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Developing Predictive Models for Upper Extremity Post–Stroke Motion Quality Estimation Using Decision Trees and Bagging Forest

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I am submitting herewith a thesis written by Sarvenaz Chaeibakhsh entitled "Developing Predictive Models for Upper Extremity Post–Stroke Motion Quality Estimation Using Decision Trees and Bagging Forest." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Mechanical Engineering.

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Developing Predictive Models for Upper Extremity Post–Stroke Motion Quality Estimation Using Decision Trees and Bagging Forest

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ABSTRACT

Stroke is one of the leading causes of long–term disability. Approximately two-thirds of stroke survivors require long-term rehabilitation, which suggests the importance of understanding the post-stroke recovery process during his activities of daily living. This problem is formulated as quantifying and estimating the post-stroke movement quality in real world settings. To address this need, we have developed an approach that quantifies physical activities and can evaluate the performance quality. Wearable accelerometer and gyroscope are used to measure the upper extremity motions and to develop a mathematical framework to objectively relates sensors' data to clinical performance indices. In this article we employ two machine learning classification methods, Bootstrap Aggregating (Bagging) Forest and Decision Tree (DT), to relate the post-stroke kinematic data to quality of the corresponding motion. We then compare the accuracy of the resulted two prediction models using cross-validation approaches. Our findings indicate that Bagging forest approach is superior to the computationally simpler DTs for unstable data sets including those derived from stroke survivors in this project.

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CHAPTER ONE:
INTRODUCTION AND MOTIVATION

Introduction

Stroke outcomes adversely affect almost every aspect of an individual's life, particularly the ability to work and earn a living. Unemployment combined with extensive medical bills can pose additional financial difficulty. According to the World Health Organization, 15 million people suffer stroke worldwide each year. Of these, five million die and another five million are permanently disabled. In developed countries, although the incidence of stroke is decreasing due to efforts to lower blood pressure and reduce smoking, the overall rate of stroke remains high due to the aging of the population [1].

Stroke is the fourth leading cause of death and one of the top causes of preventable disability in the United States. Stroke is a leading cause of death and one of the top causes of preventable long-term disabilities in the United States. Stroke kills almost 130,000 of 800,000 Americans who die from cardiovascular diseases each year. That means brain stroke is responsible for 1 among every 19 deaths from all causes in America [2]. It is the fifth leading causes of deaths in the America. On average, one American dies from stroke every 4 minutes. Stroke costs the United States an estimation of $71 billion each year. This total includes the cost of health care services, medications to treat stroke and missed days of work [3, 4]. The stroke treatment expenses are projected to become more than double in 2030 since the number of people having strokes is increasing and is expected to increase by 20 percent by 2030 according to the American Heart Association/American Stroke Association [4].

Currently about 4% of adult Americans experience stroke. The increasing number of stroke occurrence can lead to 3.4 billion stroke incidences in 2030 and $183,13 billion treatment cost [4]. The high caring cost of post stroke treatment is mainly because of post-stroke long-term disabilities.

About half of Americans (49%) have at least one of the main stroke risk factors: daily smoking, physical inactivity and being overweight, self-reported high blood pressure, or diabetes. Several other medical conditions and unhealthy lifestyle choices can increase the risk of stroke [5].

The Effect of Stroke on Brain and Body

Stroke is a brain attack. Strokes were previously called cerebral vascular accidents, which meant there was damage to brain cells due to a problem with a blood vessel in head or neck. Stroke occurs when a blood flow that carries oxygen and nutrients to an area of the brain is either blocked by clots, bursts or ruptures. About 80 percent of strokes are caused by the blockage of an artery in the neck or brain. A hemorrhagic stroke is caused by a burst blood vessel in the brain that causes bleeding into or around the brain. When the blood flow to the brain is cut off, part of the brain cannot get the oxygen it needs, so the brain cells that are deprived from oxygen begin to die. When brain cells die during a stroke, abilities controlled by that area of the brain such as memory, cognitive abilities and the power to control muscles are lost. How a person is affected by stroke depends on the region of the brain where stroke occurs and how much the brain cortex is damaged. A stroke survivor may experience temporary or permanent physical, emotional or cognition deficits. That includes sudden weakness, loss of sensation, or difficulty with speaking, seeing, or walking [6]. Lost of physical abilities, which is the primary concern of this project, can be experienced in different parts of the body with various symptoms. The most common symptoms are: a) inability to move one side of the body (*paralysis*), b) weakness on one side of the body (*hemiparesis*), c) deficient and limited coordination (*ataxia*), d) difficulty in swallowing (*dysphagia*), e) fatigue, f) numbness or strange sensations, g) pain in the hands and feet that worsens with movement and temperature changes, h) lack of ability in picking up the front part of the foot (*foot drop*), i) difficulty to control the bladder (*incontinence*), j) seizure and epilepsy, k) sleep disorder and l) deficient vision [6-8].

In this project, the effect of most common post-stroke physical disabilities on the stroke survivor upper extremity motion are under study. These categories are: paralysis, hemiparesis, and spasticity which are explained in more details in the following paragraphs.

Paralysis and hemiparesis are one of the most common disabilities that people experience after the stroke. Paralysis usually happens on the side of the body opposite to the side of the brain that is damaged by stroke. Hemiparesis is a one-sided weakness that affects 8 out of 10 stroke survivors. Hemiplegia is the most severe form of hemiparesis, which is the complete paralysis of half of the body. Paralysis and hemiparesis may affect the face, an arm, a leg, or the entire side of the body. This One-sided paralysis is called hemiplegia. Stroke patients with hemiplegia may have difficulties with their Activities of Daily Living (*ADL*). Depended on the severity of the stroke and how much of the body is involved in, the physical impairment can affect the ability to walk, to rise from a chair, to feed oneself, to write, to grasp different objects, and many other activities. Physical therapy can help stroke survivors suffering from paralysis regain strength, coordination, balance and control of movement.

As it was discussed earlier, stroke damages brain cells. In some cases, this damage blocks sending and receiving messages from muscles to the brain and vice versa. Dysfunction of parts of the nervous system that coordinate movement following stroke is called *Ataxia*. Ataxia caused by stroke usually limits to one side of the body, which is referred to as *Hemiataxia* [9]. Ataxia puts limitations on the coordination of muscles. This symptom usually appears when a group of muscles should work together. It can cause motion patterns to be awkward and jerky. Ataxia potentially can cause spasticity during time which leads to spasm and muscle cramps [10].

Stroke Recovery and Rehabilitation

Rehabilitation helps stroke survivors regain all or part of their lost abilities due to brain damage. It also helps the survivors to learn new ways of performing tasks to circumvent their permanent disabilities. Approximately two-third of stroke survivors require some kind of long-term rehabilitation. Recovery from a stroke may take months or years. Many people who have experienced stroke may never fully recover. Stroke recovery process has three phases: 1) emergency treatment, 2) preventing another stroke and 3) rehabilitation. The first two items are applied to the patient at the very first hours after stroke occurrence. Many stroke survivors recover functional independence after a stroke, but 25% are left with a minor disability and 40% experience moderate-to-severe impairments [7, 8]. Rehabilitation therapy begins after the patient's overall condition has been stabilized, which is usually within 24-48 hours after the stroke [11].

The goal of rehabilitation is to help the survivors become as independent as possible and to regain the best possible quality of life. The first rehabilitation practices after stroke are improving independent motions since many survivors are severely weakened if not paralyzed. They are asked to change their positions frequently even when they are lying in bed. They are also encouraged to get involved in passive or active range of exercises to improve their paretic limb [11]. In passive range of motion exercises, the therapist assesses the patient to move his paretic limb repeatedly. In active range of the movement exercises, the patient performs the activity receiving no physical help from the therapist [11]. Different patients may show progress differently due to various factors such as the severity of the initial brain injury. As the patient's physical conditions improve, the therapist asks the patient to perform more demanding and complex tasks, such as using a toilet or bathing. The therapist encourages the patient to employ his paretic limb while conducting different tasks. As the patient starts to regain the ability to carry out these basic tasks, he steps into the first stage of returning to an independent life.

Even though rehabilitation does not completely cure the effects of stroke, since it can not reverse brain damage, it is shown that rehabilitation can substantially help people achieve the best possible long-term outcomes [10]. Rehabilitation experts believe that carefully directed, well-focused and repetitive practice are the most important elements of any rehabilitation program. Several types of therapies can help a stroke survivor regain some or all of his functionalities damaged by the stroke. The primary post-stroke therapies include: a) physical therapy, b) occupational therapy and c) speech therapy [7, 8, 12].

The first step in physical therapy is promoting independent movement. Many individuals are paralyzed or severely weakened after stroke. Rehabilitation begins in the hospital after the person's overall condition has been stabilized. Patients are engaged in passive or active range of motion exercises to strengthen their stroke-impaired limbs. Rehabilitation therapists help patients to perform more complex and demanding tasks progressively. The implicit goal of rehabilitation exercises is engaging the stroke-impaired limb in performing tasks. Regaining the ability to carry out basic activities of daily living represents the first stage in a stroke survivor's returning to independence. For many stroke survivors, rehabilitation will be an ongoing process to maintain and refine skills. It usually involves working with specialists for months or years after the stroke which costs a massive amount of time and money.

Monitoring and evaluating the quality of performance of the patient after stroke in his activities of daily living and his use of his paretic limb are critical since they yield significant information about the recovery progress and the occurrence of the *non-use phenomenon*. The non-use phenomenon is a learning phenomenon in which the role of paretic limb motion is suppressed due to an adverse reaction or inability of conducting the task. If the stroke survivor continues surpassing the impaired limb, he may never learn that his former paretic limb has become potentially useful [12]. Additionally, by monitoring the patient's during his activities of daily living, significant information about neuroplasticity can be obtained. After a stroke, functions compromised when a particular part of the brain is damaged by stroke. Functions can sometimes be taken over by other regions of the brain. This ability to adapt and change is known as neuroplasticity.

Currently, therapists get insight into individuals' activities of daily living mostly through self-reported log sheets and questionnaires. However, it has been shown that patients overestimate their physical activities and abilities [13]. Hence, the researchers and clinicians cannot obtain accurate information of the post-stroke recovery process. This issue makes questionnaire an unreliable substitute for physical examination and does not let the physicians plan the appropriate therapies optimally [9]. Moreover, false or not accurate self-report questionnaires deprive the specialist of getting any information if the patient is learning non-use of the paretic limb [14]. The use of a sensor-based system to monitor post-stroke activities of daily living is a promising approach to improve the clinical management of patients after leaving the clinics and getting back to normal life environment. Among all body worn sensors, accelerometers have been used as an effective, non-invasive motion measurement systems. Accelerometers are portable, affordable and can be accurate enough for the purpose of recording body movements [15]. These body worn sensors provide information about the subject's physical activities pattern. The accelerometers' ability to automatically and continuously recording physical activities, gives the therapist an insight into the activities that the subject has carried out throughout the day. This feature can be used for monitoring movements' disorders as well [16].

To address the clinical needs of an autonomous system for monitoring physical activities of people who had stroke during their activities of daily living and in real world setting, a system should be developed which not only tracks the subjects' amount of physical activities but also gives an evaluation of the quality of the patient improvement.

The remainder of this article is structured as follows: In Section two we take a brief look at the studies that have been done in the post-stroke activity classification research area. Chapter three describes our project motivations. Chapter four explains the problem in hand and the proposed methods. In chapter five we go through the obtained results for our problem, using methods introduced in chapter four. Chapter six summarizes the project and its outcome as the conclusion. Finally in chapter seven, we point out some of our study’s limitations.

CHAPTER TWO:
BACKGROUND

As it was described in the previous chapter, stroke is one of the leading causes of serious long-term disabilities in the United States. Due to the commonness of stroke and the large population affected by stroke, stroke has drawn the attention of many researchers to itself during history [6, 13]. A significant number of people experience motor activity limitation after stroke [2, 3]. Post-stroke observations contain valuable information about the patient's recovery process and motor function [13]. It has been shown that the adverse reaction of impaired limb makes patient surpass his paretic arm and consequently learn the non-use [13, 14, 17-19]. The non-use phenomenon is a learning process in which the motion is surpassed by the paretic limb due to adverse reactions or failure in conducting the task. Continuing surpassing the impaired limb may not let the user know that his former paretic limb has become potentially useful [20, 21]. To track patients' use of his paretic limb and his post-stroke recovery process during his activities of daily living, questionnaires and diaries are commonly used [22, 23]. There are several problems with these self-reported schedules; People usually overestimate their activities and recovery process, and sometimes they forget what they have done [13]. Also, the subject should be able to read and write which is not the case in many of stroke survivors. Therefore, the reliability of these questionnaires is highly depended on the subjects' functioning, honesty, and recall. However, the patient's ability to perform specific tasks, defined in different questionnaires and functional assessments, not only help the patients to improve their ability of being more physically independent, but also give the therapists and researchers a standard framework for describing the patients' post-stroke condition severity and improvement [13, 24, 25]. Although these clinical tests are helpful in describing the ability of the patient in performing specific tasks, they do not give any information about the amount of physical activities the patient was involved in his activities of daily living out of laboratory and clinic and his use of paretic limb. They also do not yield any information about learning the non-use phenomenon.

