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Roldan, Jay Ryan Urbanozo

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**ROBOTIC REHABILITATION GAMING STRATEGIES AND
LOW-DIMENSIONAL ANALYSIS OF HAND TRAJECTORIES**

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

MASTER OF SCIENCE

in

COMPUTER ENGINEERING
with an emphasis in ROBOTICS AND CONTROL

by

Jay Ryan U. Roldan

September 2016

The Thesis of Jay Ryan U. Roldan
is approved:

Professor Dejan Milutinović, Chair

Professor Jacob Rosen

Professor Ricardo Sanfelice

Professor Donald Wiberg

Tyrus Miller
Vice Provost and Dean of Graduate Studies

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Table of Contents

List of Figures	v
List of Tables	viii
Abstract	ix
Dedication	xi
Acknowledgment	xii
1 Introduction	1
2 Human Arm Motion Coordination	7
2.1 Pointing and Reaching Invariant Characteristics	8
2.2 Coordination and Control	9
2.2.1 Equilibrium Point Hypothesis	10
2.2.2 Concept of Synergy	10
2.2.3 Uncontrolled Manifold Hypothesis	11
2.3 Motor Learning and Rehabilitation	11
3 Exoskeleton System	13
3.1 Human Arm Model	14
3.2 Redundant Degree of Freedom	15
3.3 Exoskeleton Kinematic Model	16
3.3.1 Forward Kinematics	18
3.3.2 Inverse Kinematics	19
3.4 Control Schemes	20
3.4.1 Gravity Compensation	21
3.4.2 Admittance Control	22
3.4.3 Assistive Control Mechanism	25

4	Software Systems	26
4.1	Exoskeleton Control Software	27
4.2	Control Panel and Data Acquisition	29
4.3	Virtual Environment and Games Architecture	31
4.3.1	Virtual Environment	31
4.3.2	Game Architecture	32
4.3.3	Rehabilitation Games	36
4.4	Limitations and Future Work	44
5	A Low-Dimensional Dissimilarity Analysis of Unilateral and Bilateral Stroke-Impacted Hand Trajectories	47
5.1	Introduction	47
5.2	Data Collection And Protocol	52
5.3	Analysis of Vertical (Z-Axis) Component Of Human Hand Trajectories .	57
5.4	Multidimensional Scaling Analysis	59
5.5	Results	62
5.5.1	Vertical Component Data Analysis	63
5.5.2	Multidimensional Scaling Analysis	65
5.6	Discussion	72
5.7	Conclusion	75
6	Conclusion	77
A	IRB Protocol	80
B	Phone Interview Questionnaire	82
C	Interview Questionnaire	84
	Bibliography	86

List of Figures

1.1	Rehabilitation system designed specifically for rehabilitation. a) MIT-Manus [43]. b) MIME [55]. c) ARM Guide [45]. d) Bi-Manu-Track [45]. e) NeReBot [56].	4
1.2	The 7-DOF EXO-UL7 upper limb robotic exoskeleton device [73].	5
3.1	a) Axes assignment of the exoskeleton arm [63]. One encoder is responsible for joint sensing of each axis rotation. b) Force/torque sensor location on the exoskeleton. The end-effector force/torque sensor is not shown. .	14
3.2	a) Frame assignment of the exoskeleton arm. b) Diagram depicting the rotation of the elbow position around the axis formed by $P_w - P_s$. c) The local frame defined at P_c which is the bases of the swivel angle calculation.	15
3.3	Controller diagram with swivel angle prediction	21
3.4	Bilateral assistive control block diagram showing the force assistance provided by the master to the slave arm. In this control scheme the slave tracks the motion of the master and feels the attractive forces from the master imposed on it. f_{act} and τ_{act} are actual forces and torques exerted by the operator on the exoskeleton, θ_{meas} and θ_{cmd} are the measured and desired joint angles respectively, and τ_{mi} and τ_{si} are the i^{th} joint torque commands to the master and slave respectively.	24
4.1	System block diagram of the exoskeleton software system.	27
4.2	Control software flow diagram showing the main stages of execution. . .	28
4.3	Flow diagram of the gap-free scope loop implementation to handle massive data acquisition.	30
4.4	Diagram showing the architecture of the Virtual Environment and Games. A plane arrow with solid line represents inheritance. The class at the arrow head is the parent class. Arrows with dotted line represent class relationship where the class at the arrow head is the instance.	32
4.5	The paint game with two partial spherical walls, one for each arm . . .	38

4.6	The flower game showing one of the 11 stages of the game where only one petal is presented. The player has to touch the blue sphere in the middle and trace the line to the edge of the petal, touching the red balls, and back to the blue sphere again. A different view of the flower is shown in the background to the right of the score board to help the player interpret the configuration.	39
4.7	The reach game. The target red balls are aligned on a plane in a semi-circular manner. The semi-circle's center is located at the arm model's center.	40
4.8	The pong game. The pong table is shown at the center of the screen. The paddles can be controlled using one of the 7 joints or the hand. . .	41
4.9	The circle game in bilateral mode showing two paddles represented by block cubes at the left and right of the cylindrical platform. Only one paddle is shown for unilateral mode	42
4.10	The pinball game. At the center is the pinball table and the flippers can be controlled by choosing the control mechanism in the drop down menu shown on the left.	43
4.11	The handball game. Two arm models are shown where the player is free to move both arms	44
5.1	Marker placement. (a) Nine reflective markers are attached to each of the left and right arm (light gray circles). Four markers are attached to the torso (dark gray circles). (b) Subject holds a T-shaped pointer with a marker attached at the tip.	51
5.2	Target workspace setup. (a) Front and (b) top view of the target workspace. The left workspace is composed of targets L1-L5 and the right one is composed of targets R1-R5. (c) The subject's shoulders are aligned with the center of the left and right workspaces.	53
5.3	Sample of the collected trajectory data relative to the motion capturing system coordinate frame. The relative position and orientation of the target workspace with respect to the chair on which the subjects sat were kept unchanged. (a) Unilateral mode trajectory data of Subject 2 from the control group. Both right and left trajectories are shown. (b) Bilateral mode trajectory data of Subject 2 from the control group. (c) Unilateral mode trajectory data of Subject 1 from the hemiparetic group. Both healthy (light gray) and unhealthy (dark gray) trajectories are shown. (d) Bilateral mode trajectory data of Subject 1 from the hemiparetic group.	56
5.4	Area ratio calculated as the ratio of the areas above and below the trajectory: S axis represents the traveled distance in the xy -plane and ΔS_k are increments of the traveled distance between trajectory data points. .	58

5.5	Two 3D trajectories with the same number of points. The coordinates of the k th sample point of the i th and j th trajectories are (x_k^i, y_k^i, z_k^i) and (x_k^j, y_k^j, z_k^j) , respectively. The measure of difference between the trajectories is based on the area between the trajectories (shaded).	60
5.6	Approximations of the area between two trajectories: (a) the area is approximated as a sum of two triangles sharing the side connecting (x_k^j, y_k^j, z_k^j) and $(x_{k+1}^i, y_{k+1}^i, z_{k+1}^i)$ (b) the area is approximated as a sum of two triangles sharing the side connecting (x_k^i, y_k^i, z_k^i) and $(x_{k+1}^j, y_{k+1}^j, z_{k+1}^j)$	61
5.7	Boxplots of the area ratio per target for two reaching modes and two groups of subjects. A ratio less than 1 means that there is an upward motion at the start of the trajectory followed by a forward motion towards the target.	63
5.8	The polynomial order per target for the trajectories from two reaching modes and two groups of subjects.	64
5.9	The MDS maps for all trajectories for targets 1 to 5 are depicted in (a) to (e), respectively: the ellipse with the shaded area describes the 95% area for the cluster of the trajectories of healthy subjects, the points corresponding to the trajectories of hemiparetic subjects in unilateral (∇) and bilateral ($\circ$) reaching modes.	66
5.10	The distances of the centers of points corresponding to the unilateral and bilateral hemiparetic trajectories to the center of the healthy subject cluster (a) and the standard deviation (b) of the distance to the center of the healthy trajectory cluster. The bar graphs show the distances and standard deviation per type of the trajectory and target.	70
5.11	Subject 2 map for all targets are shown in (a) to (e). (∇) represents the bilateral trajectories and ($\circ$)'s are unilateral reaching trajectories of subject 2. The dashed lines illustrate the separation between the unilateral and bilateral trajectories. The ellipses with the shaded areas describe the 95% area for the cluster of healthy trajectories.	71

List of Tables

3.1	Link initial positions. All values are in meters	16
3.2	Denavit-Hartenberg parameters of the exoskeleton.	18
4.1	Game Types	37

Abstract

Robotic Rehabilitation Gaming Strategies And Low-Dimensional Analysis of Hand Trajectories

by

Jay Ryan U. Roldan

An effective rehabilitation plan is a combination of a carefully thought out intervention strategies and a practical, reliable and sensitive recovery assessment method. With robot-aided therapy, these two components can be integrated into one complete system. In this thesis, we present the development of a rehabilitation software system that includes seven rehabilitation games and introduced a novel recovery assessment and tracking method using multidimensional scaling (MDS) for the purpose of extending the applicability of a 7-DOF upper limb exoskeleton device into a complete rehabilitation system.

