4	J5	J6	J7		
Cluster 1	0	4	5	0	7	3	5	24	L/M angle, L/Mspeed, H SD
Cluster 2	1 0	0	2	1 0	1	0	0	23	H angle, L speed, M SD
Cluster 3	0	5	2	0	0	0	4	11	M angle, M/H speed, M/H SD

Cluster 4	0	1	1	0	2	7	1	12	L angle, L speed, L/M SD
ABI	J 1	J2	J3	J 4	J5	J6	J7		
Cluster 1	0	6	4	1	3	3	3	20	L/M angle, L/M speed, H SD
Cluster 2	6	0	1	7	1	0	0	15	H angle, L speed, M SD
Cluster 3	0	1	1	0	0	0	0	2	M angle, M/H speed, M/H SD
Cluster 4	4	3	4	2	6	7	7	33	L angle, L speed, L/M SD

4.2 Long-Stream Data Analysis Results and Discussion

The major result of Jebsen study was to build three classes representing the seven activities. The result of long-stream data analysis was to segment the data and summarize the activities during those segments, in addition to reporting information about speed, range of motion, and standard deviation.

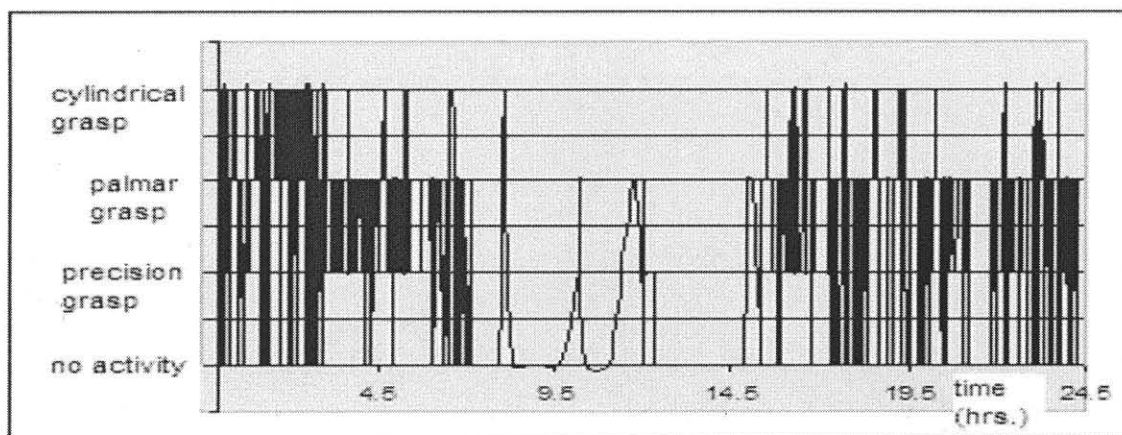


Figure 4.8 Distribution of activities during the 24 hours and 40 minutes.

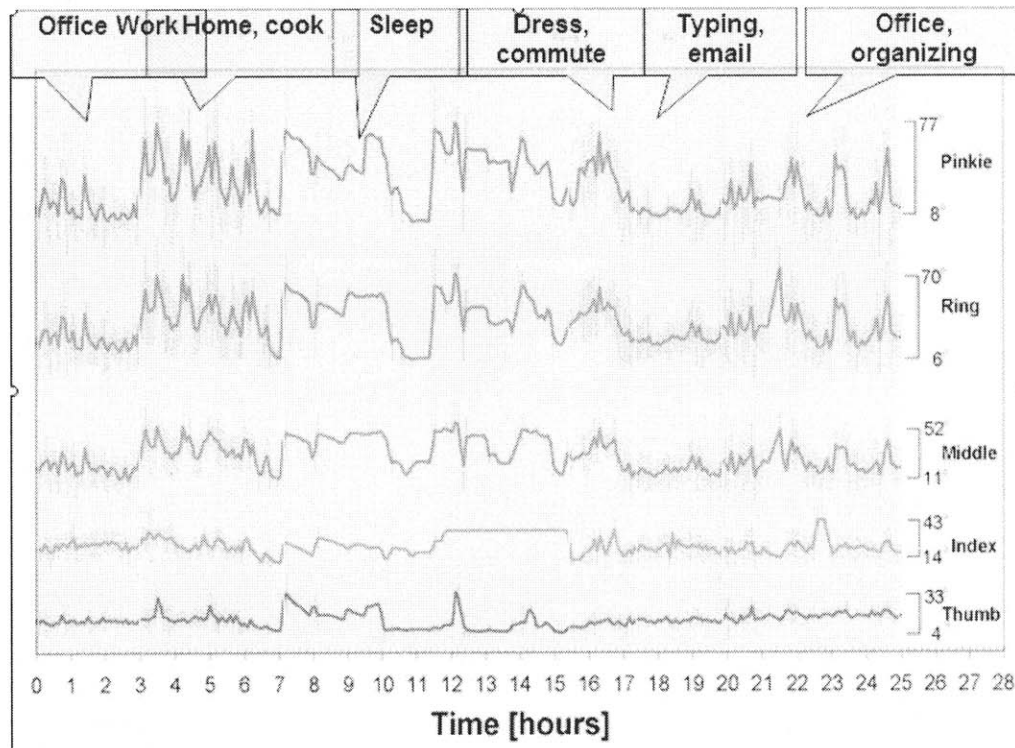


Figure 4.9 Activities during the 24 hours and 40 minutes.

With respect to activity, the activities during the 24 hours are defined in Figure (4.8). The total number of segments was 1255. The durations of the four classes of activities are summarized in Table (4.10).

Table 4.10 Summary of the Four Classes of Activities.

Activity	Duration	Average flexion speed
No Activity	8 hours, 16 minutes, and 51 seconds	6.3892 deg/sec
Precision Grasp	2 hours, 44 minutes, and 27 seconds	20.5445 deg/sec
Palmar Grasp	12 hours, 9 minutes, and 6 seconds	17.1893 deg/sec
Cylindrical Grasp	1 hour, 6 minutes, and 10 seconds	16.5747 deg/sec

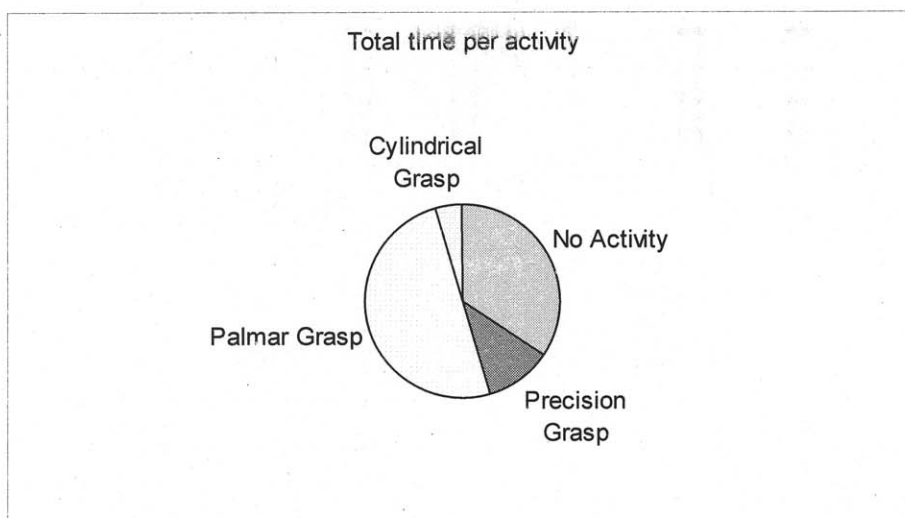


Figure 4.10 The percentage of each of the four types of activities during daily activities.

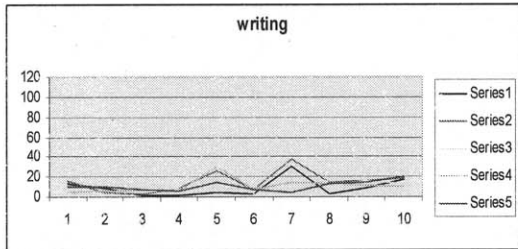
In this approach, the activities are not accurately classified, but general idea about the hand activity is deduced. Comparing Figures (4.8) with (4.9), the sleeping period in Figure (4.9) is classified in Figure (4.8) as 'no activity', the office work activities, during the first three hours, varies between the four classes. Office work activities vary between precision and palmar classes. Cooking vary between precision and palmar classes to cylindrical and no activity classes. Continuing to typing and office working, there is no accurate classification, but the general information in Figure (4.8) looks logical. However, it is very useful to evaluate hand activities for individuals with movement disorders, these general classifications would be an objective reflection of health condition.