Optical and visual systems such as VICON (Vicon Industries, Inc., NY, USA), figure 1, or CODAmotion (Charnwood Dynamics Ltd., Leicestershire, UK),figure 2, are widely used in research and clinical setting. Typical optical systems use markers to track the motion. Different markers are placed on different part of the subject's body. Oftentimes, the software coming with the optical system can recognize the markers and simulate the subject's body movements accordingly. Some motion trackers such as OptiTrack (NaturalPoint, Inc., OR, US) have the capability of simulating the subject's movement in virtual space with such a low latency that is close to real time. Also, increasing the complexity or length of the performance does not add any cumbersome tasks to the procedure. Moreover, if something goes wrong during the experiment, the examiner can reshoot the scene; it is much easier than manipulating the data. However, this is likely to happen in systems which have real-time analysis, where the examiner is able to see the data as the experiment goes on [26-28].

Despite the optical motion trackers' accurate movement capturing result, they are not a proper choice for at home setting usages. Specific hardware and setup are needed for the operation. The relatively complicated setting up procedure of the optical motion trackers requires personnel which makes prohibitive for small businesses. Depended on the camera field of view of magnetic distortion the capturing system may need specific definition of the space that it can operate in. Also, the experiment should be only done in camera range. Since these systems use their own software for simulation, not all the motions can be captured [27, 28].

Body-worn sensors are introduced as a reliable alternative for measuring physical activities. Wearable sensors have opened an avenue for non-invasive and accurate observation of patients' body movement during research and clinical rehabilitation process and in real world setting [29, 30]. Among all body worn sensors, accelerometers have been used as an effective, non-invasive motion measurement system [30]. In comparison with other motion monitor devices, accelerometers have many advantages; Accelerometer based motion tracking systems are typically affordable, portable and easy to use [31]. They usually do not need manipulation when they are in use [29] and their small size and light weight have made it possible for any human subject to wear it during the day while having real world activities outside the laboratories and in real world setting. Additionally, accelerometers are sensitive enough to detect even small motions [13, 29]. Comparing to other motion recognition systems such as commonly used VICON cameras, accelerometers offers a non-privacy-invasion system of motion recognition which makes them a more suitable choice for home monitoring [16].

Nowadays researchers widely use wearable accelerometers to get insight into the post-stroke patients' activities of daily living [16]. However, there are still some drawbacks in using accelerometers as body motion detectors. It is challenging to separate the gravitational component from the inertial data without having additional data describing the accelerometer data. There are also some difficulties related to representing all the information at a single global frame since typically each accelerometer has its own moving frame, and the data are recorded on that frame of reference. Moreover, the location and orientation of the accelerometer on the subject's body can influence the collected data. This issue usually arises when the examiner has no or limited experience in using accelerometers, or different examiners conduct the experiment. Yet, these drawbacks have the potential to compromise the quality of the recorded data [13, 15, 16, 32].

In several studies, participants were asked to keep a diary describing their everyday activities in addition to putting on wearable accelerometers during their activities of daily living. The first problem with this approach is using self-reported log sheets, which has many disadvantages as were mentioned in the previous section. Moreover, the subject should be able to read and write, which is not the case in many stroke survivors. Additionally, the extra effort and time that researchers and participants should put into keeping the diary in addition to the accelerometers, put some limits on recruitment procedure [33].

Evaluation of physical functioning has become increasingly important in stroke clinical research and rehabilitation therapy planning. Several performance assessments have been developed that correlate with other measures of health status and predict need for long-term care. There is evidence showing self-evaluation of ability and recovery improvement have low validity and high variability when are compared with measures of performance [34].

Stroke assessment scales can be categorized into five groups: (1) Prehospital stroke assessment, (2) Acute assessment, (3) Functional assessment (4) Outcome assessment and, (5) Other diagnostic and screening tests [35, 36]. The Fugl-Meyer Assessment was developed as the first quantitative evaluative instrument for measuring sensorimotor stroke recovery, based on sequential stages of motor return in the stroke patient. The Fugl-Meyer is a well-designed, feasible and efficient clinical examination method that has been tested widely in the stroke population [37]. Its primary value is the 100-point motor domain, which has received the most extensive evaluation. Based on available literature, the Fugl-Meyer Assessment is highly recommended as a clinical and research tool for evaluating changes in motor impairment following stroke [25, 37, 38].

Standardizing clinical motor assessments can be done using data based experiments; Quantitative data could be obtained by simultaneously recording data from accelerometers mounted on different parts of the body. The validation of the accelerometry data has been tested through various approaches and in different test conditions [16, 31, 32, 39]. Analyzing the recorded data can lead the researchers to identify some pre-defined activities. These pre-defined motions can later be decomposed into motion components to determine the movement patterns related to motor impairments and limitations [40]. Many researchers have focused on accurate post-stroke observation and data quantification. The development of miniature body-worn sensors, more specifically accelerometers, have opened countless possibilities of post-stroke monitoring in the field over extended periods of time [13, 41]. The ultimate goal of rehabilitation is sending back the patient to his real life environment. Wearable sensors allow clinicians and researchers to get insight into the patient's recovery process where it matters the most, in the home and community settings.

The possibility of studying different clinometric variables and their properties using accelerometers have been investigated through literature [13]. In order to explore the collected data, different properties have been measured [13, 31]. Many studies have been conducted regarding classifying post-stroke activities using body worn accelerometers. The focus of the majority of these works is on lower extremity [24]. Due to the complexity and higher degrees of freedom of upper extremity, fewer studies have been done in this area. Studies have shown that accelerometry data can be used for measuring overall upper extremity activities [15]. Wearable accelerometers have been widely used for recording the amount of activity or inactivity of the upper extremity impaired limb over a time period [42]. The information obtained from the accelerometer is limited to speed and direction. However, a significant number of patients benefit if this data can be interpreted with clinical features in the hospital and home setting [43]. It has been shown that accelerometry data can be properly correlated with most clinical assessments such as Fugl-Meyer Assessment subscale for upper extremity [15, 42]. In 2012, Rand et al. [44] claimed that the gap between the expected recovery that is estimated by clinical measurements and the real performance improvement in the daily use of the impaired limb according to accelerometer data, suggests that present clinical measurement systems are not sufficient. Interpreting the accelerometry data with clinical assessments allows researchers and clinicians to get a deeper insight into the patients' recovery improvement in their daily functioning [33, 45].

In this document, we propose an approach for estimating not only the amount of activity and inactivity of the impaired upper extremity limb but also the quality of the impaired limb physical functioning. This approach suggests that by analyzing accelerometry data, we can automatically obtain an evaluation of the patient's recovery process.

The National Institute of Neurological Disorders and Stroke (NINDS) is a component of the U.S. National Institute of Health (NIH) [46]. The NINDS is the main research sponsor of disorders of the brain and nervous system [11]. These studies include the acute phase of stroke and recovering the brain abilities after the stroke damage. The Eunice Kennedy ShriverNational Institute of Child Health and Human Development is a part of the NIH, which through its National Center for Medical Rehabilitation Research, invests in studies related to the mechanisms of post-stroke recovery and repair, as well as introducing and development of new approaches to rehabilitation and evaluation of results. The NIH's National Institute on Deafness and Other Communication Disorders is interested and financially helps studies on diagnosis and treatment of dysphagia [46]. From the Biomedical aspect, the National Institute of Biomedical Imaging and Bioengineering collaborates with NINDS and NICHD to develop new instrumentation for post-stroke treatment and rehabilitation. Also, the National Eye Institute financially assists work related to post-stroke vision recovery and rehabilitation for individuals with impaired or low vision [11].

The NINDS funds work on approaches to enhance repair and recovery of the central nervous system (CNS). Scientists funded by the NINDS usually study the brain responds to experience or its adaption to stroke injury by reorganizing its functions (plasticity). Other NINDS-funded researchers study brain's post-stroke reorganization. They also look into the brain's response to specific rehabilitative techniques, such as constraint-induced movement therapy (CIMT). They are interested in determining if methods such as CIMT and transcranial magnetic stimulation, can stimulate brain plasticity. By simulating the plasticity, the motor function will be improved, and consequently, the post-stroke disability will be decreased. Other researched are dedicated to determination of the effect of experimenting with implantation of neural stem cells, on the probability of replacing the post-stroke damaged or died brain cells [11], [5].

CHAPTER THREE:
MOTIVATION

Automating the post-stroke physical monitoring opens an avenue to post-stroke home monitoring. By virtualizing the patient's therapist, the patient has his/her therapist by his side all the time during his activities of daily living, where rehabilitation matters most. Health Centers and hospitals will benefit from this research as well the patient. Using the proposed system, they will have access to accurate information about the patient's physical improvement during his activities of daily living. For health centers and hospitals, the system functions as if they have the patient tested all the time, without the physical presence of the patient. Thus, health centers and hospitals can spend more time, space and personnel to take care of other patients who cannot leave the hospital.

The increasing rate of daily smoking, physical inactivity, being overweight, having high blood pressure, and diabetes suggests an increasing rate of stroke occurrence probability in near future. A large share of the average $100,000 post-stroke treatment costs goes to the hospitals. This massive cost can be reduced by discharging the patient for the hospital and still have him/her under the virtualized therapist's monitor. This study opens an avenue to evaluating the post-stroke physical improvement in real world setting. Using accelerometry-based sensors for human motion monitoring, suggest an accurate post-stroke motion tracking without interrupting the patients during his/her activities of daily living or invasion of his/her privacy. In the big picture, our system helps the patient to return to his activities of daily living and still be under the monitor and receives feedbacks for the best rehabilitation results. This project contributes to virtualize the physical and occupational therapists while allowing the patient to have their support and feedback all the time at a significantly lower cost.

The methodology used in this research can be developed to be used in other clinical studies. In future explorations, the accurate kinematic data quality predictor formulated in this project can be resorted to estimate patients' scale of pain, strength, soreness, muscle contraction, etc. The developed method along with task recognition frameworks will be a complete at home post-stroke monitoring system.

CHAPTER FOUR:
POST-STROKE QUALITY OF UPPER EXTREMITY MOTION ESTIMATION

Project Description

This project aims at estimating the post-stroke physical improvement in real world setting. In order to do so, the performance of the non-paretic limb was set as our reference as an un-faulty performance. Then, we investigated the patient's overall post-stroke physical capabilities by asking them to perform some tasks according to the well-known Fugl-Meyer clinical assessment. The motion of both impaired and non-impaired limbs was recorded using tri-axial motion monitors. In order to have an estimation of the paretic limb quality of movement, the kinematic data of the non-impaired limb was compared to the one of the paretic limb's. In order to relate the kinematic data to the Fugl-Meyer score, which is our initial criteria for quality of motion, mathematical features representing the kinematic attributes of human limbs' motion such as speed, smoothness and coordination should be extracted and examined in contrast.

In this thesis, the quality of the post-stroke kinematic motion is formulated as a classification problem. In the designed classification model, we classify different performed tasks according to their Fugl-Meyer score which in turn, is a scale of the performed motion quality. This score is estimated visually by the examiner therapist and will be explained in more details in the following the sections.

In order to collect the kinematic data required for our analysis, and the data presenting the quality of the performed motion task, an experiment was designed and held at the UT Medical Center. During the test, the subjects with post-stroke physical impairment were asked to wear motion monitors. Then the examiner therapist asked the patients to perform tasks according to the Fugl-Meyer Assessment subscale for the upper extremity. The patient's quality of motion estimation is expressed as the Fugl- Meyer score and was recorded by the examiner therapist. During the experiment, the patient's motions kinematic data were collected and recorded by the installed motion monitors.

After collecting the kinematic data, data segmentation is applied. In data segmentation, each segment of the kinematic data corresponding to performing each of the Fugl-Meyer tasks is isolated for further analysis.

In favor of interpreting the kinematic data collected from the motion monitors with the Fugl-Meyer scores that were recorded by the examiner therapist, one or more measurement features should be explored in kinematic data that are sensitive to the quality of motion's characteristics. In this research, we care about motion features such as accuracy, speed, coordination, and smoothness.

Machine learning supervised classification methods were used in this thesis to classify our kinematic data according to their obtained Fugl-Meyer score. As it was mentioned earlier, these scores give an estimation of the patient's capabilities of performing the required tasks.

A prediction framework can be developed using the classification results. This prediction framework categorizes the new set of kinematic data set according to its estimated Fugl-Mayer score. In other words, our classification model classifies different tasks according to their obtained Fugl-Meyer score and the prediction model, uses the classification model results to classify the new set of data and label it with the most probable Fugl-Meyer score that the new kinematic data would gain. Figure31 shows a flowchart of the proposed algorithm.

In what follows, each of the steps shown in figure. 3 is explained in more depth and details.