The rehabilitation software is composed of three components: control, data acquisition, and rehabilitation games. It is implemented into a 7-DOF upper limb exoskeleton system that acts as a haptic device providing force feedback with a virtual environment and enforces proper arm posture. We developed seven rehabilitation games for the purpose of challenging motor control coordination and promoting neuromuscular recovery. The development effort successfully produced a research platform for investigating effective rehabilitation strategies providing novel insights into the difference of

unilateral and bilateral training effectiveness, understanding of rehabilitation game design and evaluation, and uncovered evidence on the superiority of robot-aided therapy compared to conventional training.

Current state of the art assessment method such as the Fugl-Meyer and Wolf function test lacks the ability to objectively characterize stroke-impacted motions. The proposed recovery assessment and tracking method is a quantitative approach of identifying hand trajectory dissimilarity using multidimensional scaling (MDS). Using high-rate motion capture system, hand trajectories of both healthy and stroke-impacted hemiparetic subjects were captured. An MDS map was generated based on the mutual difference of two trajectories using area as a dissimilarity variable. The map reveals both structural and individual dissimilarities that presents quantifiable difference and variability of individual subjects. From this, we can identify and track the progress of recovery based on the difference of trajectory point from the cluster of healthy.

To my wife and daughter,

Ira and Cleo,

Thank you for your love and understanding.

You are my happy.

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Finally, I would like to thank my family, Mom, Dad, Ja, Jv, Nanay, and Tatay, for their love, never ending support, and for being there every step of the way.

Stand firm. Let nothing move you.

Give yourself fully to the work of the Lord,

because your labor in the Lord is not in vain

Chapter 1

Introduction

The goal of stroke rehabilitation is to promote motor recovery and regain lost skills. The main basis of rehabilitation is the fact that the central nervous system (CNS) is able to remodel itself via appropriate rehabilitation plan. Rehabilitation plans depend on the severity, type, and stage of impairment and how the patient responds to treatment. The measure of recovery progress has a direct effect on the rehabilitation plan and its effectiveness. Therefore a rehabilitation program critically depends on intervention and recovery assessment.

Traditional intervention techniques use stimulation and intervention exercises based on neuroplasticity theories [31]. Neurodevelopmental treatments such as the Bobath approach [7], Brunnstroms movement therapy [67], and Proprioceptive Neuromuscular Facilitation (PNF) [86] aim to regain normal muscle tone and proper posture by the inhibition of unhealthy movement patterns. With the Bobath approach the quality of movement is influenced by assistance to the weak muscles and prevention of exag-

gerated motions. Movements are closely monitored, assessed and the approach requires guidance of movements from therapists and nurses. The Brunnstroms movement therapy approach is to encourage flexor and extensor synergistic patterns with the goal to make these movements more controllable and voluntary. The PNF approach, on the other hand, focuses on muscle strengthening by exciting the weak muscles through the use of stronger ones [27]. From a survey in [27], these approaches have not shown strong evidence of superiority compared to other techniques. Constraint-induced Movement Therapy (CMT), which is regarded as one of the most commonly used approaches, uses harnesses to constrain the use of the healthy limb and encourages the use of the affected limb. Its goal is to overcome learned non-use of the affected limb while promoting the cortical reorganization [81]. This approach has shown evidence of faster patient upper limb recovery [23] but, it has limitations and its success is dependent on the degree of initial impairment [81]. Another recent approach that has shown a promise is the Bilateral Simultaneous Movement Training, which promotes recovery through the simultaneous use of both the healthy and stroke affected limb. This approach exploits the coupling effect of the limbs through interlimb coordination [48]. Many encouraging results have shown its advantage, but studies do not report agreement on its superiority.

In the recent decade, technological advances in robotics and virtual reality technology resulted in the surge of robot-assisted therapies. The robot-aided therapies enable automatic execution of traditional intervention approaches and evaluation of movements, and also open possibilities of a more objective and systematic rehabilitation program. A robotic device can provide the appropriate assistance and intensity

in imposing proper arm posture, inhibition or encouragement of synergies, as well as providing forces/resistance for passive range of motion exercises, and the capability to measure, classify, and provide feedback on movement quality that can be translated to quantifiable outcome. Evidence has shown the advantage of the robot-assisted therapy in comparison to traditional approaches specifically in the improvement of shoulder and elbow functionality. Some notable systems used in rehabilitation are the MIT-Manus [43], Mirror Image Motion Enabler Robot (MIME) [55], Assisted Rehabilitation and Measurement (ARM) Guide [45], Bi-Manu-Track [45], and Neuro-Rehabilitation-Robot (NeReBot) [56].

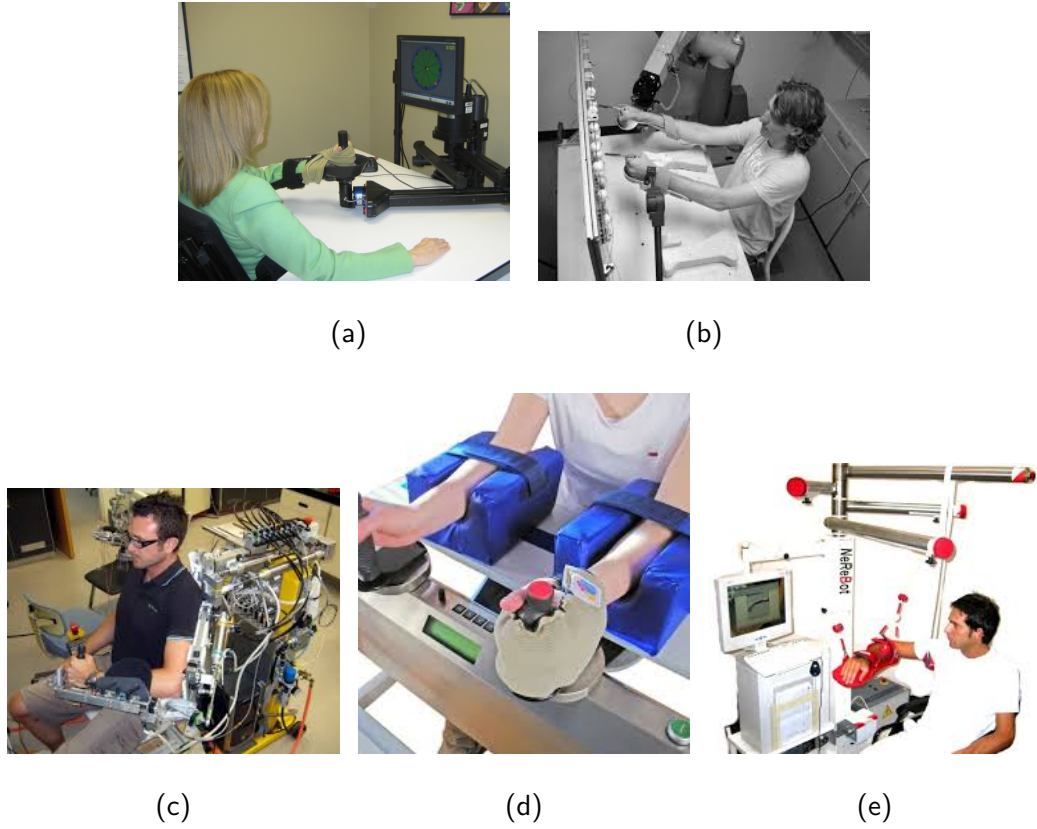


Figure 1.1: Rehabilitation system designed specifically for rehabilitation. a) MIT-Manus [43]. b) MIME [55]. c) ARM Guide [45]. d) Bi-Manu-Track [45]. e) NeReBot [56].

Virtual environment provides the necessary visual and performance feedback for the rehabilitation therapy. The environment can simulate real world activities of daily living (ADL), or introduce games that challenge motor control coordination in therapies that apply the concept of neuroplasticity. It can reduce the burdens of intensive repetitive therapy and immerse the patient into an environment of casual play. The integration of a robotic device and virtual environment may solve most if not all



Figure 1.2: The 7-DOF EXO-UL7 upper limb robotic exoskeleton device [73].

of the problems encountered in traditional rehabilitation therapies.

The work in this paper contributes to the development of EXO-UL7 upper limb robotic exoskeleton device (Fig. 1.2) as a rehabilitation device. We designed seven rehabilitation games that promote motor control coordination and challenge the neuromuscular control, muscular capabilities, and range of motion of the upper limbs. The design considered clinical applications such as diagnostic and therapeutic capabilities of each game. The games with well structured tasks are categorized as diagnostic games, while the games with less structured tasks are categorized as therapeutic games. The EXO-UL7 provides the necessary force feedback for upper limbs and virtual environment interactions and for enforcing proper arm postures. For measurement and evaluation of movements, a data acquisition application of all the exoskeleton sensors (force sensors,

and joint encoders) is also designed. The integration of virtual reality and rehabilitation game sub-systems with the exoskeleton device creates a research platform that is able to provide a novel insight into effective rehabilitation strategies.