APPENDIX A

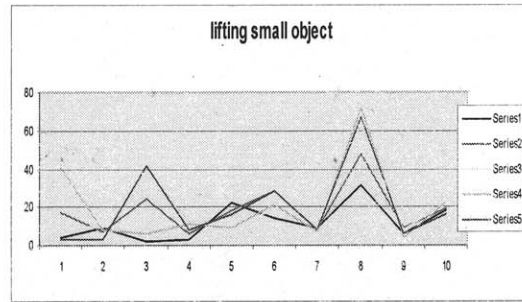
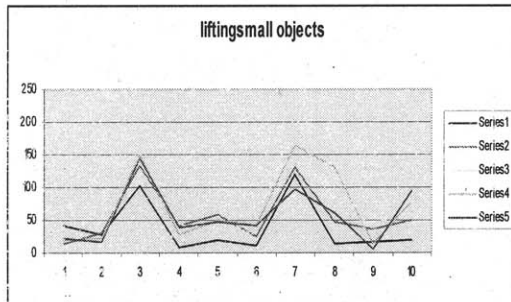
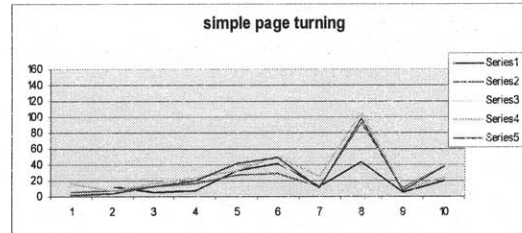
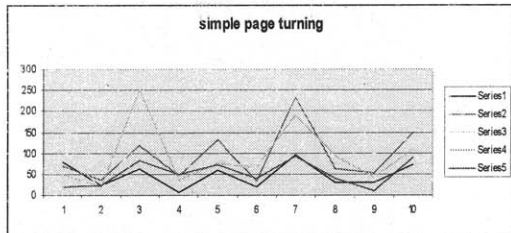
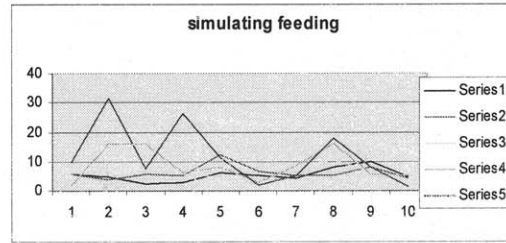
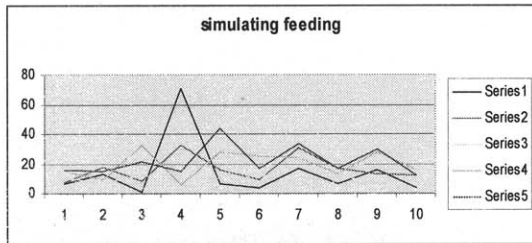
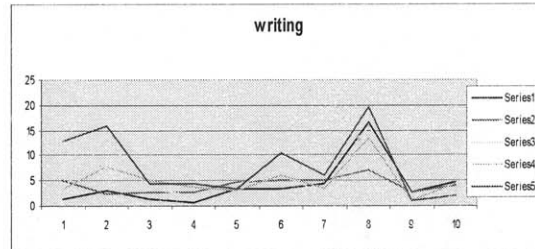
SPEED COMPARISON

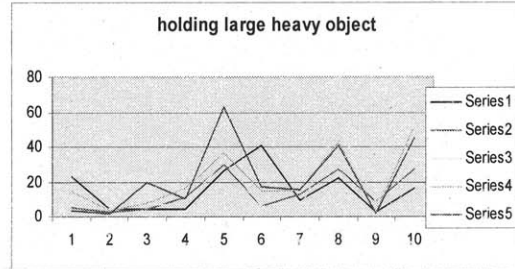
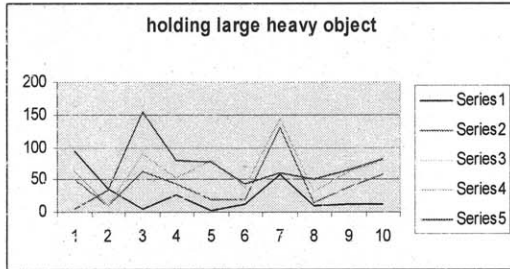
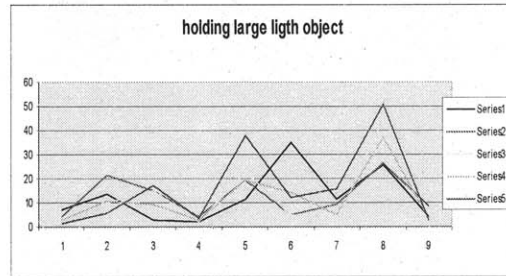
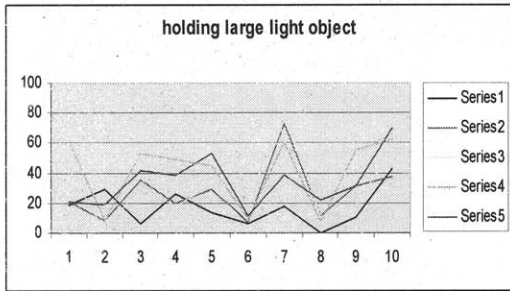
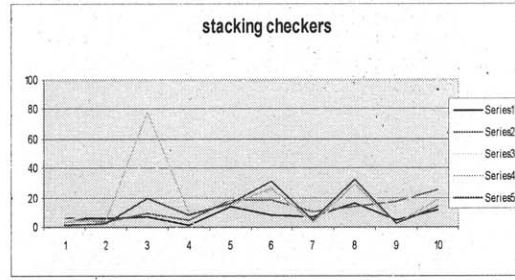
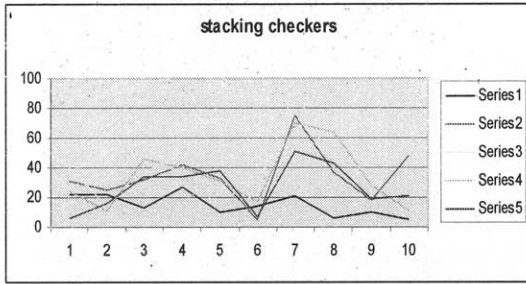
This appendix presents summary about the speed of joint angles for the 20 subjects in the two groups (HC and ABI). It is clear that speed is lower in the ABI group, the speed is variable between the seven activities in each group.

HC



ABI





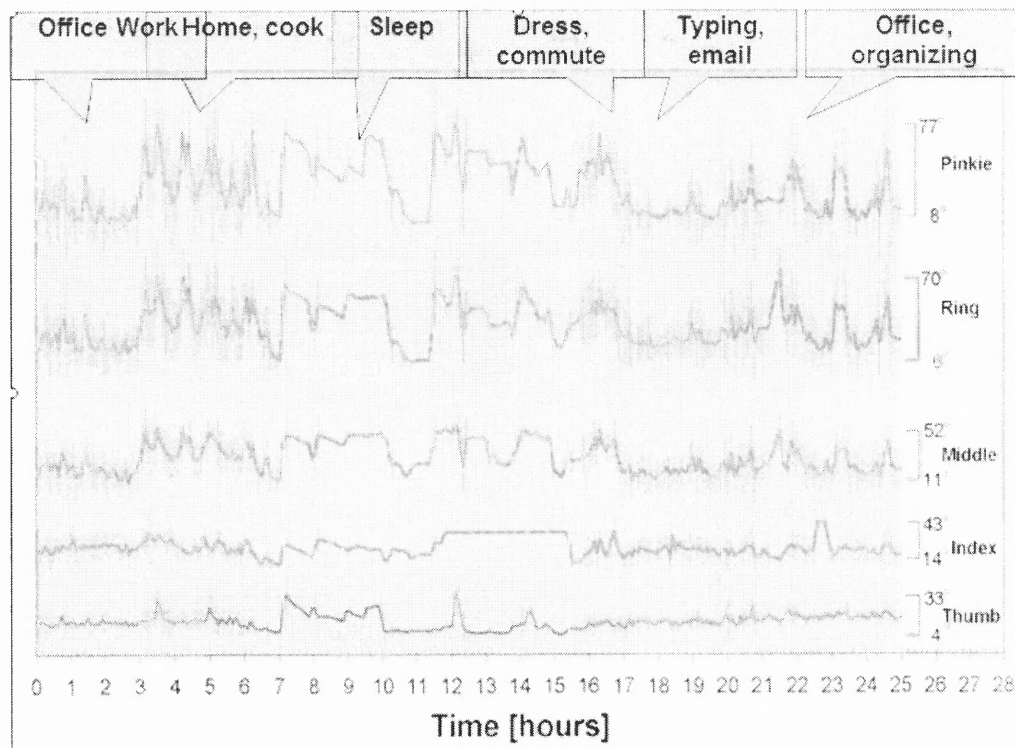


Figure 4.9 Activities during the 24 hours and 40 minutes.