Data Collection

Experimental Procedure

Participants

The subject recruitment was done at the UT Medical Center, and the experiment procedure is approved by the University of Tennessee Institutional Review Board.

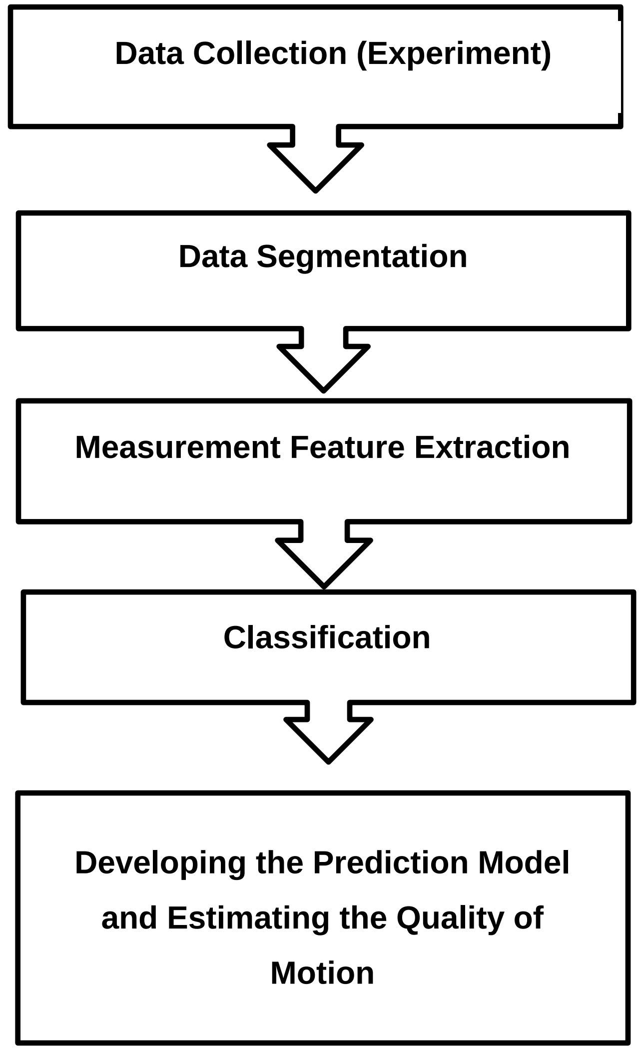


Figure 1. Flowchart of the employed algorithm to analyze accelerometer data and derive estimates of the FMA score

All participants are provided with informed consent before the experiment. Eight participants were recruited. In order to satisfy the inclusion criteria, each participant should: (1) have a positive stroke on their head CT or MRI; (2) exhibit resulting unilateral weakness of the upper extremity; (3) have cognition sufficient to follow simple commands; (4) have fair vision, and (5) have sufficient activity tolerance to sit upright and participate in the experiment.

People with the following conditions were excluded from testing: (1) completely flaccid upper extremity; (2) poor cognition (leading to inability to follow commands); (3) severe vision deficits and blindness; and (4) residual weakness from a previous stroke. Pregnant women, prisoners and people less than 18 years old were excluded as well.

Apparatus and Measures

Each participant wears five APDM Opal motion monitoring sensors (APDM Inc., OR, USA).

These motion sensors contain a tri–axial accelerometer, rate gyroscope, and magnetometer (the latter was not used in our analysis). They can record 12-16 hours of data, depended on their different recording modes. Table 1 shows this sensors specification.

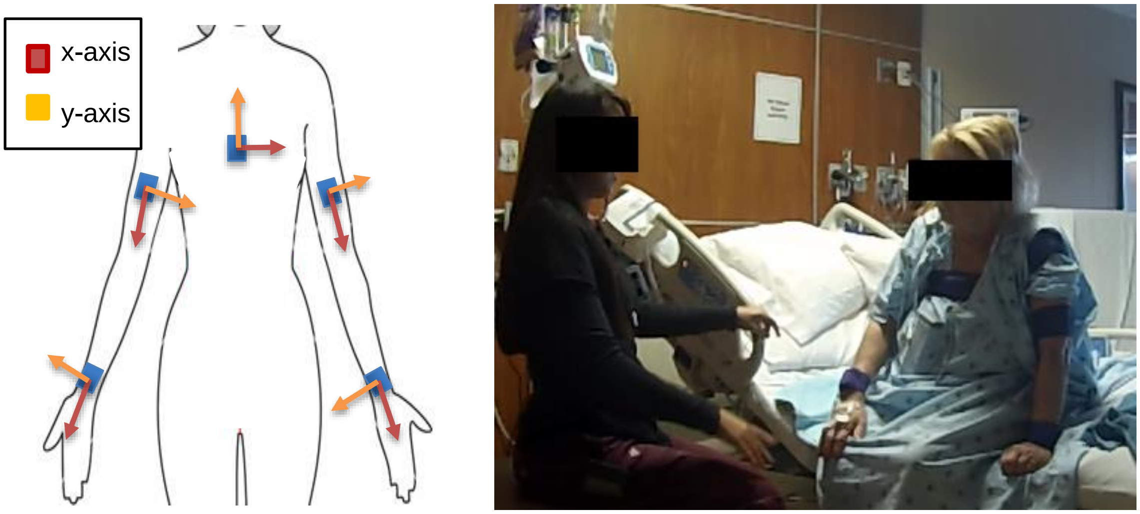
Four of these motion monitors were placed on the participants' wrists and bilateral upper arms near the elbow for capturing motion data resulting from upper extremity movement. The fifth sensor was put on the subject's chest in order to record trunk kinematic data. Sensors were attached to the subject's limbs using latex–free bandages for sanitary purposes and to minimize noise due to soft tissue motion. Figure 5.a shows the sensors' position and orientation on the subject's body. Figure 5.b depicts a participant during the experiment in a clinical setting.

Data from the two wrist–worn sensors are used for this research objective. The examiner therapist instructs each participant to perform a subset of tasks according to the upper extremity motor function Fugl-Meyer Assessment and kinematic signals resulted from the patient's movement are recorded using motion monitors. Fugl-Meyer Assessment is a stroke-specific, performance-based impairment index with a three-point (0-2) scale. A score of 0 indicates the patient's disability to conduct the task where a score of 2 means that the patient was able to carry out the task flawlessly. This well-known stroke clinical index is designed to assess motor functioning, balance, sensation and joint functioning in patients with post-stroke hemiplegia. Fugl-Meyer is specifically intended to assess the functional mobility of stroke survivors during their activities of daily living. Depended on the stroke survivor's severity of brain damage it may take about 6-30 minutes for the subject to perform the assessment tasks. The Fugl-Meyer Assessment is designed for the hemiplegic patients of all ages. It is also known as one of the most reliable assessments in test-retest scenarios [35-37].

The performed subscale of Fugl-Meyer upper extremity motor function tasks in this project includes synergy, out of synergy, combination of synergies, wrist/hand function, and fine motor coordination. According to the Fugl-Meyer procedure, the clinician scored the participant according to the three point (0–2) scale [8], [9]. A sample form of FMA used for the experiment is attached to this document. Participants repeat each task three times according to the instructor therapist, and the best attempt is scored. Scores are then totaled to give a resulted score of 66 possible points with lower scores representing greater impairment. In addition to collecting kinematic data and the Fugl-Meyer scores, the whole experiment is video recorded. Table 1 shows the participants demographic.

Data Preparation

After data collection, the kinematic data and patients' IDs should be matched. To do so, first, we match the recorded videos to the subjects' IDs. The order of the recorded videos is consistent with the order of the performed tests. Hence, the order of recorded videos is compatible with the order of different patients' IDs.



(a): Schematic representation of the motion monitor sensors location on the subject's body during the experiment

(b): APDM motion monitors positioned on the participant during administration of the FMA

Figure 2. Motion Monitors on the Subject's Body

Figures are adopted from [47]

Table 1. Demographics of Study Participants

Participant	Sex	Age	Lesion Side	Dominant Side	FMA Score
1	F	32	R	L	17
2	F	68	R	R	48
3	F	69	L	L	53
4	M	87	R	R	36
5	F	44	L	R	45
6	F	78	L	R	4
7	F	87	R	R	30
8	M	65	R	R	27

Using the videos, the length of each participant's experiment is extractable. The paper documents from the hospital show the date that the test was conducted for each participant. Having the date and length of each experiment, the dataset related to each trial can be matched. Having all of this information, the kinematic datasets, videos and paper documents, which also contain each patient's Fugl-Meyer score, can be matched.

Kinematic Data Segmentation

Since each task is scored separately during the experiment, the raw kinematic data associated with each task should be isolated. Data segmentation is performed using synchronized video and the information that were extracted from the video. In this project, data segmentation is done manually. The start time and finish time of each task for each subject are extractable using the corresponding recorded video. The difference between the start time and finish time of each task shows the time duration of each task. Table 2 shows a sample of the extracted information from the experiment recorded video.

Table 2. Information extracted from the experiment's recorded video

Motor Function	Left Wrist				Right Wrist			
	Start		Finish		Start		Finish	
	Time	Frame	Time	Frame	Time	Frame	Time	Frame
Sensor Tapping	0:16	464	0:17	494				
Reflexes biceps	5:27	9483	5:30	9571	6:09	10705	6:13	10817
Reflexes triceps	5:53	10237	5:59	10411	6:25	11165	6:35	11455

Having the time duration for each task, the segmentation windows can be produced. The isolated data for each task is demonstrated by the green and black lines in Fig. 6.b., respectively representing the start and stop times. In other words, segmentation converts Fig. 3.a to 3.b. In Fig 3.c, the flexor synergy task's kinematic data is isolated to show more details. This flexor synergy is the task that shows itself as fluctuations in figure 6.a happening between time 777 and 786 that is magnified in figure 6.c.

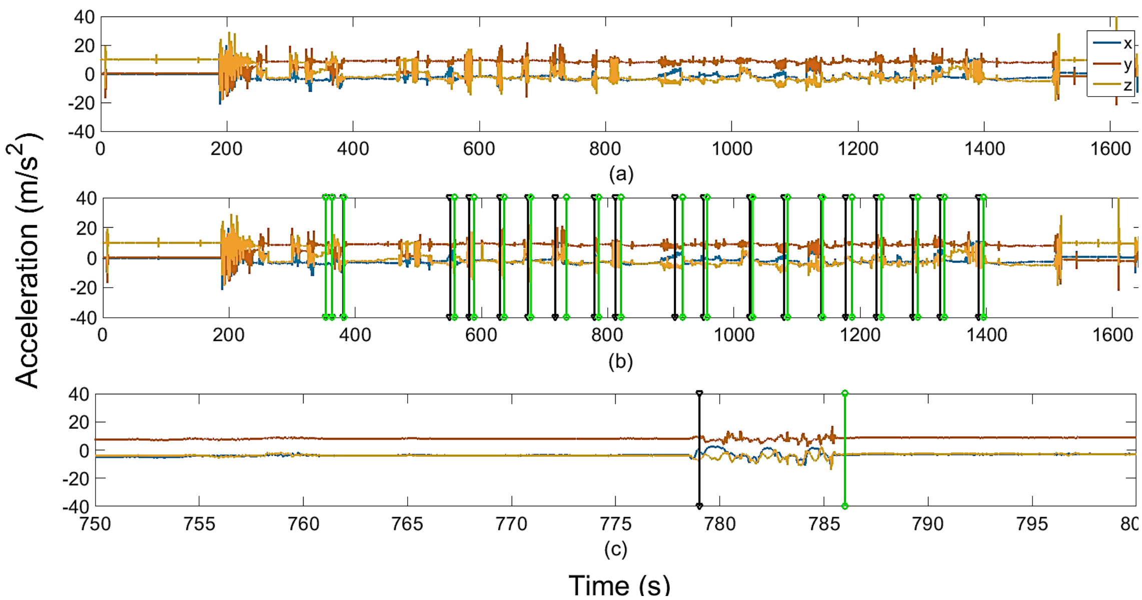


Figure 3. a) Raw kinematic data, b) Kinematic data after segmentation, c) An isolated task

Kinematic Data Measurement Feature Extraction

In order to interpret the kinematic data with meaningful clinical qualities, specific measurement features of the data should be extracted which are sensitive to mechanisms of human movement such as smoothness, speed, and coordination. In this study, we use four measurement features that are the most commonly used features in studies investigating the relation between the clinical assessments evaluating the quality of motion and kinematic data. These measured features are derived for each single task and for three time series data: acceleration, gyro, and jerk. Acceleration and rate of gyro values can be read directly from the sensors. Jerk, which gives a sense of smoothness of motion, is driven by getting the first derivation of acceleration. It is calculated for the whole acceleration signal and separately for each axis.

$$\vec{j}(t) = \frac{d\vec{a}(t)}{dt} = \dot{\vec{a}}(t) \tag{1}$$

Then we calculate the measurement attributes for each axis separately. Participants performed a total of 23 scored tasks. For task number n, we computed the gesture matrix D_j as follow:

$$D_j = \left[[F_{1_{1\times 3}}]\ [F_{2_{1\times 3}}]\ [\ldots]\ [F_{n_{1\times 3}}] \right] \tag{2}$$

Where $F_{i_{1\times 3}}$ shows the derived measured feature and n is the number of extracted features for each research objective. The subscript 1×3 indicates that each component of the matrix D_j in Eq. (2) is computed separately for each axis of data ($\hat{x}, \hat{y}$, and $\hat{z}$). Matrices D_j are calculated for acceleration ($\ddot{x}$), angular rate of change ($\dot{q}$), and jerk $x^{(3)}$. In this study we used four post-stroke kinematic measurements that are the most commonly used features in the related literature: Root Mean Square (RMS), mean value, entropy and dominant frequency. The root mean square also known as quadratic mean, is defined as the square root of mean of squares of a set of number. The root mean square or *RMS* of a set of n values as $\{x_1, x_2, \cdots, x_n\}$ is defined as:

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \cdots + x_n^2)} \tag{3}$$

The mean value has a similar definition to the RMS. In problems with discrete values, the mean value is defined as the sum of the variables over every possible value weighted by the probability of that value. In simple cases, where the probability weight of all variables is the same, the mean value will be defined as:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \tag{4}$$

In this project, by *entropy*, we are referring to the Shannon entropy [48]. Shannon entropy is a measure of random variables in a continuous probability distribution.