As part of this work we also explore a novel recovery assessment technique based on hand trajectory dissimilarities. Conventional outcome measures such as Fugl-Meyer assessment [29], or the Wolf Motor Function test [65] lack the objectivity and rely on the therapist experience. Our aim is to properly describe recovery and track its progress using quantitative measures and thus enable effective ways of designing rehabilitation schemes. Our proposed method is based on multidimensional scaling (MDS) technique [11, 10], which has been proven useful in various studies to track evolution of certain parameters [77, 44, 5]. A map of hand trajectory dissimilarities is created in which each point of the map represents a single trajectory. This method reveals types of dissimilarities among hand trajectories and allowed us to quantify the variability and consistency of trajectories.

Strategically designed rehabilitation games that drive neuroplasticity as well as the analysis of hand trajectories are significant in following the progress of recovery. The rehabilitation games provide a controlled environment and encourages structured trajectory (e.g. reaching from one target to the next or following a line) that are repeatable. Structured hand trajectories are easy to analyze because of its predictability, as a result ideal motions and patterns can be identified. The ideal motion becomes the baseline and any dissimilarity from the baseline can be tracked therefore providing historical data of the progress of recovery.

Chapter 2

Human Arm Motion Coordination

Reaching for an object seems to be an easy task because it is performed millions of times (learned) in our lifetime that we develop the skill to perform the action without putting much thought into it. However, the reality is that our central nervous system (CNS) is the primary driver of motion and together with our other senses (primarily proprioception and vision), and the musculoskeletal system of our limbs, they have to be coordinated in order to achieve the simple goal of reaching. Proper CNS signals have to be triggered at the right time along with the correct magnitude, otherwise the target will be missed.

Understanding a simple task as mundane as reaching for an object requires understanding of the kinematics and coordination of the human arm. The main objective is to have the hand touch or grasp the object. First, the location of the object needs to be known with respect to the hand. Now the question is how do we know the location of the hand? Visually, we can see the hand and the object. However, both hand

and object are not always in the visual field. Furthermore, the hand is not controlled directly, instead it is controlled by the movement of the joints. This requires that the location of the hand needs to be known with respect to the joints and the neighboring parts of the body. Proprioceptive feedback providing the information about relative position of body parts [28], is necessary.

One approach is to move the hand with an objective of minimizing the distance between the object and the hand. However there are infinite number of ways to do this. The simplest one is to traverse a straight line from the initial hand position, but this is not what actually happens in reality. There are some variations in the movements and they are slightly curved [1, 78, 26, 35, 34, 24] and there is a question of how these trajectories are planned. Although tremendous amount of research have been conducted and the base knowledge has been laid, this question remains open.

In the following section we describe the invariant characteristics of pointing and reaching. This is followed by an overview of the leading theories in the coordination and control of the human arm. Lastly, we explain its relation to motor learning and rehabilitation.

2.1 Pointing and Reaching Invariant Characteristics

Invariant characteristics of human reaching trajectories have been studied extensively. Experimental analysis by [1, 78] showed that the position profile are characterized by mostly straight line paths with bell shaped tangential velocity curves. Velocity

profiles start at zero and peak close to the middle of the trajectory paths. This smoothness of the hand paths are supported by the maximum smoothness theory [26]. The theory states that the movement is planned such that the jerk of the hand is minimized. The analysis was done with arm motions on the horizontal plane. The author in [35] provided evidence that the bell shaped velocity profile can be found in motions in the vertical plane. However, this contradicts the minimum jerk theory that position profile showed slightly curved paths. It is later explained that this curved hand paths are due to staggered joint activations [34]. The evidence that both the curved shape and bell-shaped velocity profile is due to the combination of staggered joint activation and minimum jerk theory, and that the planning is done in the joint space are provided in [24].

2.2 Coordination and Control

The human arm is a redundant mechanism that control and coordination is a difficult task. How the CNS chooses to resolve redundancy for a given task is still an open question and for roboticists a source of inspiration for resolving redundancy in robotic systems [52, 64]. In this section, we introduce three leading theories in the control and coordination of the human arm: equilibrium point hypothesis, concepts of synergy, and uncontrolled manifold hypothesis.

2.2.1 Equilibrium Point Hypothesis

Muscle tension varies with the length of the muscles and therefore changes the tension-length property. Two opposing muscles provide tension to a limb and the resting tension of these muscles results in the equilibrium configuration. Equilibrium point hypothesis states that arm postures are chosen such that they are attracted towards an equilibrium configuration [22, 25, 30]. During activation, muscle tensions are altered such that the equilibrium point changes. These changes are gradual, pulling the arm along equilibrium points [25]. Hence, during hand trajectory the configuration chosen are such that the equilibrium configuration is satisfied.

2.2.2 Concept of Synergy

The theory of muscle synergy in coordinating effectors of the arm is based on the idea that every movement recruits a group of muscles [6, 16, 17]. In other words, there is a mapping of movement states to specific muscle groups to accomplish the task. This potentially simplifies the task of the CNS dealing with a higher level of motor control, instead of controlling individual joints. According to this concept, individual muscles are activated such that the resulting joint torques are approximately proportional to each other.

Synergies are evident in impaired individuals where muscle control becomes limited and the magnitude of synergies are increased [74, 18]. As an example, for stroke impacted arms, the flexion synergy can be observed when an individual performs shoulder abduction, resulting into the flexion of elbow. The synergies can also be

observed in healthy arm movements, but at a lower magnitude.

2.2.3 Uncontrolled Manifold Hypothesis

The uncontrolled manifold (UCM) hypothesis states that the CNS uses all available degrees of freedom to maintain stability and flexibility of movement [47]. This is in disagreement to some of the earlier work [6] which states that in order to move a redundant system some degrees of freedom must be frozen first. By the UCM hypothesis, it is acceptable that there is variability in movements and that the variabilities are necessary to achieve stable yet flexible motions. In the context of upper limb control and coordination, the goal of touching or grasping an object can be achieved in infinite number of ways with infinite number of joint configurations but some performance criteria are chosen and maintained (e.g. smoothness, maximum torque/energy, stabilization, etc.) and any element of the movement beyond that can vary. For impaired limbs the performance criteria may be avoiding uncomfortable or painful joint configurations. Simply speaking, the CNS selects a subspace such that the performance remains constant, i.e. that the goal is achieved.

2.3 Motor Learning and Rehabilitation

Motor learning, in the context of reaching and grasping, is the ability to acquire new control strategies or movement patterns by repetition (e.g. practice, rehabilitation) or change in the reaching mechanism (e.g. loss of control, loss of DOF) [46, 42, 39, 48, 32]. The task of reaching and grasping or any voluntary hand motion for that matter

is a learned skill. The ability to acquire new control strategies is the main driving force in rehabilitation. A rehabilitation program relies on how an individual cope with injury by relearning normal skills (true recovery) or learning a new strategy (compensatory) [49, 70].

Compensatory strategies are characterized by the recruitment of other degrees of freedom (e.g. trunk forward motion, or swinging of the arm). Although this strategy could gain functional recovery of the limb, there is a long term side effect of learned non-use and patients typically suffer from pain and limited range of motion [49]. To achieve true recovery, focus on motion quality that exhibits invariant characteristics of a healthy upper limb motion is necessary. Tasks such as tracing a line or forcing the joints configurations to exhibit healthy characteristics enable skill relearning.

Chapter 3

Exoskeleton System

The exoskeleton is designed as a transparent extension of the human upper limb or as a rehabilitation device and its joint ranges covers 99% of the human arm motion ranges. Its joint rotations are aligned with human anatomical joint axis (Fig. 3.1a). Furthermore, it includes control strategies that aims to provide minimal human robot interaction and has the capability to impose proper arm posture and assistance when used for rehabilitation purposes.

The exoskeleton system is a set of two 7 degrees of freedom exoskeleton arm. Each joint is equipped with DC brushless motors for actuation and joint encoders for joint position sensing. In addition, it is capable of sensing force and torque interaction between the operator and the device via force/torque sensors attached to each link (upper and lower arm, and wrist) and the end-effector (Fig. 3.1b). The larger motors (3 shoulder and 1 elbow motors) are located at the base and utilize cable based actuation for low inertia.

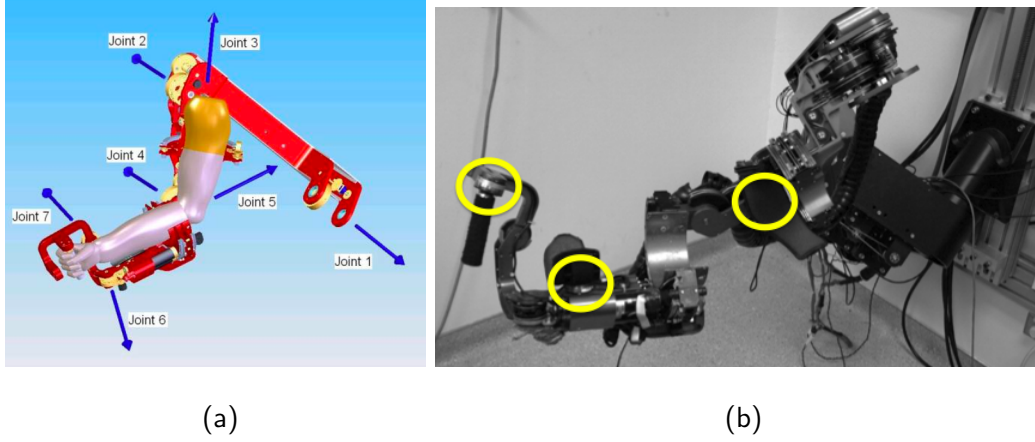


Figure 3.1: a) Axes assignment of the exoskeleton arm [63]. One encoder is responsible for joint sensing of each axis rotation. b) Force/torque sensor location on the exoskeleton. The end-effector force/torque sensor is not shown.