With respect to activity, the activities during the 24 hours are defined in Figure (4.8). The total number of segments was 1255. The durations of the four classes of activities are summarized in Table (4.10).

Table 4.10 Summary of the Four Classes of Activities.

Activity	Duration	Average flexion speed
No Activity	8 hours, 16 minutes, and 51 seconds	6.3892 deg/sec
Precision Grasp	2 hours, 44 minutes, and 27 seconds	20.5445 deg/sec
Palmar Grasp	12 hours, 9 minutes, and 6 seconds	17.1893 deg/sec
Cylindrical Grasp	1 hour, 6 minutes, and 10 seconds	16.5747 deg/sec

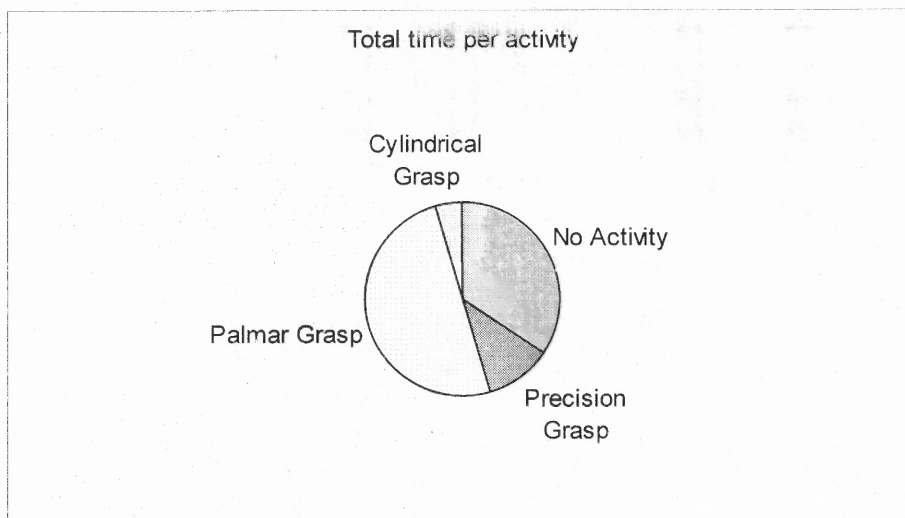


Figure 4.10 The percentage of each of the four types of activities during daily activities.

In this approach, the activities are not accurately classified, but general idea about the hand activity is deduced. Comparing Figures (4.8) with (4.9), the sleeping period in Figure (4.9) is classified in Figure (4.8) as 'no activity', the office work activities, during the first three hours, varies between the four classes. Office work activities vary between precision and palmar classes. Cooking vary between precision and palmar classes to cylindrical and no activity classes. Continuing to typing and office working, there is no accurate classification, but the general information in Figure (4.8) looks logical. However, it is very useful to evaluate hand activities for individuals with movement disorders, these general classifications would be an objective reflection of health condition.

CHAPTER 5

RECOMMENDATIONS AND CONCLUSION

In this study, the data recorded from the MCP joints were useful to generally classify hand activities, this general classification could be enough for physical therapists and clinicians. Just knowing the percentage time that an individual spent performing different postures, such as the precision grip versus cylindrical grasp, as compared to no activity at all, will provide more information than is currently available about hand function at home. However, if more detailed or accurate classifications of hand activities are needed, it is recommended to study adding sensors to record CP joint angles.

There was another concern about the choice of threshold when defining the segments in the long activity file. Lower thresholds will create shorter segments when there was actually change in activity. Higher thresholds may create longer segments that contain more than one activity. There is a need for an optimal threshold that decreases the number of segments without overlapping multiple activities in one segment. For the subject presented here, the threshold was chosen by visual inspection. This can be done for all subjects, but a method that can automatically segment the files and then perform clustering analysis and then evaluate the quality of the assessment would be a challenging but positive goal. In this study, we found that the detailed coefficients were, on average, lower for the brain injury group. Another recommendation is to study the detailed coefficients of joint activity of individuals with brain injury, looking for correlation between amplitude of detailed coefficients and severity of disease. In this study, severity was not considered, only the presence or absence of injury.

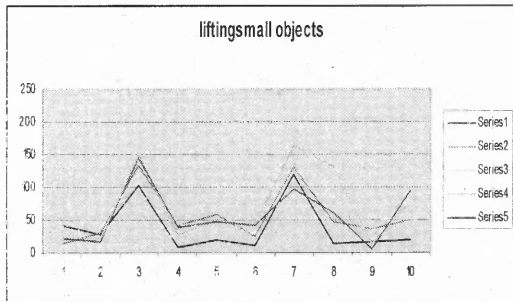
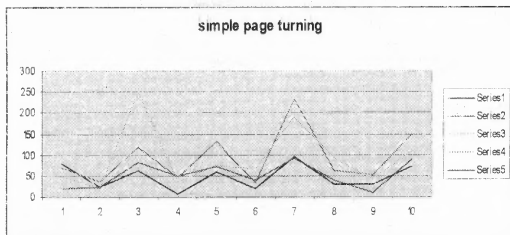
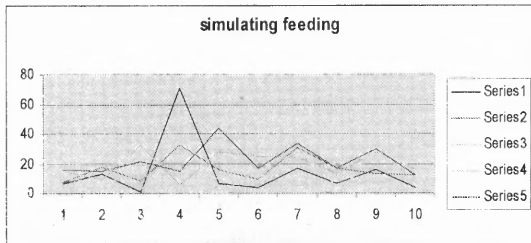
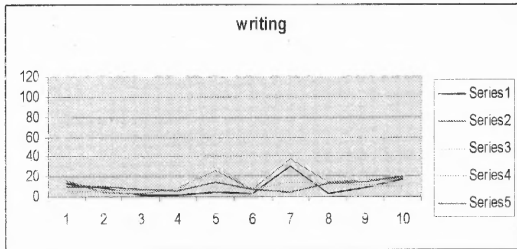
Conclusively, this study was done to find a method to identify determinants of hand activity as a first step to study hand function and posture while doing daily activities. The result was to define characteristics of three clusters that represent the general daily activities (precision, palmar, and cylindrical grasps). Using these characteristics, long-stream data were scanned and segmented; those segments were compared with those three clusters to automatically define the activity types in each segment. The result of the long stream analysis provides a report of subject activities over a 25 hour period. This type of long term reporting is currently not available to clinicians, and provides a view into how individuals use their hands at home and in the community. Using this type of continuous data analysis in conjunction with conventional methods to evaluate rehabilitation treatments, provides a new approach to evaluate daily activities of an individual. With further development, this can be new approach for rehabilitation therapy evaluation.