In this project, we used Matlab (MathWorks, Inc., MA, USA) function *wentropy()* to calculate our signal's entropy using following equation:

$$E(s) = \sum_i E(s_i) \tag{5}$$

Where s is the signal and $(s_i)_i$ is the coefficient of s in an orthonormal basis [49]. Entropy and dominant frequency are frequency domain features. In order to calculate them, the signal should be transferred from time the domain to frequency domain using Fourier transform function. To transform the discrete time series of $x_0, x_1, \cdots, x_n$ to an N-periodic sequence of complex numbers we use equation (6).

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-2\pi ikn/N} \tag{6}$$

Equation above can be interpreted to the discrete-time Fourier transform (*DTFT*) as follow:

$$X(\omega) = \sum_{n=-\infty}^{\infty} x[n]e^{-i\omega n} \tag{7}$$

Dominant frequency is the frequency that occurs most often in a signal. In this project, we obtained the dominant frequency correlated with the isolated signal of each task.

After calculating all attributes, the gesture matrices D_ns are developed according to Eq. 1:

$$D_n = \left[[RMS_{1\times3}]\ [Mean_{1\times3}]\ [Enrtopy_{1\times3}]\ [Dominant\ frequenc_{1\times3}]\right] \tag{8}$$

Where n is the number of the task. For each task, four measurement features are calculated for three axis of three time series: acceleration, gyro and jerk. Hence, the number of attributes for each task will be $4 \times 3 \times 3 = 36$. Each person performs a total number of 23 tasks according to the Fugl-Meyer upper extremity subscale. We recruited eight subjects. Therefore, the total number of attributes for our study will be: $8 \times 23 \times (4 \times 3 \times 3) = 6624$.

Table 3. Fugl-Meyer Scoring form for two different tasks

Task	Criteria	score	
Extensor Synergy	Shoulder add./int rot		0-Cannot be performed 1-Performed partly 2-Performed faultlessly
	Elbow Extension		
	Forearm pronation		
Wrist	Circumduction		0-Cannot be performed 1-performed partly 2-Performed faultlessly

In order to normalize the Fugl-Meyer score between all participants, we calculated the measured features, RMS, mean value, entropy and dominant frequency, for the impaired limb and divided each attribute to its corresponding of the non-impaired limb's, and create a matrix of the ratio of our measurements. The resulting feature matrix for participant i was then obtainable as shown in equation (9).

$$P_i = \begin{bmatrix} D_{T_1}(\ddot{x}) & D_{T_1}(\dot{\theta}) & D_{T_1}(x^{(3)}) \\ D_{T_2}(\ddot{x}) & D_{T_2}(\dot{\theta}) & D_{T_2}(x^{(3)}) \\ & \vdots & \\ D_{T_{23}}(\ddot{x}) & D_{T_{23}}(\dot{\theta}) & D_{T_{23}}(x^{(3)}) \end{bmatrix} \quad (9)$$

Fugl-Meyer scores need to be normalized as well. It should be noted that instead of using the FMA scores in our analysis, we used a *normalized* or *summarized value* derived from the Fugl-Meyer scores. The reason for this normalization is the scoring criteria variety over different tasks. For example, movement synergy tasks are scored three times between 0-2 (for hand, shoulder flexion, and forearm pronation) while wrist rotation was scored once. So the maximum obtainable score for movement synergy is 6 $(3(scoring\ criteria) \times 2(maximum\ score\ for\ each\ scoring\ criteria))$ while the maximum achievable wrist rotation score will be 2. In order to normalize our scores, we used a summarized scores which were calculated as the sum of all obtained scores divided by the maximum obtainable value. Table 3 shows an example of two performed tasks with different number of scoring criteria.

Classification and Prediction

The estimation of the quality of the impaired limb motion is formulated as a classification problem. Our classification model will classify our tasks according to their obtained Fugl-Meyer score. Therefore, all tasks receiving the same Fugl-Meyer score are categorized in one class.

Then, we use a supervised machine learning method to find the most important attributes in our classification. In machine learning supervised learning is referred to inferring a function from labeled training data [50]. In this kind of learning, each input object has an output. Supervised Leaning methods try to find an interfering function which can map the training data to the desired labels. In an optimal case, the function will be able to assign the new set of data to its potential label flawlessly. In order to use supervised learning algorithm, first, we need to define our training set. In this project, all the extracted attributes for each task were passed to out machine learning classification model as the training set. Then the summarized Fugl-Meyer scores were passed to the supervised learning model as the labels. In designing our classification model, all attributes corresponding to one task are fed to the model with the obtained Fugl-Meyer score which is the classification labels. Equations (10-11) show the input training set and label matrices.

$$input\ matrix = \tag{10}$$

$$\begin{bmatrix} RMS(P_1,T_1) & Mean(P_1,T_1) & Entropy(P_1,T_1) & Dominant\ Frequency(P_1,T_1) \\ RMS(P_1,T_2) & Mean(P_1,T_2) & Entropy(P_1,T_2) & Dominant\ Frequency(P_1,T_2) \\ \vdots & \vdots & \vdots & \vdots \\ RMS(P_1,T_{23}) & Mean(P_1,T_{23}) & Entropy(P_1,T_{23}) & Dominant\ Frequency(P_1,T_{23}) \\ RMS(P_2,T_1) & Mean(P_2,T_1) & Entropy(P_2,T_1) & Dominant\ Frequency(P_2,T_1) \\ RMS(P_2,T_2) & Mean(P_2,T_2) & Entropy(P_2,T_2) & Dominant\ Frequency(P_2,T_2) \\ \vdots & \vdots & \vdots & \vdots \\ RMS(P_8,T_{23}) & Mean(P_8,T_{23}) & Entropy(P_8,T_{23}) & Dominant\ Frequency(P_8,T_{23}) \end{bmatrix}$$

$$Labels = \begin{bmatrix} FMS(P_1, T_1) \\ FMS(P_1, T_2) \\ \vdots \\ FMS(P_1, T_{23}) \\ FMS(P_2, T_1) \\ FMS(P_2, T_2) \\ \vdots \\ FMS(P_8, T_{23}) \end{bmatrix} \quad (11)$$

In equations (10, 11), $Q(P_m, T_n)$ shows that value Q is calculated for the task n that patient number m did. In equation (11), FMS stands for the Fugl-Meyer score; $FMS(P_m, T_n)$ shows the summarized score that the patient number m obtained for performing task number n. Calculating the summarized score is described in the previous section.

Two supervised machine learning methods are used in this paper and their results are presented and compared. These two algorithms are: 1) Decision tree and, 2) Bootstrap Aggregating Forest

Decision Tree

The Decision Tree (*DT*) algorithm is one of the commonly used supervised learning classification methods in post-stroke kinematic data analysis. They are widely used in operations research especially in decision analysis. They are commonly used to find the strategy that is the most probable path to reach a goal. Moreover, they are also a well-known tool in machine learning classification problems.

Decision tree is a flowchart-like structure in which each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf accounts for a class label (decision taken after computing all attributes). The paths from the root to a leaf represents classification rules. DT does an excellent job in depicting an algorithm. One of the advantages of DT is its visual representation of data which allows observing all possible classes, as well as the likelihood of each label. Each node of a DT shows features automatically selected by the classification algorithm. Consequently, one of the strength points of DTs over other classification algorithms is its ability to automatically prioritize the significance of the measured features. When decision trees are used for classifying a set of data, the top few nodes are the most important variables within the data set and the lowest nodes are less significant. Other attributes that are not presented in the decision tree are unlikely to have important role in classifying the dataset in hand. Finally, DTs require relatively little effort from users for data preparation when compared to other machine learning approaches. For these reasons, we chose DTs as a classification approach. Figure 7 shows the grown DT for participant number 4 resulted from attributes measured for the first research objective of the project. Table 5 describes parameters represented in Figure 7. If the test on an attribute in each node is true, the algorithm moves along red lines and if the test turn out to be false, the algorithm moves on a blue line. This procedure continues until it reaches to a label.

Decision tree learning resorts decision trees as a predictive model to map the input training data set to the desired labels. This predictive model is commonly used in statistics, data mining and machine learning. Decision trees learn by splitting the training data into subsets based on an attribute value. Then the same splitting process is repeated for each derived subset of data, and new subsets will be obtained based on independent attributes. This process is called Recursive Partitioning. It is known as a recursive process since the splitting process may continue infinitely until a stopping criterion terminates the process. In an ideal case, the splitting is completed when all the subset presented at a node have the same label. However, due to the danger of overfitting, the splitting process is terminated at a certain degree of *impurity.* Impurity can be defined as the maximum percentage of the training data samples in a node that do not have the same target label value as the other subset of data at the same node. This process is an instance of a *greedy algorithm* and is the most common algorithm used by learning decision trees. Greedy algorithms are algorithms that use the problem-solving heuristic model to make the optimal local choice with the hope of finding the best global model. In general, there are two types of decision trees: Classification tree and, Regression tree. Classification trees are used when the outcome of the analysis is a class of data. On the other hand, regression trees labels are real numbers. The main difference in classification tree and regression tree procedure is determining where to split the data [51].

In a decision tree, assume that the learning data set $\mathcal{L}$ is in the form of $\{(y_n, x_n), n = 1, \cdots, N\}$; in which y_is are the class labels corresponding to data set x_i. The developed prediction function is $\Phi(x, \mathcal{L})$. If data set x is fed to Φ, label y is the predicted label. We will refer to this parameters in the following section.

Bootstrap Aggregating Forest

Bootstrap Aggregating Forest, a.k.a. Bagging Forest is an ensemble machine learning approach. Ensemble methods use multiple algorithms or models to build a superior predictive model comparing to those that were individually obtained. Bagging was first introduced by Breiman [52] in1994. Forests grow a number of DTs. To classify a new object, the input vector is fed to each tree within the forest. The forest turns the output label with the most votes as the result. The Bagging Forest capability of classifying unstable data can be pointed out as one of its most significant advantages [52].

Continuing the technical math discussion from the decision tree section, assume that there is a sequence of learning sub-sets $\mathcal{L}_k$ every of which has N independent observation from the original data set $\mathcal{L}$. We replace $\Phi(x, \mathcal{L})$ by $\Phi(x, \mathcal{L}_k)$. Assume that $\Phi(x, \mathcal{L})$ predicts a class $j \in \{1, \cdots, J\}$, and $N_j = nr\{k; \Phi(x, \mathcal{L}_k) = j\}$. Then $\Phi_A = argmax_j N_j$ where, subscript A shows aggregating. So in the case of the classification, and not regression, the algorithm returns the most voted label as the predicted label for the fed data set. For more technical details, the reader is referred to [52, 53].