3.1 Human Arm Model

The human arm is a complex structure that is made of both rigid body such as the bones and non-rigid body such as muscles and soft tissues. The structure has multiple degrees of freedom and is hard to model. For the purpose of robot design a model which accounts only for rigid parts and joints is sufficient. The model ignores muscle and soft tissues and the upper limb is modeled using rigid links and revolute joints. It turns out that a 7 DOF model is enough to represent human upper limb motions and kinematics [72, 41, 63]. The 7-DOF model is made up of 3 joints at the shoulder (rotation, extension, flexion), one at the elbow (flexion, extension), and 3 at the wrist (flexion, extension, and radial ulnar deviation).

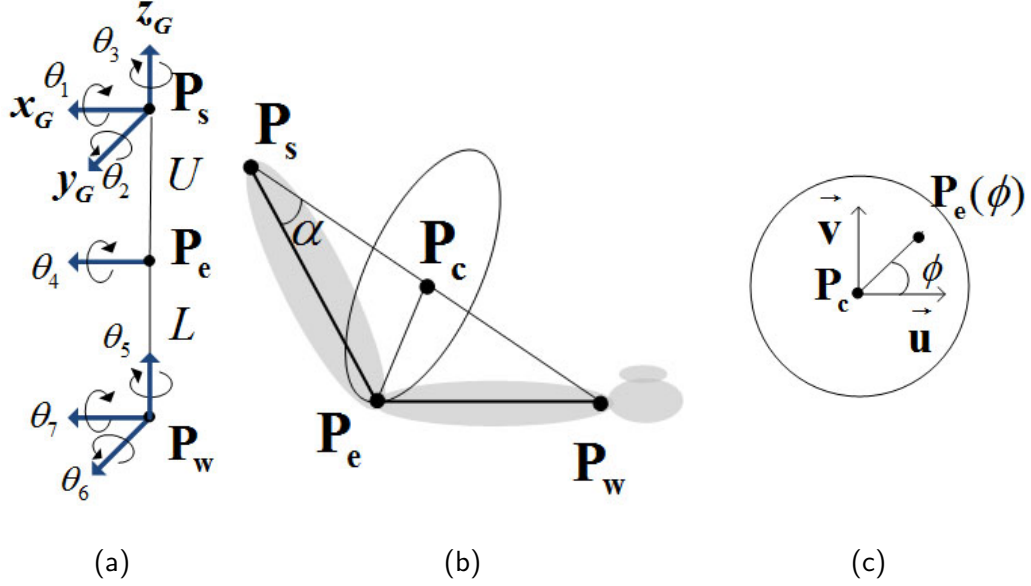


Figure 3.2: a) Frame assignment of the exoskeleton arm. b) Diagram depicting the rotation of the elbow position around the axis formed by $P_w - P_s$. c) The local frame defined at P_c which is the bases of the swivel angle calculation.

3.2 Redundant Degree of Freedom

The 7-DOF arm model describes redundant mechanical manipulator. It is redundant because the manipulator's end effector position and orientation requires only 6-DOF, therefore, given a wrist position and orientation, the elbow location can be specified in an infinite number of ways. In order to uniquely specify the arm model configuration the elbow location has to be defined by a variable called the swivel angle (ϕ). Given a local coordinate at the plane formed by the elbow point of rotation (P_c) and the elbow position (P_e), the swivel angle is the angle between the unit vector u and the vector $P_c - P_e$ (see Fig. 3.2).

While the swivel angle defines the elbow location, the location has to be defined based on a certain criterion. For example the location can be based on the manipulability ellipsoid [63]. By studying the human arm reaching motions, it is found that the arm is configured such that the most efficient motion (manipulability ellipsoid) is pointing towards the head identifying that this is because the head contains the most sensory organs. With this, a point located at the head can be specified as the determining parameter to calculate the location of the joint through out the reaching trajectory.

3.3 Exoskeleton Kinematic Model

The kinematic model of the exoskeleton has eight frame assignments, one global and 7 local frames for each joints. The global frame is at the intersection of the first and second joint (see Fig. 3.2). This stationary frame is at the center of the shoulder of the operator. Both exoskeleton arm have their own origin with the z-axis oriented to point up and the x-axis is pointing towards the right of the operator. From the origin, the location of the distal part of each link and the end effector can be determined. The initial position of the exoskeleton (i.e. all joint positions are set to 0) is such that the arm is hanging straight down with the distal link positions shown in table 4.1 (refer to Fig. 3.2a).

Table 3.1: Link initial positions. All values are in meters

Position	x	y	z
P_s	0.0000	0.0000	0.0000
P_e	0.0000	0.0000	-0.3036
P_w	0.0000	0.0000	-0.5806

The mapping between joint space and the task space can be defined using the kinematic model of the system. To be able to determine the location of the end-effector, a forward kinematic map is required to transform the joint positions to end-effector frame. Inverse kinematic, on the other hand, is the reverse of this where the joint positions is determined given the end-effector frame.

Table 3.2: Denavit-Hartenberg parameters of the exoskeleton.

Side	i-1	i	α_i	a_i	d_i	θ_i
Left	0	1	$\pi/2$	0	0	$\theta_1 + \pi - 32.94^\circ$
	1	2	$\pi/2$	0	0	$\theta_2 + \pi/2 - 28.54^\circ$
	2	3	$\pi/2$	0	0	$\theta_3 + \pi - 53.6^\circ$
	3	4	$\pi/2$	0	L_1	θ_4
	4	5	$-\pi/2$	0	0	$\theta_5 - \pi/2$
	5	6	$-\pi/2$	0	L_2	$\theta_6 + \pi/2$
	6	7	$\pi/2$	0	0	$\theta_7 + \pi$
Right	5	6	$\pi/2$	0	0	$\theta_1 - 32.94^\circ$
	1	2	$\pi/2$	0	0	$\theta_2 - \pi/2 - 28.54^\circ$
	2	3	$-\pi/2$	0	0	$\theta_3 - \pi - 53.6^\circ$
	3	4	$-\pi/2$	0	$-L_1$	θ_4
	4	5	$\pi/2$	0	0	$\theta_5 + \pi/2$
	5	6	$-\pi/2$	0	$-L_2$	$\theta_6 + \pi/2$
	6	7	$\pi/2$	0	0	$\theta_7 + \pi$

3.3.1 Forward Kinematics

The Denavit-Hartenberg [14] parameters of the kinematic model is shown in table 3.2. L_1 and L_2 are the link lengths of the upper and lower arm respectively. Theta offsets are specified to conform to the joint ranges of the human upper limb and to place the singularities outside of the reachable workspace [63]. The link frames and the link parameters were defined. Using the formula below (3.1), the homogeneous transformation matrix from link to link was calculated.

$${}^{i-1}_iT = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 & a_{i-1} \\ \sin\theta_i\cos\alpha_{i-1} & \cos\theta_i\cos\alpha_{i-1} & -\sin\alpha_{i-1} & -\sin\alpha_{i-1}d_i \\ \sin\theta_i\sin\alpha_{i-1} & \cos\theta_i\sin\alpha_{i-1} & \cos\alpha_{i-1} & \cos\alpha_{i-1}d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.1)$$

where θ_i is the joint angle, d_i is the joint offset, α_{i-1} is the link twist, a_{i-1} is the link lengths, and ${}^i_{i-1}T$ is the homogeneous transform matrix from link $i - 1$ to i . Therefore calculating the end-effector position and orientation given the joint angles is done by multiplying the transformation matrix of each link from frame 0 to 7.

$${}^0_1T {}^1_2T {}^2_3T {}^3_4T {}^4_5T {}^5_6T {}^6_7T = {}^0_7T = \begin{bmatrix} r_{11} & r_{12} & r_{13} & P_x \\ r_{21} & r_{22} & r_{23} & P_y \\ r_{31} & r_{32} & r_{33} & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.2)$$

where r_{ij} is the i^{th} row and j^{th} column element of the rotation matrix, and P_x , P_y , and P_z are the x, y, and z elements of the position vector.

3.3.2 Inverse Kinematics

From the forward kinematics map, there are 7 unknown joint configurations and only 6 required parameters (3 positions, and 3 orientations) and therefore an additional constraint must be imposed. A very good candidate for this is the elbow position.