APPENDIX A

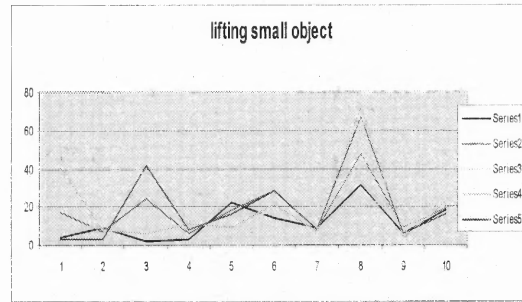
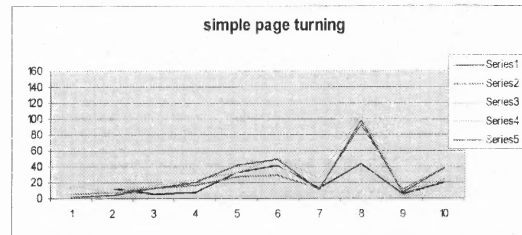
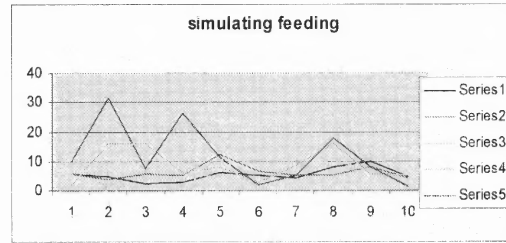
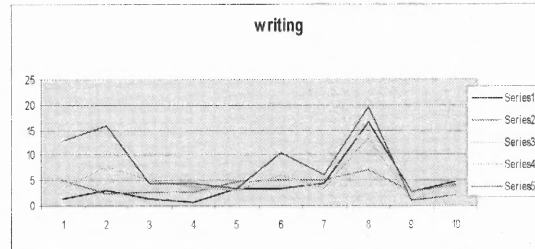
SPEED COMPARISON

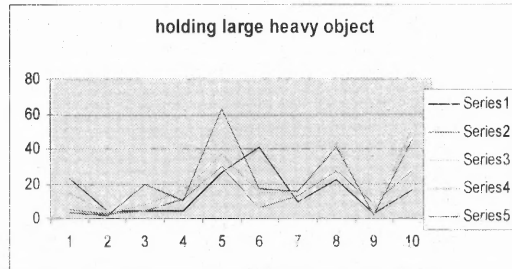
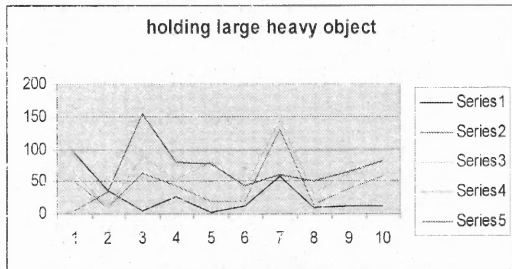
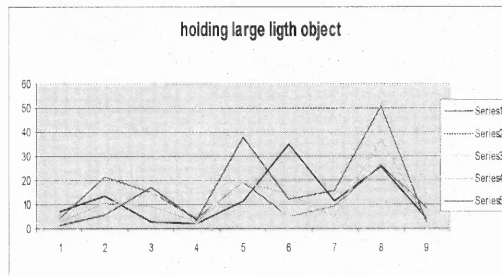
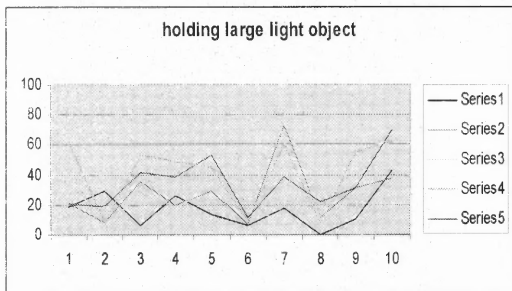
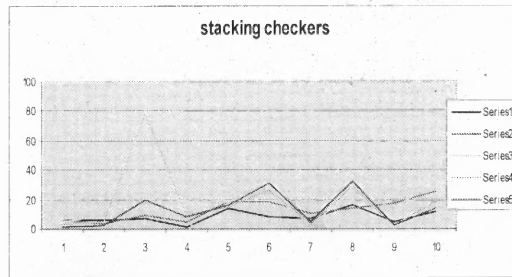
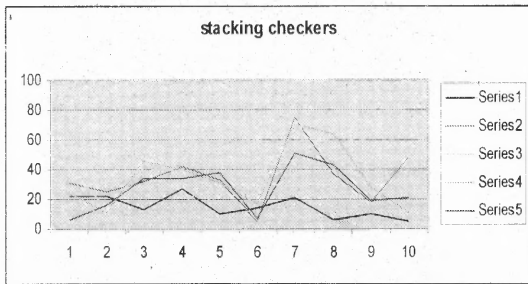
This appendix presents summary about the speed of joint angles for the 20 subjects in the two groups (HC and ABI). It is clear that speed is lower in the ABI group, the speed is variable between the seven activities in each group.

HC



ABI





APPENDIX B

DECOMPOSE

This appendix includes the matlab file built to decompose a given signal. The wavelet used is 'db8'. The signal is decompose into two approximate and detailed coefficients.

```
L=2; % Level of decomposition

w = 'db8'; % Wavelet transform (Daubechies level 8)

[c1, lll] = wavedec(s1, L, w);

%plot the 2 decomposition detailed coefficients
D1(1, :) = wrcoef('d', c1, lll, w, 1);
D1(2, :) = wrcoef('d', c1, lll, w, 2);

%read the two approximate coefficients
for i = 1:L
    Da1(i, :) = wrcoef('a', c1, lll, w, i);
end

%subplot wavelet coefficients

for i=1:2;
    subplot(2,1,i); plot(tt, D1(L-(i-1), tt), 'k');
end
figure;
for i=1:2;
    subplot(2,1,i); plot(tt, Da1(L-(i-1), tt), 'k');
end
```

APPENDIX C

CALCULATING MEAN OF JOINT ANGLES

A Matlab File that calculate mean of joint angles for writing activity and save the summary in spreadsheet file. The same steps are repeated for the other six activities in the HC and ABI group. The means of the five joints are loaded to 'calculatedmean.xls' excel file.

```
%loading writing activity
writingHC;
%calculate the mean of joint angles for the 10 subjects
HCthumbvar=[mean(thumb2) mean(thumb3) mean(thumb4) mean(thumb5)
mean(thumb6) mean(thumb7) mean(thumb8) mean(thumb9) mean(thumb13)
mean(thumb19) ];
HCindexvar=[mean(index2) mean(index3) mean(index4) mean(index5)
mean(index6) mean(index7) mean(index8) mean(index9) mean(index13)
mean(index19) ];
HCmiddlevar=[mean(middle2) mean(middle3) mean(middle4) mean(middle5)
mean(middle6) mean(middle7) mean(middle8) mean(middle9) mean(middle13)
mean(middle19) ];
HCringvar=[mean(ring2) mean(ring3) mean(ring4) mean(ring5) mean(ring6)
mean(ring7) mean(ring8) mean(ring9) mean(ring13) mean(ring19) ];
HCPinkievar=[mean(pinkie2) mean(pinkie3) mean(pinkie4) mean(pinkie5)
mean(pinkie6) mean(pinkie7) mean(pinkie8) mean(pinkie9) mean(pinkie13)
mean(pinkie19) ];

%save data to 'calculated mean.xls' file.
dlmwrite('calculatedmean.xls', HCthumbvar);
dlmwrite('calculatedmean.xls', HCindexvar, '-append');
dlmwrite('calculatedmean.xls', HCmiddlevar, '-append');
dlmwrite('calculatedmean.xls', HCringvar, '-append');
dlmwrite('calculatedmean.xls', HCPinkievar, '-append');

%loading activity
writingABI;
%calculate the mean of joint angles for the 10 subjects
ABIthumbvar=[mean(thumb10) mean(thumb11) mean(thumb12) mean(thumb14)
mean(thumb15) mean(thumb16) mean(thumb18) mean(thumb21) mean(thumb22)
mean(thumb23) ];
ABIindexvar=[mean(index10) mean(index11) mean(index12) mean(index14)
mean(index15) mean(index16) mean(index18) mean(index21) mean(index22)
mean(index23) ];
ABImiddlevar=[mean(middle10) mean(middle11) mean(middle12)
mean(middle14) mean(middle15) mean(middle16) mean(middle18)
mean(middle21) mean(middle22) mean(middle23) ];
ABIringvar=[mean(ring10) mean(ring11) mean(ring12) mean(ring14)
mean(ring15) mean(ring16) mean(ring18) mean(ring21) mean(ring22)
mean(ring23) ];
ABIPinkievar=[mean(pinkie10) mean(pinkie11) mean(pinkie12)
var(pinkie14) var(pinkie15) var(pinkie16) var(pinkie18) var(pinkie21)
var(pinkie22) var(pinkie23) ];
```

```
mean(index23) ];
ABImiddlevar=[mean(middle10) mean(middle11) mean(middle12)
mean(middle14) mean(middle15) mean(middle16) mean(middle18)
mean(middle21) mean(middle22) mean(middle23) ];
ABIRingvar=[mean(ring10) mean(ring11) mean(ring12) mean(ring14)
mean(ring15) mean(ring16) mean(ring18) mean(ring21) mean(ring22)
mean(ring23) ];
ABIPinkievar=[mean(pinkie10) mean(pinkie11) mean(pinkie12)
var(pinkie14) var(pinkie15) var(pinkie16) var(pinkie18) var(pinkie21)
var(pinkie22) var(pinkie23) ];
```