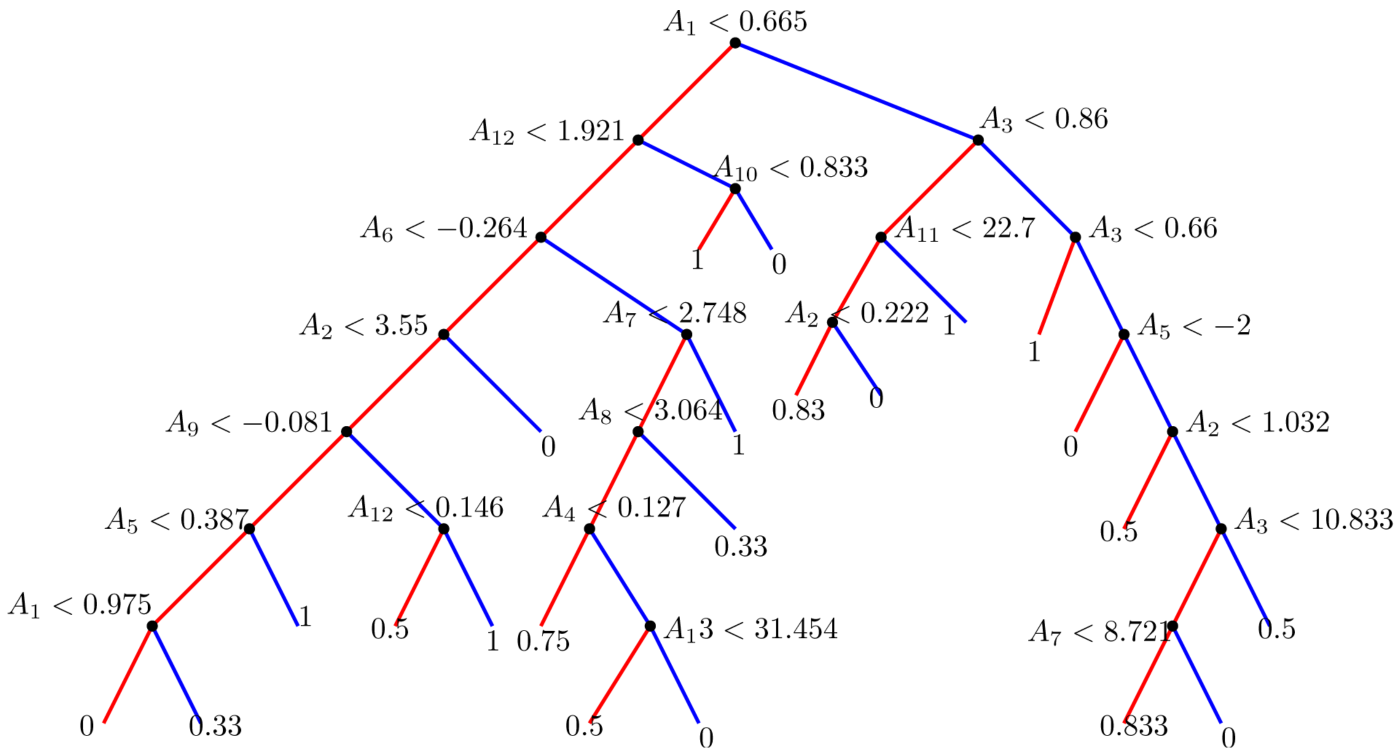


Figure 4. Generated Decision Tree for Participant No. 2

Table 4. Description of Figure 4 Parameters

Parameter	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
Feature	RMS	RMS	RMS	RMS	Mean	Mean	Mean	Mean	Mean
Time series	Gyro	Gyro	Gyro	Jerk	Acc.	Acc.	Acc.	Gyro	Jerk
Axis	x	y	z	z	x	y	z	z	Z
Parameter	A_{10}	A_{11}	A_{12}	A_{13}					
Feature	Dom. Freq.	Entropy	Entropy	Entropy					
Time series	Jerk	Acc.	Acc.	Jerk					
Axis	y	x	z	X					

As the number of trees ($\mathcal{L}_k$) in a forest grows, the cost of calculation and the probability of over–fitting increases. To the best of the author's knowledge, there no straight forward analytical method of determining and estimating the optimal number of trees in a given forest is introduced so far. In general, the number of grown trees in a forest is a compromise between data over–fitting and classification error. Considering the number of data sets in this study, seven trees were grown for each Bagging Forest. Similar to the DTs, we used the summary scores as class labels.

Predictive Model Validation

Leave-One-Out Cross Validation

In order to evaluate the classification accuracy of the two resorted approaches, the Leave One Out (*LOO*) cross-validation method is used [54]. LOO is widely employed in problems where the goal is prediction. It is also known as Jackknife. LOO cross-validation is one of the comprehensive cross-validation methods that breaks down the original data set into a learning data set and a test data set; this is done by leaving one data set out as the test data to estimate the prediction accuracy [54], [55]. LOO cross-validation performs dividing the initial data sets into learning and validation $C_n^1 = n$ times, where n is equal to the number of data sets. For this reason, LOO cross validation is recommended for relatively small data sets [54].

Confusion Matrix

Confusion matrices are utilized to visualize the performance of each classification methods. Each row of a confusion matrix shows the instances belonging to an actual class while each column shows predicted values [56]. Various metrics may be utilized to evaluate the accuracy of the prediction model based on the confusion matrix [56]. The Rate of False Discovery (*FDR*) is used in this project to find the relaying error of prediction, which can be expressed as:

$$FDR = \frac{FP}{FP + TP} \tag{12}$$

Where FP is the number of false positives and TP stands for the number of true positives. Equation (13) shows an example of confusion matrix calculations for participant 8 using methods DT, Eq. 13.a, and Bagging Forest, Eq. 13.b.

$$C_{DT} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 2 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 12 \end{bmatrix} \tag{13.a}$$

$$C_{Bagging} = \begin{bmatrix} 3 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 13 \end{bmatrix} \tag{13.b}$$

The corresponding FDR errors can then be calculated as:

$$FDR_{DT} = \left(\frac{(1 + 2 + 1)}{(1 + 2 + 1) + (2 + 1 + 12)}\right) \times 100 = 21\% \tag{14.a}$$

$$FDR_{Bagging} = \left(\frac{0}{(3 + 2 + 1 + 13)}\right) \times 100 = 0\% \tag{14.b}$$

The mean FDR value for all LOO cross-validation attempts trials was calculated.

$$FDR_{mean} = \frac{FDR_1 + FDR_2 + \cdots + FDR_8}{8} \tag{15}$$

The result value was used to define the total error for each approach. The resulting FDR_{mean} for the DT and Bagging Forest approaches (for n trials, $n = 8$) were compared using the paired t-test at the 5% significance level. Statistical test t-test is a commonly used method to determine if two data sets are significantly different. It is a test of null hypothesis that indicates if the difference of the mean value of two data sets, which were measured with the same units, is zero.

CHAPTER FIVE:
RESULTS AND DISCUSSION

Data collection and preparation is done according to what was explained in chapter three. In order to interpret the post-stroke kinematic data with clinical features, some attributes of the data should be extracted which are capable of representing the characteristics of the nature of human upper extremity movements such as speed, smoothness, and accuracy.

After data collection and data preparation, gesture matrices were produced according to equations (8, 9). These gesture matrices are used along with the summarized Fugl-Meyer score obtained for each task in the form of equations (10, 11) to develop a classification model. The classification model then was used to generate our predictive model to estimate the quality of the new set of kinematic data according to the Fugl-Meyer standard. We used both DT and Bagging forest methods to create our prediction system. LOO cross-validation method was then resorted to evaluate the accuracy of our predictive frameworks as described in chapter three. Figure 8 depicts a summary of the proposed frameworks outcomes. The Bagging Forest approach results show statistically significantly lower FDR error than the DT ($t(7) = 5.6756, p < 0.001$, Figure 8). The mean value of error for the Bagging Forest approach ($2.5 \pm 2.5\%$) was lower than that of the DT method ($18.2 \pm 9.5\%$).

Decision Tree

The DT approach has many advantages that make it a suitable choice for classification of post-stroke kinematic data. The visual representation of data in DTs provides the opportunity to observe all alternatives for a solution and the associated possibility of each label's occurrence. When decision trees are used for classifying a set of data, the proximal (primary and secondary) nodes are the most sensitive features within the data set measured features while the furthest nodes show the least sensitive features.

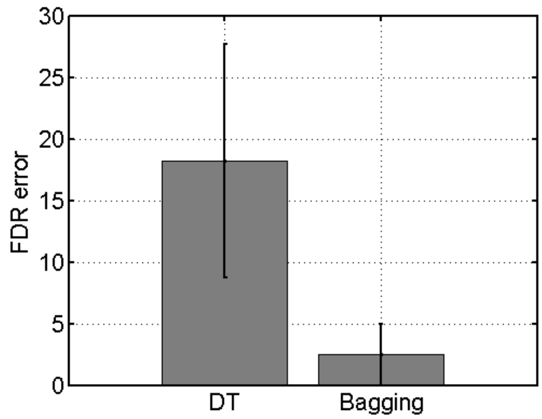


Figure 5. FDR Prediction Error for the DT and Bagging Forest Methods

Figure is adopted from [47]

Since we had eight subjects in this study, the LOO cross-validation algorithm was performed $C_8^1 = 8$ times. In every LOO attempt, one of the patient's data set is left out as the test data set. The prediction model developed using DT results showed that the entropy of acceleration (of all three axes) was the primary node in all trees. The entropy of x –axis acceleration was the most important variable in our data classification, appearing as the primary node for 75% of all DTs that were generated by the LOO cross validation approach. In the remaining 25% of DTs, the y – and z – axis of entropy of acceleration were the primary nodes. Figure 6 shows all the measured features that appeared in the first two nodes of our DTs in eight LOO trials. Additionally, about 75% of the secondary nodes of all DTs were frequency domain features. The combined 83.3% representation of frequency domain features in the primary and secondary nodes of the DTs shows the high sensitivity of frequency domain features to post stroke kinematic motion quality which is consistent with the literature [57, 58]. Additionally, some Fugl-Meyer tasks (such as those requiring motion synergy) may be similar in the frequency domain but not the time domain. This conclusion is consistent with the existing literature [59].

Furthermore, features extracted from acceleration and jerk appeared in approximately 80% of all primary and secondary nodes, and gyro rates showed up is approximately 20%. This finding emphasizes on the significance of acceleration and acceleration–derived features relative to gyro data in our classification method. Acceleration and Jerk are known to be representors of the motion smoothness, while gyro can be a useful criterion for coordination. The obtained results demonstrate and explain the ability of the DT approach in providing rich information from exploratory analyses.

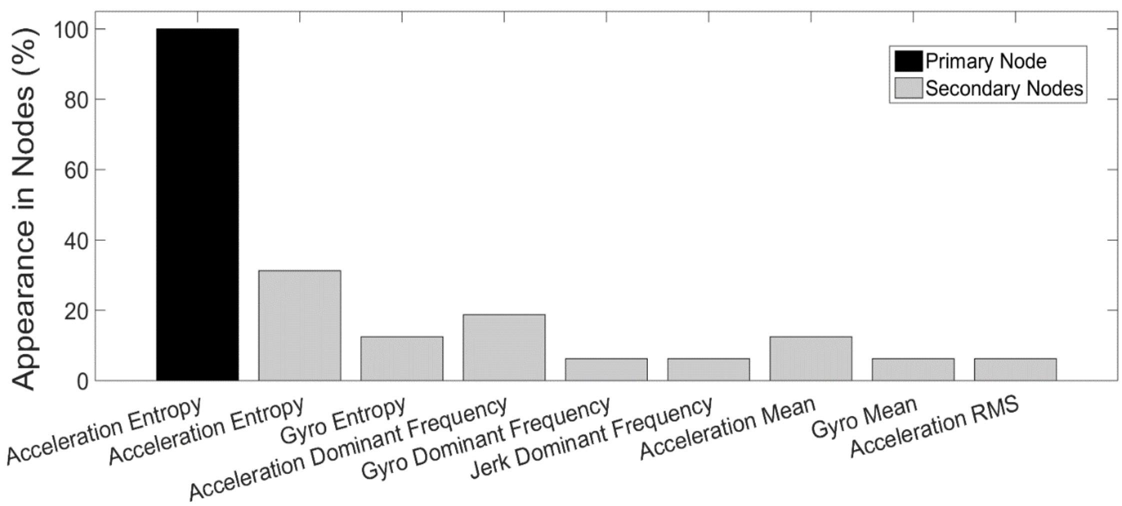


Figure 6. Representation of Measured Features in Two Primary Nodes

Figure is adopted from [47]

Bagging Forest Approach

Despite the informative results that we obtained using DT method, the mean value of FDR error of 18.2% for the DT approach may be unsatisfactory for analyses of motion outside of the clinical setting considering unpredicted disturbances that our system will experience in real world. As shown in figure 10, Participants 1 and 6 have significantly lower FMA scores relative to other subjects. This ***instability*** of data set resulted in prediction accuracy variability across the different LOO cross-validation attempts. A data set is considered unstable if small changes in the training set results in large changes of the predicted value [60].

The instability of data suggested the use of machine learning ensemble methods which are known to excel in analyses dealing with unstable data [52],[60, 61]. Unlike the more commonly used Random Forest approach which searches through a specific number of features to find the best features for growing trees, the Bagging Forest algorithm searches at each node of a tree for the attributes that best splits the data at that node. We chose a set of features known to be relevant to post-stroke kinematic data classification for our analyses. Considering this and the capability of Bagging Forest over Random Forest in classifying unstable data, Bagging Forest was chosen for our further analysis [13].

The thorough search algorithm of the Bagging Forest for growing the best trees for classification and its privilege in classifying the unstable data sets resulted in a low error rate for our data. The 2.5% FDR error of our Bagging Forest model confirms that this approach can be used as a reliable classification algorithm in the presence of unstable data.