Given the wrist P_w , elbow P_e , and shoulder P_s position, θ_4 can be determined using the law of cosine.

$$\cos(\theta_4) = \frac{U^2 + L^2 - \|P_w - P_s\|}{2UL} \quad (3.3)$$

where U is the length of the upper arm, L is the length of the lower arm. With θ_4 known, the homogeneous transform 3_4T is also known. With this, θ_1 and θ_2 can be solved based on the position of the elbow.

$${}^0_4T = {}^0_1T {}^1_2T {}^2_3T {}^3_4T = \begin{bmatrix} r_{11} & r_{12} & r_{13} & P_{ex} \\ r_{21} & r_{22} & r_{23} & P_{ey} \\ r_{31} & r_{32} & r_{33} & P_{ez} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.4)$$

Manipulating equation 3.2 by pre-multiplying the inverse of 0_1T and 1_2T , θ_3 can be derived from the solution to the x coordination of the wrist position.

$${}^2_7T = ({}^1_2T^{-1})({}^0_1T^{-1})({}^0_7T) \quad (3.5)$$

As for the joint angles θ_5 , θ_6 , and θ_7 , they can be calculated from the homogeneous transform defined by the wrist with respect to the elbow, 4_7T . This can be solved by pre-multiplying equation 3.2 with the inverse of 0_1T , 1_2T , and 2_3T . Joint angle θ_6 can be derived from the solution of r_{w23} and then θ_5 , and θ_7 can be derived from the solution of r_{w13} and r_{w22} respectively.

$${}^4_7T = ({}^3_4T^{-1})({}^2_3T^{-1})({}^1_2T^{-1})({}^0_1T^{-1})({}^0_7T) \quad (3.6)$$

3.4 Control Schemes

One of the challenges in exoskeleton design are the control schemes. The exoskeleton should be as transparent as possible to the user during natural arm motion and at the same time be able to provide the proper assistance needed during rehabilitation. In this section, the control schemes used to address the mentioned requirements

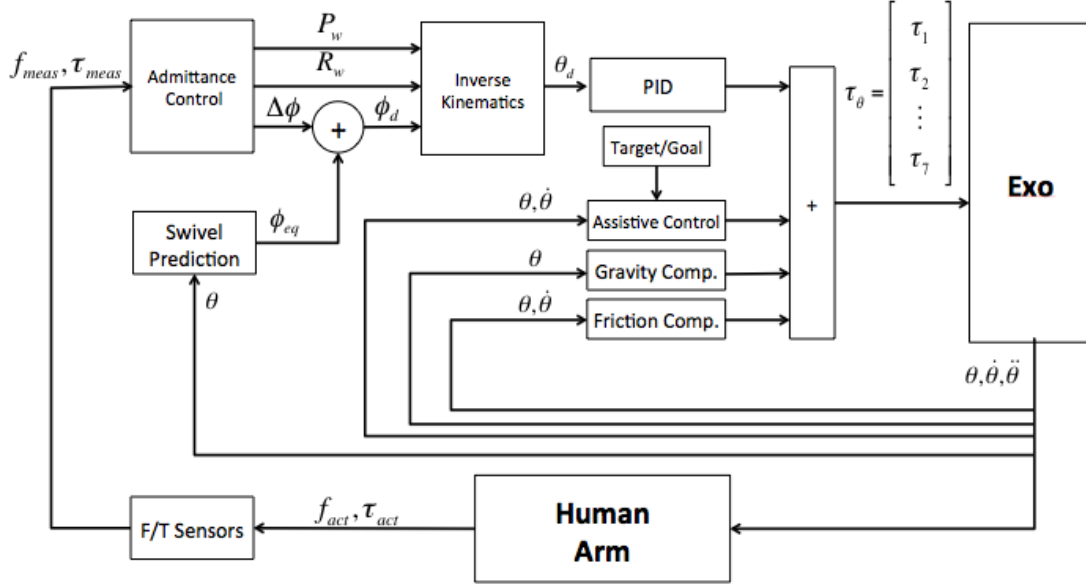


Figure 3.3: Controller diagram with swivel angle prediction

are explained. First the base control scheme of gravity compensation is explained and then two control modes, admittance and assistive control, are described.

3.4.1 Gravity Compensation

The weight of the exoskeleton arm provides additional hindrance in achieving human robot transparency. In order to mitigate the effect of gravity, gravity compensation was added. This enables the exoskeleton arm to support its own weight enabling the arm to hold position at any joint configurations.

This control scheme cancels the effect of gravity on the exoskeleton arm by applying a torque that is equal and opposite to the torque caused by gravity. This is a simple model based control scheme where the opposing torque relies on the a feedforward

gravity model. From the dynamic model of the arm (3.7), the negative of the gravity term, $G(\Theta)$ is added to the torque calculation of each joint.

$$\tau = M(\Theta)\ddot{\Theta} + V(\Theta, \dot{\Theta}) + Fr(\Theta, \dot{\Theta}) + G(\Theta) \quad (3.7)$$

where τ is the torque vector, M is the mass matrix, V terms dependent on joint velocities, Fr contains the friction model, G is the gravity term, and $\Theta = \theta_1, \theta_2, \dots, \theta_7$.

3.4.2 Admittance Control

Admittance control reduces the interaction forces of the operator and the exoskeleton system. The robot is viewed as an environment that admits forces from the operator altering its position to maintain human-robot interaction. By sensing the interaction force, this control scheme provides the necessary reaction position to regulate the interaction forces sensed by the robot. The typical setup is that the force sensor is located at the end effector of the robot and the control algorithm calculates the resulting end-effector position in the direction of the force. However for an exoskeleton device with 7-DOF, the redundant nature of the system presents a problem; the elbow location cant be specified given the end-effector position and orientation. Because of this, the control scheme uses all four force sensors providing force feedback on all the links of the upper limb (upper arm, lower arm, and hand) and the external environment (end effector force sensor). The end-effector and elbow position are calculated independently. The end-effector trajectory is determined based on the information of all force sensors. Local forces (upper, lower arm, and wrist) are translated to the resulting forces in a

common global frame. Equation 3.9 translates local forces to the global frame.

$$\vec{f}' = R_1 R_2 \dots R_n \vec{f}_{meas} \quad (3.8)$$

where n is the frame from which the sensor is attached, $\vec{f}_{meas}$ is a vector of local forces as measured by the force sensors, R_i is the rotation matrix of the i^{th} frame, and $\vec{f}'$ is the common global frame.

Since the goal is to maintain zero interaction force, the reference force is set to zero and the force error between the user and the exoskeleton is the sum of all the forces translated to the common frame. The equation will be

$$\vec{f}_e' = \vec{f}_u' + \vec{f}_l' + \vec{f}_w' + \vec{f}_t' \quad (3.9)$$

where $\vec{f}_e'$ is the force error at the common frame, $\vec{f}_u'$, $\vec{f}_l'$, $\vec{f}_w'$, and $\vec{f}_t'$ are the forces translated to the common frame of the upper limb, lower limb, wrist, and tip respectively. This error is then transformed into changes in wrist position. For the wrist orientation, the torque acting on the wrist and handle force sensors are used to calculate the orientation changes of the wrist. Like the wrist position calculation, this too must be translated to a common global frame.

$$\vec{\tau}_w' = R_1 R_2 \dots R_7 \vec{\tau}_w \quad (3.10)$$

where τ_w is the total torque contribution of the wrist and end-effector force sensors. In addition, the swivel angle position change is also calculated based on the forces acting on the swivel axis ($\bar{P}_w - \bar{P}_s$). A swivel angle prediction algorithm based on biological need is included [38]. This prediction algorithm anticipates the motion of the swivel angle

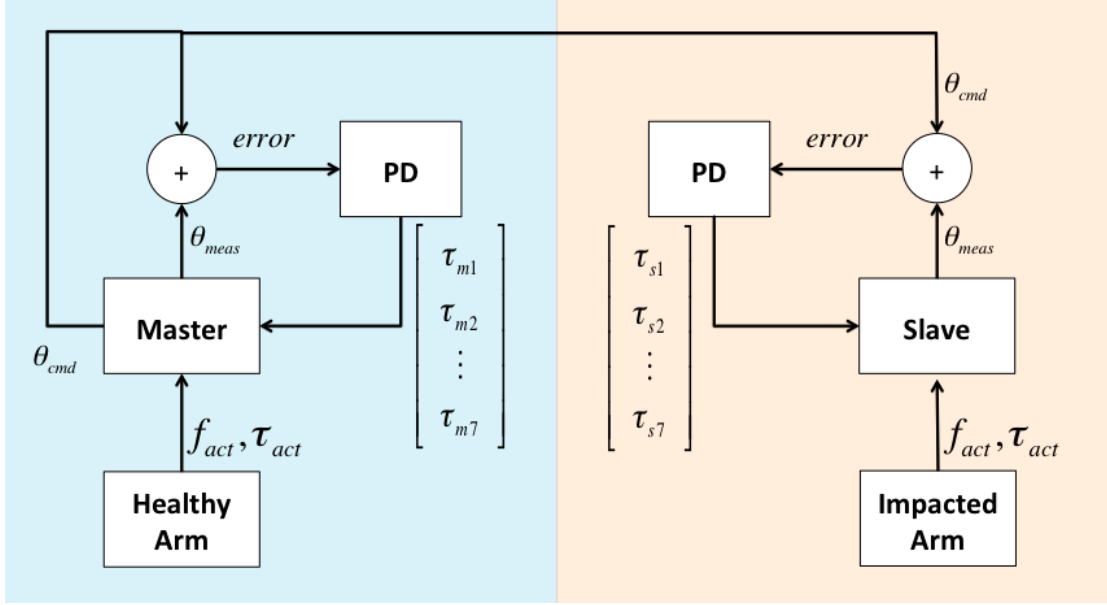


Figure 3.4: Bilateral assistive control block diagram showing the force assistance provided by the master to the slave arm. In this control scheme the slave tracks the motion of the master and feels the attractive forces from the master imposed on it. f_{act} and τ_{act} are actual forces and torques exerted by the operator on the exoskeleton, θ_{meas} and θ_{cmd} are the measured and desired joint angles respectively, and τ_{mi} and τ_{si} are the i^{th} joint torque commands to the master and slave respectively.

decreasing the force difference on the upper and lower arm. Given the end-effector and elbow information, the motion of the robot can now be calculated using inverse kinematics. At the lower level, joint position tracking is done through PID control. Details of the admittance control scheme is provided in [38].