Save data to 'calculatedmean.xls' file.

```
dlmwrite('calculatedmean.xls', ABIThumbvar, '-append');
dlmwrite('calculatedmean.xls', ABIindexvar, '-append');
dlmwrite('calculatedmean.xls', ABImiddlevar, '-append');
dlmwrite('calculatedmean.xls', ABIRingvar, '-append');
dlmwrite('calculatedmean.xls', ABIPinkievar, '-append');
```

APPENDIX D

CALCULATING STANDARD DEVIATION

A Matlab File that calculate standard deviation of joint angles for writing activity and save the summary in spreadsheet file. The same steps are repeated for the other six activities in the HC and ABI group. The standard deviation of the five joints are loaded to 'stdreport.xls' excel file.

```
%load activity data
writingHC;
    % calculating standard deviation of the 10 subjects
HCthumbvar=[std(thumb2) std(thumb3) std(thumb4) std(thumb5) std(thumb6)
std(thumb7) std(thumb8) std(thumb9) std(thumb13) std(thumb19) ];
HCindexvar=[std(index2) std(index3) std(index4) std(index5) std(index6)
std(index7) std(index8) std(index9) std(index13) std(index19) ];
HCmiddlevar=[std(middle2) std(middle3) std(middle4) std(middle5)
std(middle6) std(middle7) std(middle8) std(middle9) std(middle13)
std(middle19) ];
HCringvar=[std(ring2) std(ring3) std(ring4) std(ring5) std(ring6)
std(ring7) std(ring8) std(ring9) std(ring13) std(ring19) ];
HCpinkievar=[std(pinkie2) std(pinkie3) std(pinkie4) std(pinkie5)
std(pinkie6) std(pinkie7) std(pinkie8) std(pinkie9) std(pinkie13)
std(pinkie19) ];

Y1=[max(HCthumbvar) max(HCindexvar) max(HCmiddlevar) max(HCringvar)
max(HCpinkievar)];
Y1_m=[min(HCthumbvar) min(HCindexvar) min(HCmiddlevar) min(HCringvar)
min(HCpinkievar)];

    % Save the result in spreadsheet file 'stdreport.xls'
dlmwrite('stdreport.xls', HCthumbvar);
dlmwrite('stdreport.xls', HCindexvar, '-append');
dlmwrite('stdreport.xls', HCmiddlevar, '-append');
dlmwrite('stdreport.xls', HCringvar, '-append');
dlmwrite('stdreport.xls', HCpinkievar, '-append');

%load activity data
writingABI;
    % calculating standard deviation of the 10 subjects
ABIthumbvar=[std(thumb10) std(thumb11) std(thumb12) std(thumb14)
std(thumb15) std(thumb16) std(thumb18) std(thumb21) std(thumb22)
std(thumb23) ];
ABIindexvar=[std(index10) std(index11) std(index12) std(index14)
std(index15) std(index16) std(index18) std(index21) std(index22)
std(index23) ];
ABImiddlevar=[std(middle10) std(middle11) std(middle12) std(middle14)
std(middle15) std(middle16) std(middle18) std(middle21) std(middle22)
```



```
std(middle23) ];
ABIRingvar=[std(ring10) std(ring11) std(ring12) std(ring14) std(ring15)
std(ring16) std(ring18) std(ring21) std(ring22) std(ring23) ];
ABIPinkievar=[std(pinkie10) std(pinkie11) std(pinkie12) std(pinkie14)
std(pinkie15) std(pinkie16) std(pinkie18) std(pinkie21) std(pinkie22)
std(pinkie23) ];
Y8=[max(HCthumbvar) max(HCindexvar) max(HCmiddlevar) max(HCringvar)
max(HCpinkievar)];
Y8_m=[min(HCthumbvar) min(HCindexvar) min(HCmiddlevar) min(HCringvar)
min(HCpinkievar)];
```

```
% Save the result in spreadsheet file 'stdreport.xls'
dlmwrite('stdreport.xls', ABITHUMBVAR, '-append');
dlmwrite('stdreport.xls', ABIINDEXVAR, '-append');
dlmwrite('stdreport.xls', ABIMIDDLEVAR, '-append');
dlmwrite('stdreport.xls', ABIRINGVAR, '-append');
dlmwrite('stdreport.xls', ABIPINKIEVAR, '-append');
```

APPENDIX E

SPEED ANALYSIS FUNCTION

This appendix includes the speed analysis matlab function. This function calculate the speed of joint activity, and derive the average of flexion and extension speeds, in addition to the maximum and minimum flexion and extension speeds.

```
%% Speed analysis function that computes the speed the activity, the
%% flexion and extension speed ( averages, max, and min)

% the input values are data and time while output is speed flexion
average,
% extension average, max and min flexion speed, max and min extension
% speeds, respectively
function [speed flexionaverage extensionaverage maxflexion minflexion
maxextension minextension]=speedanalysis(data,time)
%clc
L=length(data);

    speed(2)=((data(2)-data(1))/(time(2)-time(1))); %initial value
for n=3:(L);
    if (time(n)-time(n-1)) % checking if difference is positive since
the '.csv' files shows 4 digits
        %after the decimal so sometimes there is repeated samples of
time
        speed(n)=((data(n)-data(n-1))/(time(n)-time(n-1)));
    else
        speed(n)=speed(n-1); % in case 0 difference of time, we
consider the speed at that sample same as
        %in the instance before
    end
end

flexion_speed_average=0;
Nf=0;
extension_speed_average=0;
Ne=1;

% dividing the speed as extension and flexion average speed as flexion
is
% positive and extension negative
for n=2:(L-1);
if(speed(n)>=0 )
    flexion_speed_average=flexion_speed_average+speed(n);
    Nf=Nf+1;
else
    Ne=Ne+1;
```

```

extension_speed_average=extension_speed_average+speed(n);
end
end

flexionaverage=flexion_speed_average./Nf;
extensionaverage=extension_speed_average./Ne;

% max extension is the min speed which is negative and max flexion is
the
% maximum positive speed
minextension=min(speed);
maxflexion=max(speed);

% set initial values of minimum extension and flexion as equal to the
% maximum values before going to the loop to compute these values
maxextension=minextension;
minflexion=maxflexion;

for n=2:(L-1);
if(speed(n)>=0 && speed(n)<minflexion )
    minflexion=speed(n);
end
if(speed(n)<0 && speed(n)>minextension )
    maxextension=speed(n);
end
end

minflexion;
minextension;
%[f,x]=ksdensity(data);
ROM=max(data)-min(data);