Despite the Bagging Forest accurate estimation of the FMA scores, there are certain drawbacks in using this classification method. The Bagging Forest is a machine learning black box approach, which makes an intuitive interpretation of the results almost impossible [53]. Hence, we are unable to hypothesize readily why the performance of one forest differed from the others. However, a post hoc investigation of our results indicates that that the maximum error of 5% (the highest error in Bagging Forest) occurred when Participant number 6's data (one of the two unstable data sets) were left out as the test data set. This finding indicates although the Bagging Forest approach is less sensitive to this instability when compared to the DT method, the instability of data still affects the result and remains apparent.

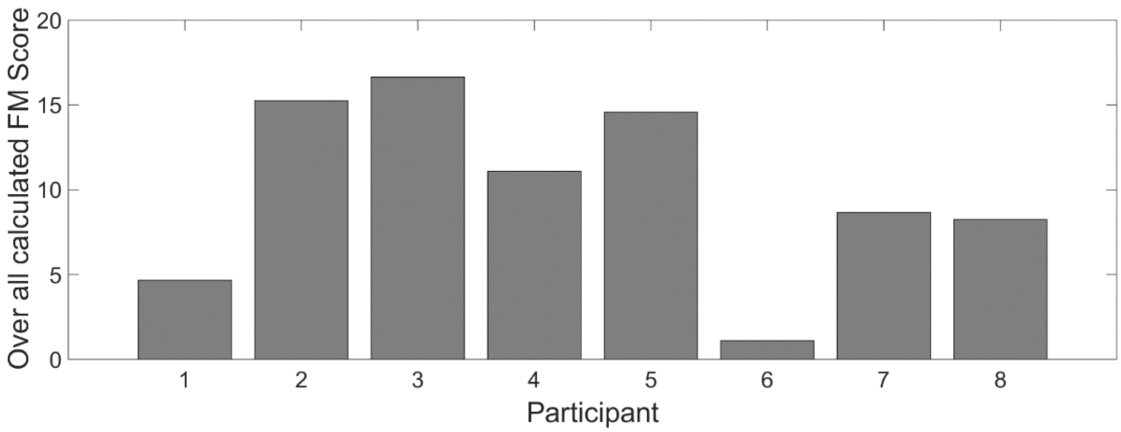


Figure 7. Summarized FM Score for each participant

CHAPTER SIX:
CONCLUSION

The increasing rate of daily smoking, physical inactivity, being overweight, having high blood pressure, and diabetes suggests an increasing rate of stroke occurrence probability in near future. A large share of the average $100,000 post-stroke treatment cost goes to the health-care services. This massive cost can be reduced by discharging the patient from the hospital and still have him/her under the virtualized therapist's monitor. This study opens an avenue to evaluating the post-stroke physical improvement in real world setting. Using accelerometry-based sensors for human motion monitoring, suggests an accurate post-stroke motion tracking without interrupting the patients during his/her activities of daily living or invasion of privacy. This project contributes to virtualizing the physical and occupational therapists while allowing the patient to have their support and feedback all the time and at a lower cost.

This thesis studies the possibility of estimating post-stroke quality of motion in real-world setting. To do so, an experiment was designed in which the participants wore motion monitors and performed physical tasks according to the Fugl-Meyer Assessment subscale for upper-extremity. The examiner therapist evaluated the subjects' performance visually and scored his quality of motion according to the Fug-Meyer criteria. Then the collected kinematic data and Fugl-Meyer scores were used to develop predictive models to evaluate the quality of motions corresponded to the input kinematic data. Four measurement features were extracted from three time series of kinematic data: Root mean square, mean value, entropy and dominant frequency and they are derived for acceleration, rate of gyro and jerk. The extracted measurement features and the obtained Fugl-Meyer scores were fed into our classification models to categorize the kinematic data according to the obtained Fugl-Meyer score. Two supervised machine learning methods were employed, and their results were used to develop predictive models. These two machine learning methods were: Decision Tree and Bootstrap Aggregating Forest.

After developing the two predictive models, the Leave-One-Out method was used to evaluate the accuracy of the developed models. Confusion matrices were resorted to visualize the leave-one-out results. The validation resulted in $18.2 \pm 2.5\%$ of prediction error for the decision tree while this error was $2.5 \pm 2.5\%$ for the bagging forest. The instability of data was recognized as the most important reason in error reduction between the two resorted methods. Moreover, the presence of frequency domain features in all primary nodes, and 75% of the secondary nodes can be interpreted as the importance of frequency domain variables in classifying human kinematic data.

The methodology used in this research can be developed to be used in other clinical studies. In future explorations, the quality of motion predictor modelled in this project can be resorted to estimate patients' scale of pain, strength, soreness, muscle, etc. The developed method along with task recognition frameworks will be a complete at home post-stroke monitoring system.

CHAPTER SEVEN:
STUDY LIMITATIONS

There were certain limitations in the current study that might affect the results. First of all, the sample size was limited. Further validation of this method needs applying to a larger population of subjects. Also, the Fugl-Meyer tasks were done in an active rehabilitation center. Thus, certain environmental distractions might occur during the experiment. Moreover, the physical condition of our participants needed frequent rests or broken–up sessions in some cases. Finally, using two examiner therapists may have increased variance in clinician scoring on the Fugl-Meyer tasks. In future work, more participants should be recruited to increase the data size and consequently, improve the prediction model through the investigation of other clinically meaningful features.

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APPENDIX

The presented Fugl-Meyer form in this chapter is adopted from [62]

APPENDIX A

FUGL- MEYER ASSESSMENT OF PHYSICAL PERFORMANCE

General Procedure and Rules

PROCEDURE	GENERAL RULES
Description: This assessment is a measure of upper extremity (UE) and lower extremity (LE) motor and sensory impairment. **Equipment:** A chair, bedside table, reflex hammer, cotton ball, pencil, small piece of cardboard or paper, small can, tennis ball, stop watch, and blindfold. **Administration:** The complete assessment usually requires 45 minutes.	Perform the assessment in a quiet area when the patient is maximally alert. *Volitional movement assessment:* This includes flexor synergy, extensor synergy, movement combining synergies, movement out of synergy, wrist, hand, and coordination/speed. For all tests of volitional motion, these guidelines are to be followed: 1. Give clear and concise instructions. Mime as well as verbal instructions permissible. 2. Have patient perform the movement with non-affected extremity first. On affected side, check for available passive range of motion (PROM) prior to asking patient to perform the movement. 3. Repeat each movement 3x on the affected side and score best performance. If full score is attained on trials 1 or 2, do not have to repeat 3 times. Only test Coordination/speed, one time. 4. Do not assist patient, however verbal encouragement is permitted. 5. Test the wrist and hand function independently of the arm. **During the wrist tests (items 7a-e), support under the elbow may be provided to decrease demand at the shoulder; however, the patient should be activating the elbow flexors during the elbow at 90 degree tests and activating the elbow extensors during the elbow at 0 degree tests. In contrast, assistance can be provided to the arm at the elbow and just proximal to the wrist in order to position the arm during the hand tests (items 8a-g).**

Fugl-Meyer Motor Assessment

Lower Extremity

Item	Procedure	Scoring

I. Reflex activity	• Patient is supine or sitting.
	• Attempt to elicit the Achilles and patellar reflexes.
	• Assess the unaffected side first.
	• Test affected side.
		• *Scoring* (Maximum possible score = 4):
		  • (0) - No reflex activity can be elicited;
		  • (2) - Reflex activity can be elicited. Items to be scored are Achilles and patellar reflexes.

IIA. Flexor synergy	• Patient is supine.
	• Have patient perform movement with unaffected side first.
	• On the affected side, check patient's available PROM at each joint to be tested.
	• Start with leg fully extended at hip, knee, and ankle. Instruct the patient to "bring your knee to your chest and
		• *Scoring* (Maximum possible score = 6):
		  • (0) - Cannot be performed at all
		  • (1) – Partial motion
		  • (2) – Full motion

Locomotor Experience Applied Post-Stroke (LEAPS) (NIH/NINDS/NCMRR R01 NS05056-01A1)
Sullivan et al for LEAPS Investigative Team

	pull up your toes" (therapist is observing for evidence of hip, knee, ankle flexion in order to assess the presence of all components of the flexor synergy). Therapist can cue the patient to move any missing component. • Test 3x on the affected side and score best movement at each joint.	• Items to be scored are: Hip flexion, knee flexion, ankle dorsiflexion.

IIB. <u>Extensor synergy</u>	• Patient is sidelying.
	• Have patient perform movement with unaffected side first.
	• On the affected side, check patient's available PROM at each joint to be tested.
	• Start in 90 degrees hip flexion, 90 degrees knee flexion and ankle dorsiflexion.
	• Instruct the patient to "push your foot down and kick down and back". (Ankle plantarflexion, knee extension, hip adduction and hip extension.)
	• Slight resistance should be applied in adduction which is gravity-assisted in this position to ensure patient is actively adducting.
	• Test 3x on the affected side and score best movement at each joint.
		• *Scoring* (Maximum possible score = 8):
		  • (0) – No motion
		  • (1) – Partial motion
		  • (2) – Full motion
		• Items to be scored are: Hip extension, hip adduction, knee extension, ankle plantarflexion.

III. <u>Movement combining synergies (in sitting)</u>	<u>3a. Knee flexion beyond 90°:</u>
	• Patient is sitting, feet on floor, with knees free of chair. Knee to be tested is slightly extended beyond 90° knee flexion. Calf muscles should not be on stretch. To decrease friction, patient's shoes can be removed, but socks should remain on.
	• Have patient perform movement with unaffected side first.
	• Check patient's available PROM on the affected side for this motion.
	• Patient is instructed to "pull your heel back and under the chair."
	• Test 3x on the affected side and score best movement.
		• *Scoring* (Maximum possible score = 2):
		  • (0) – No active motion
		  • (1) – From slightly extended position, knee can be flexed but not beyond 90° or hip flexes while attempting to flex knee
		  • (2) – Knee flexion beyond 90°

	<u>3b. Ankle Dorsiflexion:</u>
	• Patient is sitting, feet on floor, with knees free of chair. Calf muscles should not be on stretch.
	• Have patient perform movement with unaffected side first.
	• On the affected side, check patient's available PROM at the ankle joint.
	• Patient is instructed to "keeping your heel on the floor, lift your foot."
	• Test 3x on the affected side and score best movement.
		• *Scoring* (Maximum possible score = 2):
		  • (0) – No active motion
		  • (1) – Incomplete active flexion (heel must remain on floor with medial and lateral borders of the forefoot clearing the floor during dorsiflexion)
		  • (2) – Normal dorsiflexion (full within available ROM, heel remains on the floor)

IV. Movement out of synergy (Standing, hip at 0 degrees)	4a. Knee Flexion: • Patient is standing, hip at 0 degrees (or full available ROM up to 0 degrees). On leg that is being tested, hip is at 0 degrees (or full available ROM up to 0 degrees), but the knee is flexed, and the patient's toes are touching the floor slightly behind. Evaluator can provide assistance to maintain balance and patient can rest hands on a table. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to "keeping your hip back, kick your bottom with your heel." • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Knee cannot flex without hip flexion • (1) – Knee flexion begins without hip flexion but does not reach to 90° or hip begins to flex in later phase of motion • (2) – Knee flexion beyond 90° (Knee flexion beyond 90 degrees with hip maintained in extension)
IV. Movement out of synergy (Standing, hip at 0 degrees)	4b. Ankle Dorsiflexion: • Patient is standing, hip at 0 degrees. If patient's calf muscle length is limiting active dorsiflexion in this starting position, then leg that is being tested can be positioned forward, so the hip is at approximately 5 degrees of flexion, and calf muscles are in lengthened position. Knee must stay fully extended. Evaluator can provide assistance to maintain balance and patient can rest hands on a table. • Have patient perform movement with unaffected side first. • On the affected side, check patient's available dorsiflexion PROM. • Patient is instructed to "keeping your knee extended and your heel on the floor, lift your foot." • Test 3x on the affected side and score best movement	• *Scoring* (Maximum possible score = 2): • (0) – No active motion • (1) – Partial motion (less than full available range with knee extended; heel must remain on floor with medial and lateral borders of the forefoot clearing the floor during dorsiflexion, or hip and/or knee flexes during motion while attempting dorsiflexion) • (2) – Full motion (within available dorsiflexion range with knee extended and heel on the floor)
V. Normal Reflexes (sitting)	• This item is only included if the patient achieves a maximum score on all previous lower extremity items, otherwise score 0 . • The examiner shall elicit patellar and Achilles phasic reflexes with a reflex hammer and knee flexors with quick stretch of the affected leg and note if the reflexes are hyperactive or not.	• *Scoring* (Maximum possible score = 2): • (0) - At least 2 of the 3 phasic reflexes are markedly hyperactive • (1) – One reflex is markedly hyperactive or at least 2 reflexes are lively • (2) - No more than one reflex is lively and none are hyperactive