3.4.3 Assistive Control Mechanism

The goal of the assistive control mechanism is to provide the necessary assistance to achieve a specific objective during rehabilitation. The objective could be maintaining proper arm configuration, reaching a desired target, or maintaining symmetric motion in bilateral symmetric reaching. In this control scheme an attractive force is generated using Position-Derivative (PD) control that drives the error between the desired configuration and the arm configuration to zero. For reaching assistance in unilateral mode, the error between the target and the hand position is driven to zero. In addition to this, the swivel angle error between the actual exoskeleton and the desired swivel angle has to be regulated as well to fully define the arm configuration. With this mechanism, it not only provides assistance towards the target but also enforces proper arm configuration. For bilateral symmetric reaching, the joint position error between the master and the slave arm is minimized (See Fig. 3.4).

Chapter 4

Software Systems

The software system architecture is depicted in Fig. 4.1. The control software is an xPC target [59] application running under xPC target real-time kernel. At the core of it is a Simulink model that communicates with the input and output ports of the exoskeleton actuators and sensors. A graphical user interface and data acquisition application initiates and terminates executions of the control and data acquisition software. It also allows the user to assign subjects and trial identification numbers. The virtual environment and rehabilitation games execution is on a dedicated computer and their communications with xPC platform is through a local area network User Datagram Protocol (UDP).

The chapter starts with the control and the data acquisition software implementation. In addition, a detail discussion of the virtual environment and rehabilitation game architecture is presented. Lastly, the limitation of the current software system and a proposed architecture based on Chai3d is discussed.

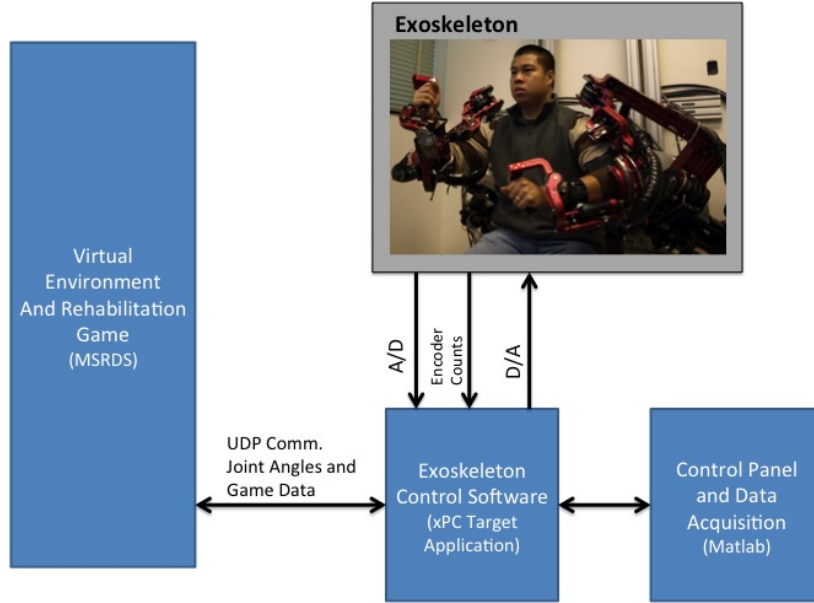


Figure 4.1: System block diagram of the exoskeleton software system.

4.1 Exoskeleton Control Software

The exoskeleton control software is an xPC target application written in C language and conforms to the S-function standard [58]. A user defined S-function block is created in Matlab Simulink and this executes the code base for the control software. The Simulink model has interface with the physical systems through MATLAB supported A/D, D/A card and network blocks. An xPC target application is created using this model and installed as a standalone application on the xPC target dedicated computer.

The Simulink model executes in three stages. First, the model initialization stage, and then followed by the actual simulation loop stage, and finally the termination stage to perform exit routines such as memory cleanup.

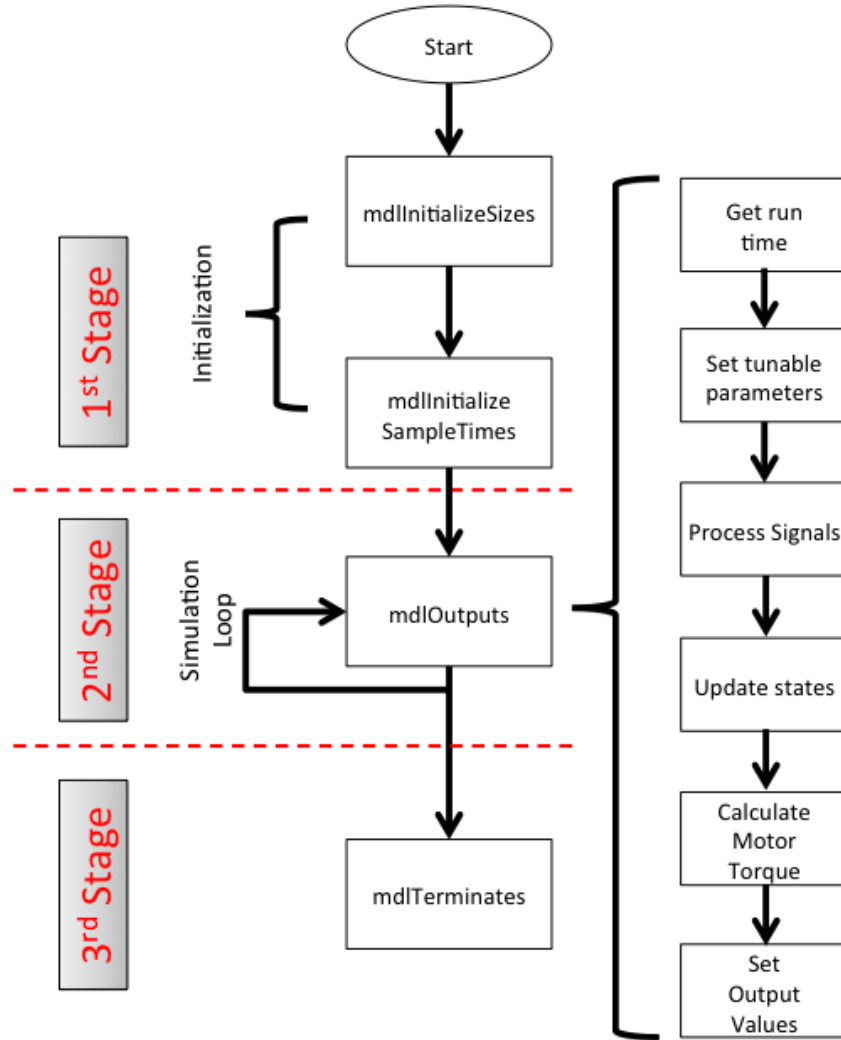


Figure 4.2: Control software flow diagram showing the main stages of execution.

In the model initialization stage, **mdlInitializeSizes** and **mdlInitializeSampleTimes** methods are called. The purpose of these two methods is to declare a number of parameters, initialize states and input and output ports, define sample times and offset times. In our implementation, the sample time is 1 millisecond.

The simulation loop performs all the calculations. This stage is executed indefinitely until the user decides to terminate the simulation process. The **mdlOutputs** method is called every sample period (1 ms) to update all the outputs of each Simulink block model. The **mdlOutputs** method sets all user relevant parameters for the exoskeleton (enable button, game modes, etc.), signal processing (sensor signal filtering and conversions), robot state updates (end-effector location, velocities, and forces), and calculation of motor torques.

The last stage of execution is the termination. The **mdlTerminate** method is called in this stage. This function is mandatory and have to be included in the code even without any user defined operations.

4.2 Control Panel and Data Acquisition

A control panel and data acquisition application was developed using Matlabs graphical user interface development environment (GUIDE) [60]. The application uses the signal-logging feature of xPC target real-time kernel. It communicates with the control software through the xPC target object that resides in the host computer. To run the control software the Simulink model is loaded to the target PC, an xPC target object is created, and then a start command is called to start the application.