```

APPENDIX F

LONGSTREAM DATA ANALYSIS

This is the Matlab File that loads the 36 spreadsheet files that include the long-stream data. After loading each file, the index data is decomposed and the files are segments as described in chapter 3. After segmenting the data based on locating peaks in the detailed coefficients, the decision is called to decide the activity during specific duration and to report the speed analysis about the segments. These indexes present the steps done for the first two file, the same steps are repeated till data file prepared_data_angles_SPLIT_035.csv.

```
%% Extracting columns from data file prepared_data_angles_SPLIT_000.csv
clear all; close all;
time=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_000
.csv',0,0,[0 0 62050 0]);
thumb=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_00
0.csv',0,1,[0 1 62050 1]);
index=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_00
0.csv',0,2,[0 2 62050 2]);
middle=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_0
00.csv',0,3,[0 3 62050 3]);
ring=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_000
.csv',0,4,[0 4 62050 4]);
pinkie=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_0
00.csv',0,5,[0 5 62050 5]);
```

```
%%
s1=middle;
decompose;
close all;
segmental;
T=['duration' ' ' 'activity' ' ' 'precision_conf' ' '
'palmar_conf' ' ' 'cyllindrical_conf' ' ' 'avgROM' ' ' 'avgflexion'
' ' 'avgextension' ' ' 'maxflexion' ' ' 'maxextension' ' '
'avgstd'];
R=[du;ac;precision;palmar;cyllindrical;avgROM;avgmaxflex;avfmaxex;avfle
x;avex;avgstd];
dlmwrite('result.csv',T,'delimiter','\t','precision',8);
dlmwrite('result.csv',R,'-append');
```

```
%% %%
% Extracting columns from data file prepared_data_angles_SPLIT_000.csv
clear all; close all;
time=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_001
.csv',0,0,[0 0 61424 0]);
thumb=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_00
1.csv',0,1,[0 1 61424 1]);
index=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_00
1.csv',0,2,[0 2 61424 2]);
```

```
middle=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_001.csv',0,3,[0 3 61424 3]);
ring=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_001.csv',0,4,[0 4 61424 4]);
pinkie=csvread('C:\Users\soha\Desktop\data\prepared_data_angles_SPLIT_001.csv',0,5,[0 5 61424 5]);

s1=middle;
decompose;
close all;
segmental;
T=['duration' ' ' 'activity' ' ' 'precision_conf' ' ' ' '
'palmar_conf' ' ' 'cylindrical_conf' ' ' 'avgROM' ' ' 'avgflexion'
' ' 'avgextension' ' ' 'maxflexion' ' ' 'maxextension' ' '
'avgstd'];
R=[du;ac;precision;palmar;cylindrical;avgROM;avgmaxflex;avfmaxex;avflex;avex;avgstd];
dlmwrite('result.csv','R','-append');
```

APPENDIX G

SEGMENTING FUNCTION

This appendix includes the matlab file that is called to segment the data files and call the decision function. The lower bound of initial segment is set to 1. Decomposition action is called, and the detailed coefficients are compared with threshold 3. If the difference between the segment index at the peak and the lower bound is greater than 500 samples, the upper bound is set equal to that index. The data between lower and upper bound is classified as a segment, to which the duration is calculated. The decision function is then called to find the statistical information about the segment and to define the activity.

```
l=length(D1);

lb=1; % lower bound of the segment
count=0; % count of segments
ub=1; % upper bound of the segment
k=1;
for n=1:l,
    %if (D1(2,n)>2)
    %if (D1(2,n)>3)
    %if (D1(2,n)>4)

        %if (D1(n)>5)
        if (D1(2,n)>3)
m(n)=1;
else
m(n)=0;
end
end
numel(m);

l2=0;

%
while k<l,
    %
    for n=1:l,
        %if (D1(2,n)>2)
        %if (D1(2,n)>3)
        %if (D1(2,n)>4)
            if (D1(2,n)>3) % defining the threshold at which segmenting
                m(n)=1;
            else
                m(n)=0;
            end
    end
end
```

```

end

numel(m);
%
if (m(k)==1) || (k==(l-1))

i=k-lb;
%
if i>500
    count=count+1;
    ub=k;
    tt=0;
    A=0; B=0; C=C; D=0; E=0;
    o=lb:ub;

        tt=time(o);
        A=index(o);
        B=middle(o);
        C=ring(o);
        D=pinkie(o);
        E=thumb(c);
        length(o);
l2=i;

Decision;

du(count)=time(ub)-time(lb);

ac(count)=activity;
precision(count)=classone_conf;
palmar(count)=classtwo_conf;
cylindrical(count)=classthree_conf;
avgROM(count)=averageROM;
avgstd(count)=averagestdv;
avgmaxflex(count)=avg_maxflexion;
avfmaxex(count)=avg_maxextension;
avflex(count)=avg_flexionavg;
avex(count)=avg_extensionavg;
numel(m);
lb=ub;

end
%
end

k=k+1;
End

```

APPENDIX H

DECISION

This appendix includes the matlab file that derive the activity during a defined segment, in addition to finding all needed information about speed, range of motion and standard deviation.

```
%call the four classes (class one for precision, two for palmar, three
for cylindrical, and four for nothing)
```

```
classone;
classtwo;
classthree;
classfour;
```

```
%look for the class with highest power, activity is 0 if power
for class four is the highest, 1 if class one power is the highest, 2
if that of class three is the highest, and 3 if the power of class
three is the highest.
```

```
if classonepower>classtwopower
    %activity='PRECISION GRIP';
    activity=1;
    power=classonepower;
else
    %activity='PALMAR GRASP';
    activity=2;
    power=classtwopower;
end
if classthreepower>power
    %activity='CYLINDRICAL GRASP';
    power=classthreepower;
    activity=3;
end
if classfourpower>power
    power=classfourpower;
    activity=0;
end
```

```
% calculate the confidence proportion for each class power
classone_conf=classonepower/240;
classtwo_conf=classtwopower/240;
classthree_conf=classthreepower/240;
```

```
% calculate the average ROM
averageROM=( (max(E)-min(E))+(max(A)-min(A))+(max(B)-min(B))+(max(C)-
min(C))+(max(D)-min(D)) ) ./5;
averagestdv=(std(E)+std(A)+std(B)+std(C)+std(D)) ./5
```

```
t=tt;
```



```
data=E;
```

```
    * calculating the speed information
```

```
[th_speed th_flexionavg th_extensionavg th_maxf th_minf th_maxe  
th_mine]=speedanalysis(data,t);
```

```
data=A;
```

```
[i_speed i_flexionavg i_extensionavg i_maxf i_minf i_maxe  
i_mine]=speedanalysis(data,t);
```

```
data=B;
```

```
[m_speed m_flexionavg m_extensionavg m_maxf m_minf m_maxe  
m_mine]=speedanalysis(data,t);
```

```
data=C;
```

```
[r_speed r_flexionavg r_extensionavg r_maxf r_minf r_maxe  
r_mine]=speedanalysis(data,t);
```

```
data=D;
```

```
[p_speed p_flexionavg p_extensionavg p_maxf p_minf p_maxe  
p_mine]=speedanalysis(data,t);
```

```
avgspeed=(th_speed+i_speed+m_speed+r_speed+p_speed)/5;
```

```
avg_flexionavg=(th_flexionavg+i_flexionavg+m_flexionavg+r_flexionavg+p_  
flexionavg)/5;
```

```
avg_extensionavg=(th_extensionavg+i_extensionavg+m_extensionavg+r_exten  
sionavg+p_extensionavg)/5;
```

```
avg_maxflexion=(th_maxf+i_maxf+m_maxf+r_maxf+p_maxf)/5;
```

```
avg_maxextension=(th_maxe+i_maxe+m_maxe+r_maxe+p_maxe)/5;
```

```
avg_minflexion=(th_minf+i_minf+m_minf+r_minf+p_minf)/5;
```

```
avg_minextension=(th_mine+i_mine+m_mine+r_mine+p_mine)/5;
```