VI. <u>Coordination/speed - Sitting: Heel to opposite knee repetitions in rapid succession</u>	• Patient positioned in sitting with eyes open.
	• Starting position is with heel to be tested resting on opposite ankle.
	• Have patient perform movement with unaffected side first.
	• Check available PROM on the affected side.
	• Patient is instructed to "Bring your heel from your opposite ankle to your opposite knee, keeping your heel on your shin bone, move as fast as possible."
	• Use a stopwatch to time how long it takes the patient to do 5 full (ankle to knee to ankle) repetitions.
	• Use the full achieved active ROM on the unaffected limb as the comparison for the affected limb. If active ROM of affected limb is significantly less than that of unaffected limb, patient should be scored "0" for speed.
	• Repeat the same movement with the affected leg. Record the time for both the unaffected and affected sides. Observe for evidence of tremor or dysmetria during the movement
	• NOTE: This item attempts to discriminate between basal ganglia, thalamic, or cerebellar strokes in which tremor or dysmetria may result as a direct result of lesion to these areas. The majority of stroke cases are in the middle cerebral artery or basilar artery distributions where we expect to observe paralysis that affects movement speed but does not cause tremor or dysmetria. In cases of complete paralysis, observe for any indication of tremor or dysmetria that may be evident in face, voice, arms or legs. If there are no indicators of tremor or dysmetria, then score these items 2 and score speed 0.
		• *Scoring Tremor* (Maximum possible score = 2):
		  • (0) - Marked tremor
		  • (1) – Slight tremor
		  • (2) – No tremor
		• *Scoring Dysmetria* (Maximum possible score = 2):
		  • (0) - Pronounced or unsystematic dysmetria
		  • (1) – Slight or systematic dysmetria
		  • (2) – No dysmetria
		• *Scoring Speed* (Maximum possible score = 2):
		  • (0) - Activity is more than 6 seconds longer than unaffected leg
		  • (1) – 2-5.9 seconds longer than unaffected leg
		  • (2) - less than 2 seconds difference

Upper Extremity		
Item	**Instructions**	**Scoring**

I. <u>Reflex activity</u>	• Patient is sitting.
	• Attempt to elicit the biceps and triceps reflexes.
	• Test reflexes on unaffected side first.
	• Test affected side.
		• *Scoring* (Maximum possible score = 4):
		  • (0) - No reflex activity can be elicited
		  • (2) - Reflex activity can be elicited

II. <u>Flexor synergy</u>	• Patient is sitting.
	• Have patient perform movement with unaffected side first.
	• On the affected side, check patient's available PROM at each joint to be tested.
	• The starting position should be that of full extensor synergy. If the patient cannot actively achieve the starting position, the limb may be passively placed extended towards opposite knee in shoulder adduction/internal rotation, elbow extension, and forearm pronation.
	• Instruct the patient to fully supinate his/her forearm, flex the elbow, and bring the hand to the ear of the affected side. The shoulder should be abducted at least 90 degrees.
	• Test 3x on the affected side and score best movement at each joint
		• *Scoring* (Maximum possible score = 12):
		  • (0) - Cannot be performed at all
		  • (1) - Performed partly
		  • (2) - Performed faultlessly
		• Items to be scored are: Elevation (scapular), shoulder retraction (scapular), shoulder abduction (at least 90 degrees) and external rotation, elbow flexion, and forearm supination.
		  •

III. <u>Extensor synergy</u>	• Patient is sitting.
	• Have patient perform movement with unaffected side first.
	• On the affected side, check patient's available PROM at each joint to be tested.
	• The starting position should be that the limb is passively placed at patient's side in elbow flexion and supination. The examiner must ensure that the patient does not rotate and flex the trunk forward, thereby allowing gravity to assist with the movement. The pectoralis major and triceps brachii tendons may be palpated to assess active movement.
	• Instruct the patient to adduct & internally rotate the shoulder, extend his arm towards the unaffected knee with the forearm pronated.
	• Test 3x on the affected side and score best movement at each joint.
		• *Scoring* (Maximum possible score = 6):
		  • (0) - Cannot be performed at all
		  • (1) - Performed partly
		  • (2) - Performed faultlessly
		• Items to be scored are: Shoulder adduction/internal rotation, elbow extension, and forearm pronation.

IV. <u>Movement combining synergies</u> **The patient is asked to perform**	4a. Hand to lumbar spine: • Patient is sitting with arm at side, shoulder at 0°, elbow at 0°. • Have patient perform movement with unaffected side first.	• *Scoring* (Maximum possible score = 2): • (0) – No specific action is performed (or patient moves but does not reach

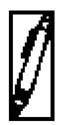
three separate movements (4a, 4b, 4c).	• Check patient's available PROM on the affected side for this motion. • Patient is instructed to actively position the affected hand on the lumbar spine by asking them to "put your hand behind your back". • Test 3x on the affected side and score best movement.	ASIS) • (1) - Hand must pass anterior superior iliac spine (performed partly) • (2) - Performed faultlessly (patient clears ASIS and can extend arm behind back towards sacrum; full elbow extension is not required to score a 2)
	4b. Shoulder flexion to 90°, elbow at 0°: • Patient is sitting with hand resting on lap. • Have patient perform movement with unaffected side first. • On the affected side, check patient's available PROM for shoulder flexion to 90° and full elbow extension. • Patient is instructed to flex the shoulder to 90°, keeping the elbow extended. The elbow must be fully extended throughout the shoulder flexor movement; the forearm can be in pronation or in a mid-position between pronation and supination. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Arm is immediately abducted, or elbow flexes at start of motion • (1) - Abduction or elbow flexion occurs in later phase of motion • (2) - Performed faultlessly (patient can flex shoulder keeping elbow extended)
	4c. Pronation/supination of forearm, elbow at 90°, shoulder at 0°: • Patient is sitting with arm at side, elbow flexed, and forearm in supination. • Have patient perform movement with unaffected side first. • On the affected side, check patient's available PROM for end range of pronation and supination. • Patient is instructed to actively flex the elbow to 90° and pronate/supinate the forearm through the full available ROM. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Correct position of shoulder held in adduction at side of body and elbow flexion, and/or pronation or supination cannot be performed. • (1) – Active pronation or supination can be performed even within a limited range of motion, with elbow flexed at 90° and arm at side. • (2) - Complete pronation and supination with with elbow flexed at 90° and arm at side.
<u>V. Movement out of synergy</u> **The patient is asked to perform three separate movements (5a, 5b, 5c).**	5a. Shoulder abduction to 90°, elbow at 0°, and forearm pronated: • Patient is sitting with arm and hand resting at side. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to abduct the shoulder to 90°, in a pure abduction motion, with the elbow fully extended	• *Scoring* (Maximum possible score = 2): • (0) – Initial elbow flexion occurs, or any deviation from pronated forearm occurs • (1) - Motion can be performed partly, or, if during motion, elbow is

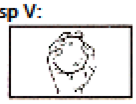
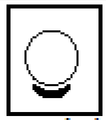
	and the forearm pronated. • Test 3x on the affected side and score best movement.	flexed, or forearm cannot be kept in pronation; • (2) - Performed faultlessly (patient can fully abduct shoulder, keeping forearm pronated with no elbow flexion)
	5b. Shoulder flexion from 90°-180°, elbow at 0°, and forearm in mid-position: • Patient is sitting with elbow extended, hand resting on knee. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to flex the shoulder above 90°, with the elbow fully extended and the forearm in the mid-position between pronation and supination. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Initial flexion of elbow or shoulder abduction occurs (arm is immediately abducted, or elbow flexes at start of motion) • (1) – Elbow flexion or shoulder abduction occurs during shoulder flexion (in later phases of motion) • (2) - Performed faultlessly (patient can flex shoulder above, with forearm in mid-position and no elbow flexion)
	5c. Pronation/supination of forearm, elbow at 0°, and shoulder at 30°-90° of flexion: • Patient is sitting with elbow extended, shoulder between 30°-90° of flexion. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to pronate and supinate the forearm as the shoulder remains flexed between 30-90° and the elbow is fully extended. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Supination and pronation cannot be performed at all, or elbow and shoulder positions cannot be attained • (1) – Elbow and shoulder properly positioned and supination performed in a limited range • (2) - Performed faultlessly (complete pronation and supination with correct positions at elbow and shoulder)
VI. <u>Normal Reflexes</u> (sitting)	• This item is only included if the patient achieves a maximum score on all previous upper extremity items, otherwise score 0. • The examiner shall elicit biceps and triceps phasic reflexes with a reflex hammer and finger flexors with quick stretch and note if the reflexes are hyperactive or not.	• *Scoring* (Maximum possible score = 2): • (0) - At least 2 of the 3 phasic reflexes are markedly hyperactive • (1) – One reflex is markedly hyperactive or at least 2 reflexes are lively • (2) - No more than one

<table>
<tr><td></td><td></td><td>reflex is lively, and none are hyperactive</td></tr>
<tr><td rowspan="4"><u>VII. Wrist</u>

During the wrist tests, support under the elbow to may be provided to decrease demand at the shoulder; however, the patient should be activating the elbow flexors during the elbow at 90 degree tests and activating the elbow extensors during the elbow at 0 degree tests. The patient is asked to perform five separate movements (7a, 7b, 7c, 7d, 7e).</td><td>7a. Stability, elbow at 90°, and shoulder at 0°:
• Patient is sitting with arm and hand resting at side.
• Have patient perform movement with unaffected side first.
• Check patient's available PROM on the affected side for this motion.
• Patient is instructed to dorsiflex (extend) the wrist to the full range of 15° (or full available range) with the elbow at 90° flexion and the shoulder at 0°. If full range of dorsiflexion is attained, slight resistance is given.
• Test 3x on the affected side and score best movement.</td><td>• Scoring (Maximum possible score = 2):
• (0) - Patient cannot dorsiflex wrist to required 15°
• (1) – Dorsiflexion is accomplished, but no resistance is taken
• (2) - Position can be maintained with some (slight) resistance</td></tr>
<tr><td>7b. Flexion/extension, elbow at 90°, and shoulder at 0°:
• Patient is sitting with arm and hand resting at side.
• Have patient perform movement with unaffected side first.
• Patient is instructed to perform repeated smooth alternating movements from 15 degrees of flexion (wrist extension) to 15 degrees of extension.
• Test 3x on the affected side and score best movement</td><td>• Scoring (Maximum possible score = 2):
• (0) - Volitional movement does not occur
• (1) – Patient cannot actively move through the wrist joint throughout the total range of motion
• (2) – Faultless, smooth movement (repetitive through full available ROM)</td></tr>
<tr><td>7c. Stability, elbow at 0°, and shoulder at 30° flexion:
• Patient is sitting with elbow extended, hand resting on knee and forearm pronated.
• Have patient perform movement with unaffected side first.
• Check patient's available PROM on the affected side for this motion.
• Patient is instructed to dorsiflex (extend) the wrist to the full range of 15° (or full available range) with the elbow fully extended and the shoulder at 30° flexion. If full range of dorsiflexion is attained, slight resistance is given.
• Test 3x on the affected side and score best movement.</td><td>• Scoring (Maximum possible score = 2):
• (0) - Patient cannot dorsiflex wrist to required 15°
• (1) – Dorsiflexion is accomplished, but no resistance is taken
• (2) - Position can be maintained with some (slight) resistance</td></tr>
<tr><td>7d. Flexion/extension, elbow at 0°, and shoulder at 30° flexion:
• Patient is sitting with elbow extended, hand resting on knee and forearm pronated.
• Have patient perform movement with unaffected side first.
• Patient is instructed to perform repeated smooth alternating movements from maximum dorsiflexion to maximum volar flexion with the fingers somewhat flexed to the full range of 15° (or full available range)</td><td>• Scoring (Maximum possible score = 2):
• (0) - Volitional movement does not occur
• (1) – Patient cannot actively move throughout the total range of motion;
• (2) – Faultlessly, smooth movement (repetitive through full ROM)</td></tr>
</table>

	with the elbow fully extended and the shoulder at 30° flex. • Test 3x on the affected side and score best movement.	
	7e. Circumduction: • Patient is sitting with arm at side elbow flexed to 90°, and forearm pronated. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to circumduct the wrist with smooth alternating movements throughout the full range of circumduction. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Cannot be performed (volitional movement does not occur) • (1) – Jerky motion or incomplete circumduction • (2) – Complete motion with smoothness (performs faultlessly, smooth, repetitive movement through full ROM)
VIII. Hand During the hand tests, assistance can be provided to the arm at the elbow and just proximal to the wrist in order to position the arm for the grasp tasks. The patient is asked to perform seven separate movements (8a, 8b, 8c, 8d, 8e, 8f, 8g). The object is not placed in the hand but presented to the patient so that it requires sufficient opening to grasp test object, closure on object, ability to hold against a slight tug.	8a. Finger mass flexion:  • Patient is sitting with arm on bedside table or lap. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Starting from the position of finger extension (this may be attained passively if necessary), instruct the patient to fully flex all fingers. • Test 3x on the affected side and score best movement	• *Scoring* (Maximum possible score = 2): • (0) – No flexion occurs • (1) – Some flexion, but not full motion • (2) – Completed active flexion (compared to unaffected hand)
	8b. Finger mass extension:  • Patient is sitting with arm on bedside table or lap. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Starting from the position of finger flexion (this may be attained passively if necessary), instruct the patient to fully extend all fingers. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – No extension occurs • (1) – Patient can release an active mass flexion grasp • (2) – Full active extension (compared to unaffected side)
	8c. Grasp I: • Patient is sitting with arm on bedside table. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for	• *Scoring* (Maximum possible score = 2): • (0) – Required position cannot be attained • (1) – Grasp is weak