For data acquisition, scope objects [59] were added. They are used for visualization and analysis of data from the target application. Scope objects were defined as host types. They are the representation of scopes in the target application but they are

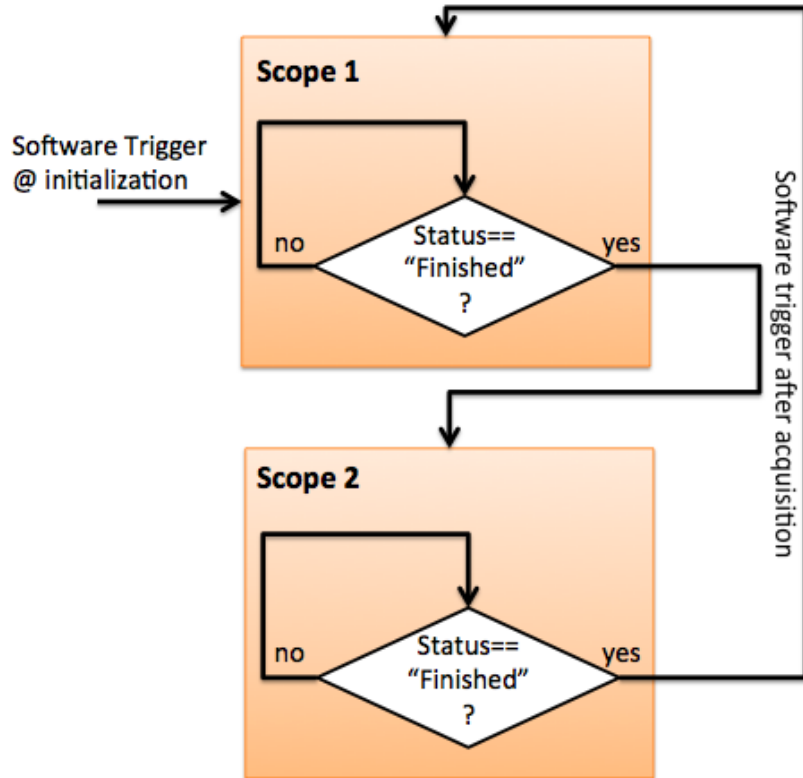


Figure 4.3: Flow diagram of the gap-free scope loop implementation to handle massive data acquisition.

only viewable in the host computer. As oppose to target scope types, the data can be used only after the scope has finished acquiring.

Figure 4.3 depicts the implementation of the scope objects to accomplish a gap-free data. The method uses two scope objects both receiving the same data but at different time frames, alternating between each other. The first scope is set active and triggers upon execution. During data acquisition, the process keeps checking if the active scopes status has finished. If it has then it is set to stop and the second scope

is set as the active scope and commanded to start. The data and time stamps of the first scope is dumped to a variable that will be maintained through out the execution of the code. The first and second scope will keep alternating role as the active scope, dumping data to the variable. The content of the variable will be saved to an ASCII formatted text file in the host computer.

4.3 Virtual Environment and Games Architecture

The simulation environment and rehabilitation games are implemented using Microsoft Robotics Developer Studio (MSRDS) [62]. The design takes advantage of the simulation engine and the readily available robot simulation templates that come with the MRSDDS software.

4.3.1 Virtual Environment

The simulation engine is a Decentralized Software Service (DSS) [61]. The DSS addresses some of the problems resulting from a highly complex, multi process applications for robotics. Such problems addressed are software robustness, composability, and observability [61]. The simulation engine uses a physics engine called Ageia Physics engine and the 3D rendering is based on XNA graphics library.

The simulation environment is composed of entities that represent real world objects. Each entity has physical and visual components. Physical component defines the physical properties of the object and determines the interaction between the object and the environment. Visual component defines visual properties of the object and deals

with the object's rendering. The virtual environment implementation challenge was in creation and manipulating these two components.

4.3.2 Game Architecture

The rehabilitation game architecture is composed of five classes: Controller, MainControl, MainForm, Game, and GameShell.

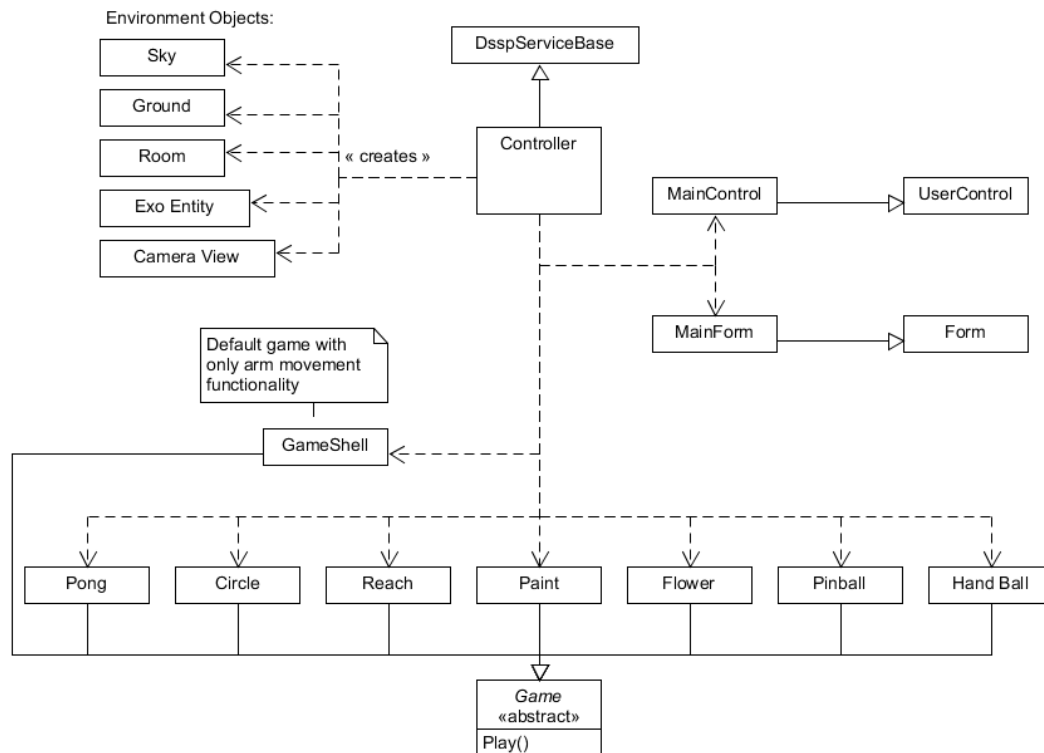


Figure 4.4: Diagram showing the architecture of the Virtual Environment and Games.

A plane arrow with solid line represents inheritance. The class at the arrow head is the parent class. Arrows with dotted line represent class relationship where the class at the arrow head is the instance.

The very first class to be executed is the Controller class. This class inherits DsspServiceBase, which is the service protocol used by MSRDS to interact with other services like the simulation engine. Generally, the role of a service is to facilitate information and keep track of the state of the program. In this architecture, the Controller's specific function is to act as the entry and exit point for common game specific methods and variables that are shared by all games. Since it has ownership of these, it promotes the synchronization of game processes such as starting a play thread or ending a game. In the Controller, a Game class is declared and depending on the game being played this object gets instantiated with the game object chosen. Upon a call to start in the Controller is executed, the simulation engine service starts, the connection to the exoskeleton is established, the main window form is posted, and populates the environment with common entities such as the game room, the sky, and a human model. In addition to these, the default game shell is instantiated and a play thread is created and started. Starting the default game shell enables the user to move the arm model.

The MainForm class is a main window form and is implemented as a Windows Form class. It has three functions it holds the main control panel and the game specific controls, controls the camera settings, and contains the button to end the games. It is posted within the call to start of the Controller service. Once the main window form is posted the main user control is added to the form. The main user control is implemented as MainControl class. The main user control gives the user the option to choose which game to play. Each button invokes a function in the Controller which updates the game object to point to the user specified game class and a corresponding game thread is

defined and started. The index of the game is passed to the function and a new game object is assigned as the current game. Prior to game assignment, the current game thread is aborted and exit routines to end the current game is performed. The main form control panel which is the MainControl class is then removed and replaced by the game specific control panel of the assigned game.

Each game has common functionalities and attributes inherited from the parent class Game. The Game class includes methods for adding and removing entities, updating arm encoder data, and subscribing for contact notifications. Since each game plays differently, the the abstract class also includes the method Play(). This method is inherited and implemented in child classes that are specific for each game. The method Play() implements the main loop of the game and it is referenced by the play thread during a call to its start method.

Most games require that the user reaches certain object or follows a certain path. The objects are modeled as single shape entities, for example circles or squares. For complex graphical rendering, mesh files were imported into the material property of the entity. Object that could not be represented as a single shape or has irregular shape were created using third party software such as Solidworks and generated as an object (.obj) file.

For physical interaction, objects have to subscribe for contact notification with the Controller. By doing this, the service determines what kind of interaction occurred and provides the resulting object behavior. Normally, the physical property of the object is set first prior to using it. To update the physical property of an object, a method to

update was created and a Task class is used to determine the appropriate schedule of the update method to execute. Tasks enables the simulation engine to execute asynchronous calls in a safe manner and ensures that all tasks are executed correctly and at the right time.

The object properties cannot be easily changed after the object is created. In the case of the Color property, this obstacle is avoided by creation of multiple objects with different colors. During the instantiation, one of the objects is placed in the users view and the others are hidden from the view. If the color needs to change, the positions of the objects were swapped. This technique has the advantage that both the objects are readily available just after the execution of start and has already an allocated memory. The technique mentioned is different to the previously implemented design approach that was deleting and recreating the object at runtime, which has the disadvantage of being slow.