APPENDIX I

ACTIVITY CLASSES

I.1 CLASS 1

This is the matlab file where ranges of mean and maximum variance for precision grasp are summarized. Mean and variance of a given segment is compared with these values to find the power of the class in that segment.

```
% CLASS ONE (PRECISION GRASP)

% WRITING (EXTERNAL PRECISION GRIP)
classonepower1=0;
i=mean(A);
v=var(A);
if i>40 & i<60 & v<100
    indexpower=60;
    classonepower1=classonepower1+indexpower;
elseif i>30 & i <40 & v <100
    indexpower=40;
    classonepower1=classonepower1+indexpower;
elseif i>20 & i<30 & v<100
    indexpower=20;
    classonepower1=classonepower1+indexpower;
end

m=mean(B);
v=var(B);
if m>50 & m<80 & v<300
    middlepower=60;
    classonepower1=classonepower1+middlepower;
elseif m>40 & m<50 & v<300
    middlepower=40;
    classonepower1=classonepower1+middlepower;
elseif m>30 & m<40 & v<300
    middlepower=20;
    classonepower1=classonepower1+middlepower;
end

r=mean(C);
v=var(C);
if r>60 & r<80 & v<100
    ringpower=60;
    classonepower1=classonepower1+ringpower;
elseif (r>50 & r<60) || (r>80 & r<90) & v<100
    ringpower=40;
    classonepower1=classonepower1+ringpower;
elseif (r>40 & r<50) & v<100
    ringpower=20
    classonepower1=classonepower1+ringpower;
```

```

end

p=mean(D);
v=var(D);
if (p>60 & p<80) || (p>0 & p<10) & v<200
    pinkiepower=60;
    classonepower1=classonepower1+pinkiepower;
elseif (p>10 & p<20) || (p>80 & p<90) & v <200
    pinkiepower=40;
    classonepower1=classonepower1+pinkiepower;
end

** SIMULATING FEEDING (INTERNAL PRECISION GRIP)
classonepower2=0;
i=mean(A);
v=var(A);
if i>30 & i<40 & v<100
    indexpower=60;
    classonepower2=classonepower2+indexpower;
elseif i>40 & i<50 & v <100
    indexpower=40;
    classonepower2=classonepower2+indexpower;
elseif (i>10 & i<30) || (i>50 & i<80) & v<100
    indexpower=20;
    classonepower2=classonepower2+indexpower;
end

m=mean(B);
v=var(B);
if m>40 & m<60 & v<300
    middlepower=60;
    classonepower2=classonepower2+middlepower;
elseif (m>20 & m<40) || (m>60 & m<80) & v<300
    middlepower=40;
    classonepower2=classonepower2+middlepower;
elseif m>70 & m<80 & v<300
    middlepower=20;
    classonepower2=classonepower2+middlepower;
end

r=mean(C);
v=var(C);
if (r>40 & r<50) || (r>80 & r<90) & v<300
    ringpower=60;
    classonepower2=classonepower2+ringpower;
elseif r>50 & r<80 & v<100
    ringpower=40;
    classonepower2=classonepower2+ringpower;
elseif r>30 & r<40 & v<100
    ringpower=20;
    classonepower2=classonepower2+ringpower;
end

pi=mean(D);
v=var(D);
if (p>10 & p<20) & (p>40 & p<60) & v<400

```

```

    pinkiepower=60;
        classonepower2=classonepower2+pinkiepower;
elseif ((p>20 & p<40) || (p>60 & p<100)) & v<400
    pinkiepower=40;
        classonepower2=classonepower2+pinkiepower;
end

%%
if classonepower1>classonepower2
    classonepower=classonepower1;
else
    classonepower=classonepower2;
end

```

I.2 CLASS 2

This is the matlab file where ranges of mean and maximum variance for palmar grasp are summarized. Mean and variance of a given segment is compared with these values to find the power of the class in that segment.

```

%% CLASS TWO (PALMAR GRASP)

% single page turning
classtwopower1=0;
i=mean(A);
v=var(A);
if i>10 & i<20 & v<500
    indexpower=60;
    classtwopower1=classtwopower1+indexpower;
elseif i>30 & i <50 & v <500
    indexpower=40;
    classtwopower1=classtwopower1+indexpower;
end

m=mean(B);
v=var(B);
if m>20 & m<40 & v<800
    middlepower=60;
    classtwopower1=classtwopower1+middlepower;
elseif (m>10 & m<20) & v<800
    middlepower=40;
    classtwopower1=classtwopower1+middlepower;
end

r=mean(C);
v=var(C);
if r>10 & r<30 & v<700
    ringpower=60;
    classtwopower1=classtwopower1+ringpower;
elseif (r>0 & r<10) || (r>30 & r<40) & v<700
    ringpower=40;
    classtwopower1=classtwopower1+ringpower;
end

```

```

end

p=mean(D);
v=var(D);
if p>0 & p<20 & v<10000
    pinkiepower=60;
    classtwopower1=classtwopower1+pinkiepower;
elseif (p>20 & p<30) & v <10000
    pinkiepower=40;
    classtwopower1=classtwopower1+pinkiepower;
end

%
* stacking checkers
classtwopower2=0;
i=mean(A);
v=var(A);
if i>30 & i<40 & v<200
    indexpower=60;
    classtwopower2=classtwopower2+indexpower;
elseif (i>20 & i <30) || (i>40 & i <50) & v <200
    indexpower=40;
    classtwopower2=classtwopower2+indexpower;
elseif (i>10 & i<20) || (i>50 & i<50) & v<200
    indexpower=20;
    classtwopower2=classtwopower2+indexpower;
end

m=mean(B);
v=var(B);
if m>20 & m<40 & v<300
    middlepower=60;
    classtwopower2=classtwopower2+middlepower;
elseif (m>10 & m<20) || (m>40 & m<50) & v<300
    middlepower=40;
    classtwopower2=classtwopower2+middlepower;
elseif (m>0 & m<10) || (m>50 & m<60) & v<300
    middlepower=20;
    classtwopower2=classtwopower2+middlepower;
end

r=mean(C);
v=var(C);
if r>10 & r<40 & v<500
    ringpower=60;
    classtwopower2=classtwopower2+ringpower;
elseif r>0 & r<10 & v<500
    ringpower=40;
    classtwopower2=classtwopower2+ringpower;
end

p=mean(D);
v=var(D);
if p>30 & p<40 & v<1000
    pinkiepower=60;
    classtwopower2=classtwopower2+pinkiepower;

```

```

elseif p>20 & p<30 & v<1000
    pinkiepower=40;
    classtwopower2=classtwopower2+pinkiepower;
elseif (p>0 & p<10) || (p>40 & p<70) & v<1000
    pinkiepower=20;
    classtwopower2=classtwopower2+pinkiepower;
end

%%
% small obj lift
classtwopower3=0;
i=mean(A);
v=var(A);
if i>30 & i<60 & v<500
    indexpower=60;
    classtwopower3=classtwopower3+indexpower;
elseif (i>10 & i<30) & v<600
    indexpower=40;
    classtwopower3=classtwopower3+indexpower;
elseif (i>60 & i<70) & v<600
    indexpower=20;
    classtwopower3=classtwopower3+indexpower;
end

m=mean(B);
v=var(B);
if (m>10 & m<20) || (m>30 & m<40) & v<900
    middlepower=60;
    classtwopower3=classtwopower3+middlepower;
elseif (m>0 & m<10) || (m>30 & m<40) || (m>60 & m<80) & v<900
    middlepower=40;
    classtwopower3=classtwopower3+middlepower;
end

r=mean(C);
v=var(C);
if r>30 & r<40 & v<900
    ringpower=60;
    classtwopower3=classtwopower3+middlepower;
elseif r>20 & r<30 & v<900
    ringpower=40;
    classtwopower3=classtwopower3+middlepower;
elseif (r>0 & r<20) || (r>50 & r<70) & v<900
    ringpower=20;
    classtwopower3=classtwopower3+middlepower;
end

p=mean(D);
v=var(D);
if p>10 & p<20 & v<900
    pinkiepower=60;
    classtwopower3=classtwopower3+pinkiepower;
elseif (p>0 & p<10) || (p>20 & p<50) & v<900
    pinkiepower=40;
    classtwopower3=classtwopower3+pinkiepower;
end

```

```

if classtwopower1>classtwopower2
    classtwopower=classtwopower1;
else
    classtwopower=classtwopower2;
end

if classtwopower3>classtwopower
    classtwopower=classtwopower3;
end