	this motion. • Instruct the patient to extend the metacarpophalangeal joints of digits II-V and flex the proximal & distal interphalangeal joints. Test this grip against resistance. You can tell the patient "pretend you are holding the handle of a briefcase." • Test 3x on the affected side and score best movement.	• (2) – Grasp can be maintained against relatively great resistance
	8d. Grasp II:   • • Patient is sitting with arm on bedside table. • Have patient perform movement with unaffected side first. • Instruct the patient to abduct the thumb to grasp a piece of paper. Then ask the patient to perform pure thumb adduction with the scrap of paper interposed between the thumb and first digit (as in figure). Test this grip against resistance by asking the patient to hold as you attempt to pull the paper out with a slight tug. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Function cannot be performed • (1) – Scrap of paper interposed between the thumb and index finger can be kept in place, but not against a slight tug • (2) – Paper is held firmly against a tug
	8e. Grasp III:   • Patient is sitting with arm on bedside table. • Have patient perform movement with unaffected side first. • Instruct the patient to grasp a pen or pencil by opposing the thumb and index finger pads around the pen. The tester may support the patient's arm but may not assist with the hand function required for the retrieval task. The pen may not be stabilized by the therapist or the patient's other hand. To minimize excessive movement, however, a pen with a 'pocket clip' that prevents rolling more than 180° may be used. • Once the pencil is retrieved, instruct the patient to oppose the thumb pad against the pad of the index finger with a pencil interposed. Test this grip against resistance by asking the patient to hold as you attempt to pull the pencil out with a slight tug upwards. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) – Function cannot be performed • (1) – A pencil interposed between the thumb pad and the pad of the index finger can be kept in place, but not against a slight tug • (2) – Pencil is held firmly against a tug
	8f. Grasp IV:  • Patient is sitting with arm on bedside table.	• *Scoring* (Maximum possible score = 2): • (0) Function cannot be performed • (1) – A can interposed between the thumb and

	• Have patient perform movement with unaffected side first. • Instruct the patient to grasp a small can (placed upright on a table without stabilization) by opening the fingers and opposing the volar surfaces of the thumb and digits. The arm may be supported but the tester may not assist with hand function. • Once the can is grasped, test this grip against resistance by asking the patient to hold as you attempt to pull the can out with a slight tug. Test 3x on the affected side and score best movement.	index finger can be kept in place, but not against a slight tug • (2) – Can is held firmly against a tug • NOTE: the hand must open and close on the can; it is not acceptable to have the patient grasp can by coming down from the top of the can.
	8g. Grasp V:   • Patient is sitting with arm on bedside table. • Have patient perform movement with unaffected side first. • Instruct the patient to perform a spherical grasp by grasping a tennis ball The tester may support the patient's arm but may not assist with the hand function required for the retrieval task. The ball may not be stabilized by the therapist or the patient's other hand. To minimize excessive movement, the ball can be placed on an object that reduces rolling. An inverted medium-sized bottle cap placed under the ball to prevent rolling is acceptable. Once the tennis ball is grasped, test this grip against resistance by asking the patient to hold as you attempt to pull the ball out with a slight tug. • Test 3x on the affected side and score best movement.	• *Scoring* (Maximum possible score = 2): • (0) Function cannot be performed • (1) – A tennis ball can be kept in place with a spherical grasp, but not against a slight tug • (2) – Tennis ball is held firmly against a tug
IX. Coordination and speed - Sitting: Finger to nose (5 repetitions in rapid succession)	• Patient positioned in sitting with eyes open. • Starting position is with hand on lap. • Have patient perform movement with unaffected side first. • Check patient's available PROM on the affected side for this motion. • Patient is instructed to "bring your finger from your knee to your nose, as fast as possible." • Use a stopwatch to time how long it takes the patient to do 5 repetitions. • Repeat the same movement with the affected arm. Record the time for both the unaffected and affected sides. Observe for evidence of tremor or dysmetria during the movement. • NOTE: This item attempts to discriminate between basal ganglia, thalamic, or cerebellar strokes in which tremor or dysmetria may result as a direct result of lesion to these areas. The majority of stroke cases are	• *Scoring Tremor* (Maximum possible score = 2): • (0) - Marked tremor • (1) – Slight tremor • (2) – No tremor • *Scoring Dysmetria* (Maximum possible score = 2): • (0)- Pronounced or unsystematic dysmetria • (1) – Slight or systematic dysmetria • (2) – No dysmetria • *Scoring Speed* (Maximum possible score = 2): • (0) – Activity is more than 6 seconds longer than unaffected hand • (1) – (2-5.9) seconds longer

	in the middle cerebral artery or basilar artery where we expect to observe paralysis that affects movement speed but does not cause tremor or dysmetria. In cases of complete paralysis, observe for any indication of tremor or dysmetria that may be evident in face, voice, arms or legs. If there are no indicators of tremor or dysmetria, then score these items 2 and score speed 0. If active ROM of affected limb is significantly less than that of affected limb, patient should be scored "0" for speed.	than unaffected side • (2) – less than 2 seconds difference

Fugl Meyer Sensory Assessment		
Light Touch	**Procedure:** • For light touch assessment, area of skin to be touched, should be free of clothing and exposed. • The procedure can be tested in the sitting or supine positions. Explain to the patient with their eyes open, "I am going to touch you with this cotton ball and I would like you to tell me if you can feel that you are being touched." Lightly touch patient with cotton ball over the unaffected muscle belly. Ask them, "Can you feel that you are being touched?" This part of the procedure confirms that the patient understands the test. • Explain to the patient, "I am going to ask you to close your eyes. Then I am going to touch you with the cotton ball on your right/left (unaffected) side followed by your right/left (affected) side. When I ask you, tell me if you can feel the touch." Ask the patient to close their eyes. Lightly touch unaffected area with cotton ball and ask, "Do you feel this?" Lightly touch affected area with cotton ball and ask "Do you feel this?" If the patient says they feel the touch on both sides, then repeat the procedure by touching first the unaffected side immediately followed by the affected side and ask the following question. "Does 'this' (unaffected area touch) feel the same as 'this' (affected area touch)?" The intent is to determine if there are differences in the characteristics of the touch between the two sides. • If the tester is not confident that the patient understands this procedure or that the response is inconsistent, the tester may confirm their impression by using the following procedure. With the eyes closed, touch the patient on the affected side and ask them to point to where they were touched with the unaffected side. If the patient does not recognize that they are being touched, the score would be absent. If they recognize the touch but are not accurate on the localization, the score will be impaired. If they recognize the touch and are accurate on the localization, the score will be intact. **Upper Extremity** • <u>Upper arm:</u> Follow above procedure by touching patient over the unaffected and affected biceps muscle belly. • <u>Palmar surface of the hand</u>: Follow above procedure by touching patient over the unaffected and affected palmar surface of the hand.	• *Scoring :* • (0) – Absent - If the patient states that he does not feel the touch on the affected side, the score is absent. • (1) – Impaired - If the patient states that he feels the touch on the affected side and the touch does not feel the same between affected and unaffected sides or the response is delayed or unsure, the score is impaired. • (2) – Intact - If the patient states that he feels the touch on the affected side and the touch feels the same between affected and unaffected sides, the score is intact.

	Lower Extremity • <u>Thigh</u>: Follow above procedure by touching patient over the unaffected and affected thigh of the leg. • <u>Sole of foot</u>: Follow above procedure by touching patient over the unaffected and affected sole of the foot.	

Proprioception
The objective of this test is to determine a consistent response that is accurate and timely. If unsure, the tester can add additional repetitions to determine if a missed response is true sensory loss or an error by the patient due to test length not sensory loss.
	Procedure:
	• Proprioception can be tested in the sitting or supine positions for the upper extremity and in supine for the lower extremity. Start with the unaffected limb. Explain to the patient with their eyes open, "I am going to move your arm. This is up; this is down (demonstrate test). I want you to close your eyes and tell me if I am moving you up or down." Use the hand positions described below for each joint movement.
	• Move the joint through a small range of motion (approximately 10 degrees for the limb joints and 5 degrees for the digit joints of the hand and foot). Move the limb at least 3 times in random directions. If the patient is wrong on any direction, then add several more repetitions to determine if the accuracy is great than 75% (score 2) or 75% or less (score 1).
	• Start with the most proximal limb joint on the unaffected side. Move to the same joint on the affected side. The intent is to determine if there are differences in the perception of proprioception between the two sides. For example, if the patient identifies the movement stimulus with the same accuracy and responsiveness of the unaffected side then the score would be 2. However, if the patient is accurate but responses are delayed or unsure then the score would be 1. (At this point, you could ask the patient if the movement on this side feels the same as the other side). No perception of joint movement is scored 0.
	
	Upper Extremity
	• <u>Shoulder:</u> Therapist supports patient's arm by the medial and lateral epicondyles of the humerus and at the distal ulnar and radius. Have patient look at arm. Move shoulder, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your shoulder in either direction. I want you to tell me "up" or "down." Randomly move arm approximately 10 degrees, 4 times (more if needed), keeping track of correct responses.
	• <u>Elbow:</u> Therapist supports patient's arm by the medial and lateral epicondyles and the distal ulnar and radius. Have patient look at elbow. Move elbow, saying "This is up. This is down." I am now going to have you close
		• *Scoring:*
		  • (0) – Absent (no sensation)
		  • (1) – Impaired (inconsistent response or three quarters of answers are correct, but considerable difference in sensation compared with unaffected side)
		  • (2) – Intact (all answers are correct, little or no difference).

	your eyes and I'm going to move your elbow in either direction. I want you to tell me "up" or "down." Randomly move elbow approximately 10 degrees, 4 times (more if needed) keeping track of correct responses. • Wrist: Therapist supports patient's wrist at the distal ulna and radius and the heads of the 2nd and 5th metacarpal. Have patient look at wrist. Move wrist, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your wrist in either direction. I want you to tell me "up" or "down." Randomly move wrist approximately 10 degrees, 4 times (more if needed), keeping track of correct responses. • Thumb: Therapist supports patient's thumb proximal to the interphalangeal joint and either side of the most distal aspect of the thumb. Have patient look at thumb. Move thumb at interphalangeal joint, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your thumb in either direction. I want you to tell me "up" or "down." Randomly move thumb approximately 10 degrees, 4 times (more if needed), keeping track of correct responses. **Lower Extremity** • The hip and knee should be tested in the supine position. The ankle and toe can be tested in the supine or sitting position. • Hip: Therapist supports patient's leg at the femoral condyles and the medial and lateral malleolus. Have patient look at leg. Move hip, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your hip in either direction. I want you to tell me "up" or "down." Randomly move hip approximately 10 degrees, 4 times (more if needed), keeping track of correct responses. • Knee: Therapist supports patient's leg at the femoral condyles and the medial and lateral malleolus. Have patient look at knee. Move knee, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your knee in either direction. I want you to tell me "up" or "down." Randomly move knee approximately 10 degrees, 4 times (more if needed), keeping track of correct responses. • Ankle: Therapist supports patient's leg at the medial and lateral malleoli and the heads of the 1st and 5th metatarsal. Have patient look at ankle. Move ankle, saying "This is up. This is down." I am now going to	

	have you close your eyes and I'm going to move your ankle in either direction. I want you to tell me "up" or "down." Randomly move ankle approximately 10 degrees, 4 times (more if needed), keeping track of correct responses. • <u>Toe:</u> Therapist supports patient's toe at the interphalangeal joint and either side of the most distal aspect of the great toe. Have patient look at great toe. Move interphalangeal joint, saying "This is up. This is down." I am now going to have you close your eyes and I'm going to move your big toe in either direction. I want you to tell me "up" or "down." Randomly move great toe approximately 10 degrees, 4 times (more if needed), keeping track of correct responses.	

VITA

Sarvenaz Chaeibakhsh was born in Tehran, Iran on December 16, 1989. During her high school studies, she won the third prize in the 2nd International Young Mathematicians Convention (IYMC, 2006). After receiving her mathematical and physics diploma degree in 2008, she entered the Khaje Nasir Toosi University of Technology (KNTU). Between 2008 and 2013 she studied Mechanical Engineering at the KNTU along with being the leader of robotic teams. In 2013 and 2014, she received two international prizes from the 9th and 10th International IranOpen Robotic Contest, respectively. After receiving her Bachelor of Science degree from the KNTU in 2013, she entered the University of Tennessee at Knoxville in 2014 to pursue her graduate studies and received her Master of Science degree in 2016.