```

I.3 CLASS 3

This is the matlab file where ranges of mean and maximum variance for precision grasp are summarized. Mean and variance of a given segment is compared with these values to find the power of the class in that segment.

```

% CLASS THREE (CYLLINDRICAL GRASP)
classthreepower1=0;
% LARGE LIGHT OBJ
i=mean(index);
v=var(index);
if i>10 & i<20 & v<200
    indexpower=60;
    classthreepower1=classthreepower1+indexpower;
elseif i>0 & i<10 & v<200
    indexpower=40;
    classthreepower1=classthreepower1+indexpower;
elseif i>20 & i<30 & v<200
    indexpower=20;
    classthreepower1=classthreepower1+indexpower;
end

m=mean(middle);
v=var(middle);
if m>0 & m<20 & v<300
    middlepower=60;
    classthreepower1=classthreepower1+middlepower;
elseif m>20 & m<30 & v<300
    middlepower=40;
    classthreepower1=classthreepower1+middlepower;
elseif m>30 & m<40 & v<300
    middlepower=20;
    classthreepower1=classthreepower1+middlepower;
end

r=mean(ring);
v=var(ring);
if r>0 & r<10 & v<400
    ringpower=60;
    classthreepower1=classthreepower1+ringpower;
elseif r>10 & r<40 & v<400

```

```

        ringpower=40;
        classthreepower1=classthreepower1+ringpower;
elseif r>-10 & r<0 & v<400
    ringpower=20
    classthreepower1=classthreepower1+ringpower;
end

p=mean(pinkie);
v=var(pinkie);
if p>0 & p<10 & v<900
    pinkiepower=60;
    classthreepower1=classthreepower1+pinkiepower;
elseif p>40 & p<70 & v <900
    pinkiepower=40;
    classthreepower1=classthreepower1+pinkiepower;
end

% large heavy obj
classthreepower2=0;
i=mean(index);
variance=var(index);
if i>0 & i<20 & variance<400
    indexpower=60;
    classthreepower2=classthreepower2+indexpower;
elseif i>20 & i<40 & variance <400
    indexpower=40;
    classthreepower2=classthreepower2+indexpower;
elseif i>40 & i<50 & variance<400
    indexpower=20;
    classthreepower2=classthreepower2+indexpower;
end

m=mean(middle);
variance=var(middle);
if m>0 & m<20 & variance<400
    middlepower=60;
    classthreepower2=classthreepower2+middlepower;
elseif m>20 & m<30 & variance<400
    middlepower=40;
    classthreepower2=classthreepower2+middlepower;
elseif m>30 & m<40 & variance<400
    middlepower=20;
    classthreepower2=classthreepower2+middlepower;
end

r=mean(ring);
variance=var(ring);
if r>0 & r<20 & variance<800
    ringpower=60;
    classthreepower2=classthreepower2+ringpower;
elseif r>20 & r<40 & variance<800
    ringpower=40;
    classthreepower2=classthreepower2+ringpower;
elseif (r>-10 & r<0) || (r>40 & r<60) & variance<800
    ringpower=20;
    classthreepower2=classthreepower2+ringpower;

```



```

end

p=mean(pinkie);
variance=var(pinkie);
if p>0 & p<10 & variance<800
    pinkiepower=60;
    classthreepower2=classthreepower2+pinkiepower;
elseif p>10 & p<40 & variance<800
    pinkiepower=40;
    classthreepower2=classthreepower2+pinkiepower;
elseif p>40 & p<70 & variance<800
    pinkiepower=20;
    classthreepower2=classthreepower2+pinkiepower;
end

%%
if classthreepower1>classthreepower2
    classthreepower=classthreepower1;
else
    classthreepower=classthreepower2;
end

```

I.4 CLASS 4

This is the matlab file used to find if there is an activity or the hand joints are not active. The standard deviation for the five joint are compared with a threshold of six degrees. If the five joints have low standard deviation then the hand is not active and class four power (power of "no activity") is set to 240.

```

S1=std(E);
S2=std(A);
S3=std(B);
S4=std(C);
S5=std(D);
classfourpower=0;

if (S1<6) & (S2<6) & (S3<6) & (S4<6)
    classfourpower=240;
end

```

REFERENCES

1. Vanderbloeg., Rodney, et. al., "Traumatic Brain Injury", Veterans Health Initiation
2. R. Boyd, and L. Ada, "Physiotherapy Management of Spasticity", in *Upper Motor Neurone Syndrome and Spasticity*. New York: Cambridge University Press, 2001, pp. 99-102.
3. Center for Disease Control and Prevention, <http://www.cdc.gov/ncipc/images/figure8.gif>.
4. L. Simone, E. Elovic, and R. Zafonte, "Outcome assessment for spasticity management in the patient with traumatic brain injury," *Journal of Head Trauma Rehabilitation*, vol. 19, pp. 155-177, 2004.
5. E. Finch, D. Brooks, P. W. Stratford, and N. E. Mayo. *Physical Rehabilitation Outcome Measures: A Guide to Enhanced Decision Making* (2nd edition). Hamilton, Ontario, Canada: BC Decker, 2001.
6. G. R. Johnson, "Measurement of Spasticity", in *Upper Motor Neurone Syndrome and Spasticity*, New York: Cambridge University Press, 2001, pp. 81-84.
7. D. Winter, *Biomechanics and Motor Control of Human Movement* (3rd edition). New Jersey: John Wiley and Sons, Inc., 2005, pp. 16-18.
8. S. Wise, et. al., "Evaluation of a fiber optic glove for semi-automated goniometric measurements," *Journal of Rehabilitation Research and Development*, vol. 27, no. 4, pp. 411-424, 1990.
9. From the World Wide Web: <http://www.sulekhab2b.com/indiamedicoinstruments>.
10. S. Eisentein, et. al., "Analysis of Clustering Techniques to Detect Hand Signs," *Proceedings of the International Symposium on Intelligent Multimedia, Video and Speech Processing*, pp. 259-262, 2001.
11. L. Simone, N. Sundarrajan, Y. Jia, and D. Kamper, "A low cost instrumented glove for extended monitoring and functional hand assessment," *Journal of Neuroscience Methods*, 2006.
12. L. Simone, N. Sundarrajan, E. Elovic, and D. Kamper, "Characterization of a novel sensor glove to explore hand movement disorders following brain injury," 2005.
13. From Immersion Corporation available at the world wide web: http://www.immersion.com/3d/products/cyber_glove.php

14. From the Humanware available at the world wide web:
http://www.hmw.it/download/glove/HumanGlove_Leaflet.pdf
15. T. Zurbrugg, Dynamic grasp assessment for smart electrodes (GRASSY), Wearable Computing Lab, ETH Zurich, available at:
<http://www.wearable.ethz.ch/grassy.0.html>
16. L. Simone, E. Elovic, U. Kalambur, and Kamper, D, "A low cost method to measure flexion in individuals with reduced hand and finger range of motion," 2004.
17. N. Webster, Webster's New Twentieth Century Unabridged Dictionary, 2nd edition, 1962.
18. C. L. Mackenzie, *The Grasping Hand*. Amsterdam, The Netherlands: Elsevier Science. 1994
19. M. Vetterli, and C. Herley, "Wavelets and filter banks: theory and design," *IEEE Transactions on Signal Processing*, vol. 40, pp. 2207-2232, 1992.
20. S. Jaffard, Y. Meyer, and R. D. Ryan, R.D, *Wavelets: Tools for Science and Technology*. Philadelphia, PA: Society for Industrial and Applied Mathematics (SIAM), 2001.
21. K. H. Kim, and S. J. Kim. "A wavelet-based method for action potential detection from extracellular neural signal recording with low signal-to-noise ratio," *IEEE Transactions on Biomedical Engineering*, vol. 50, pp. 999-1011, 2003.
22. Li, B.L., and Wu, H, "Change detection in nonlinear biosignal processing by wavelets," *Proceedings of the 1996 Fifteenth Southern Biomedical Engineering Conference* , vol. 29, pp. 307-310, 1996.
23. Wavelet Matlab Toolbox R2006b.
24. L. Debnath, *Wavelet Transforms and their Applications*. Boston: Birkhauser, 2002.
25. E. Hernandez, and G. Weiss, *A First Course on Wavelets*. Boca Raton, Florida: CRC Press, 1996.
26. M. Weeks, *Digital Signal Processing using Matlab and Wavelets*. Hingham, MA: Infinity Science Press, 2006.
27. J. Wilen, "Wavelet Transform Methods for Identifying Onset of sEMG Activity," M.S. thesis, New Jersey Institute of Technology, Newark, NJ, USA, 2004.
28. A. Ismail, and S. Asfour, "Continuous wavelet transform application to EMG signals during human gait," in *Record of the thirty-second Asilomotor Conference on Signals, Systems, and Computers*, 1998, vol. 1, pp. 325-329.