Several design approach were entertained at the early stage of development and several iterations were involved. As an example, the initial design approach of the spherical wall of the paint game has undergone several iterations. The first design was to use a sphere model as a SingleShapeEntity and change the color of each pixel as the user touches them. However, this idea was not feasible because the developer does not have access to that level of the code. The second approach was to use triangles to build the spherical wall. This approach comes with its own obstacles. First, building a perfect sphere with triangles requires that the triangles have varying sizes. The triangles had to be created offline and loaded as a mesh. Since we have to have varying sizes

of triangles, we have to pre-calculate the sphere and at least one copy of each size of the triangles. It also requires that the placement of the triangles have to be calculated. Secondly, the color of the triangles could not be changed dynamically at runtime. To be able to do this, the effects (.fx) file used for rendering had to be overridden and a custom entity had to be defined based on this. This approach of creating a custom entity worked as expected but creating multiple triangles and building a sphere out of it was not practical.

4.3.3 Rehabilitation Games

There are seven games implemented. Games are designed to be simple, familiar, and easy to understand. Their clinical applicability are also considered and therefore the games are designed to challenge motor control coordination and promote neuromuscular plasticity.

The gaming environment and gameplay are designed to either require the user to move in the joint or task space and the environment is either structured in 2D or 3D space. Joint space motions provide isolation of impairment to a single joint focusing the training and evaluation to that joint. Focus on a single joint promotes joint strength and range of motion improvement. Movements in task space, on the other hand, train joint coordination. Tasks such as following straight or curved lines, or moving in a 2D plane require the brain to perform significant inverse kinematic calculations and path planning that enable neural control recovery. With both joint and task space capability, therapist are presented with a wide range of options in structuring patient specific therapy.

Another important feature to note are the target types. Both static and dynamic targets are employed. Static targets challenge motion accuracy and smoothness. Additionally, they provide an ideal deterministic path that could easily be a baseline for trajectory evaluation. Dynamic targets on the other hand challenge hand-eye coordination and timing. Games with these target types resemble activities of daily living and are adapted from traditional games. Because of the time-varying and unpredictable nature of these games, they are characterized by increased difficulty and are meant for casual free flowing game play, avoiding the repetitive nature of traditional therapy.

The following sections describe the games: paint, flower, reach, pong, circle, pinball, and handball.

Table 4.1: Game Types

Game Types	Target Types	Joint Space	Task Space
Paint	Static		X
Flower	Static		X
Reach	Static		X
Pong	Dynamic	X	X
Circle	Dynamic	X	X
Pinball	Dynamic	X	X
Hand Ball	Dynamic		X

4.3.3.1 Paint

The goal of the game is to change the color of the red balls to green by touching them (see Fig. 4.5). The player is presented with half a sphere of red balls in front of them and by touching the red balls they turn into green as if the user is painting a wall, hence the name. The radius of the sphere wall can be altered to challenge the patient's range of motion.

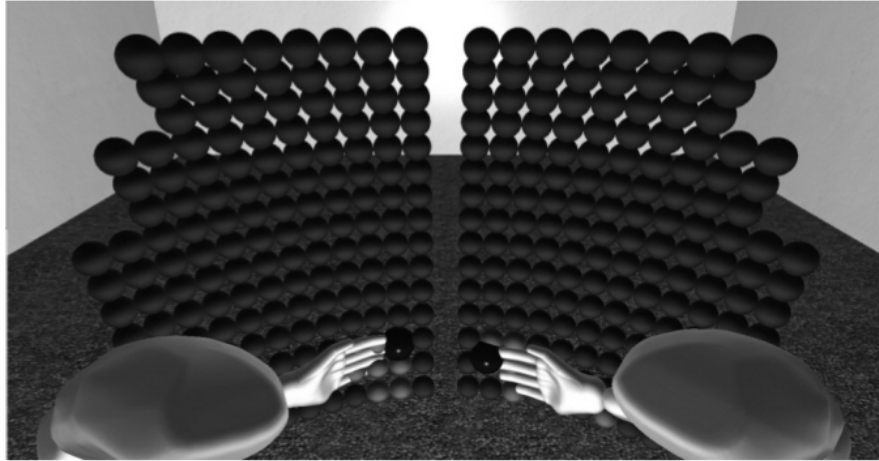


Figure 4.5: The paint game with two partial spherical walls, one for each arm

4.3.3.2 Flower

In this game, 11 different configuration of a flowers petal is presented in front of the player and the goal, starting at the middle, is to trace the line to the edge of the petals and back to the middle again. The petal is represented as a line with three red balls placed equidistant from each other and the starting point at the middle is represented by a blue sphere (see Fig. 4.6). Only one configuration of the flower is presented at a time. Once the player completes the configuration by successfully following the line from the middle to the end and back, another configuration is presented. In unilateral mode, the player is only required to trace the affected side of the petal. In this mode, a force field is turned on to assist the affected arm towards the line. For bilateral mode, both hands must touch the center and then trace the ipsilateral side of the petals. The healthy side assists the affected side.

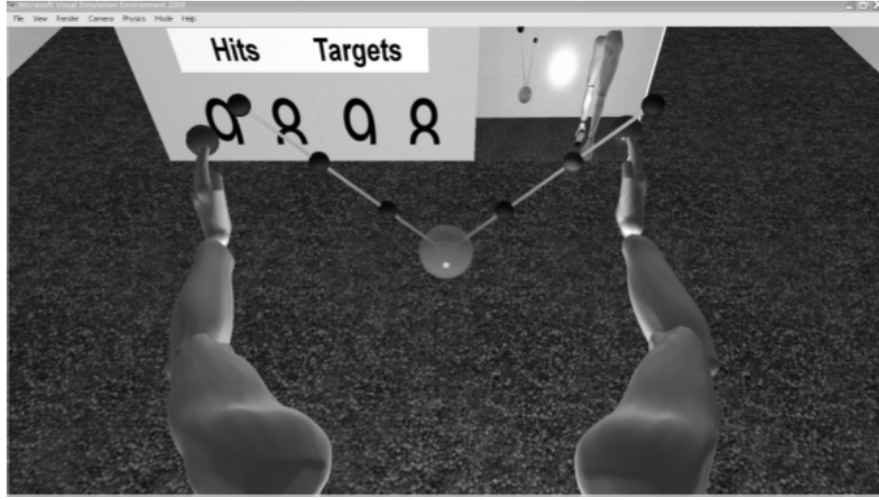


Figure 4.6: The flower game showing one of the 11 stages of the game where only one petal is presented. The player has to touch the blue sphere in the middle and trace the line to the edge of the petal, touching the red balls, and back to the blue sphere again. A different view of the flower is shown in the background to the right of the score board to help the player interpret the configuration.

4.3.3.3 Reach

The objective of this game is to knock the red balls positioned on a plane in front of the player (see Fig. 4.7). Once the hand touches any of the balls, its gravity property is enabled and the red balls fall on the floor. By default, the plane is positioned at around 80% of the length of the arm and oriented parallel to the body. Therapists and operator has the option to change the position and orientation of the plane and the size of the balls. Positioning the balls on a plane forces the player to create in-plane trajectories. By altering the position and orientation of the plane, it allows therapists

to modify the game to suit the players rehabilitation needs. Additionally, by decreasing the sizes of the balls, the games difficulty is increased.

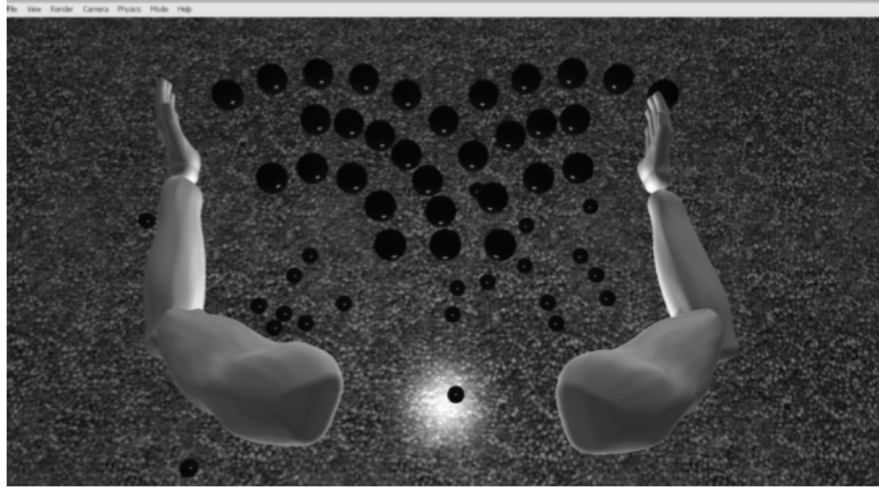


Figure 4.7: The reach game. The target red balls are aligned on a plane in a semi-circular manner. The semi-circle's center is located at the arm model's center.

4.3.3.4 Pong

The pong game is played like the traditional pong game where the goal is to hit a ball using a paddle towards the opponent's side, scoring if the opponent fails to return the ball (see Fig. 4.8). It can be played in both unilateral and bilateral mode. In the unilateral mode, both CPU and the player use one paddle. The bilateral mode on the other hand uses two paddles. The paddles are controlled by both exoskeleton arm where the healthy side of the exoskeleton acts as a master and provides assistance to the unhealthy side making the paddles move in a symmetric way. The paddles are controlled using any of the 7 joints or the hand.

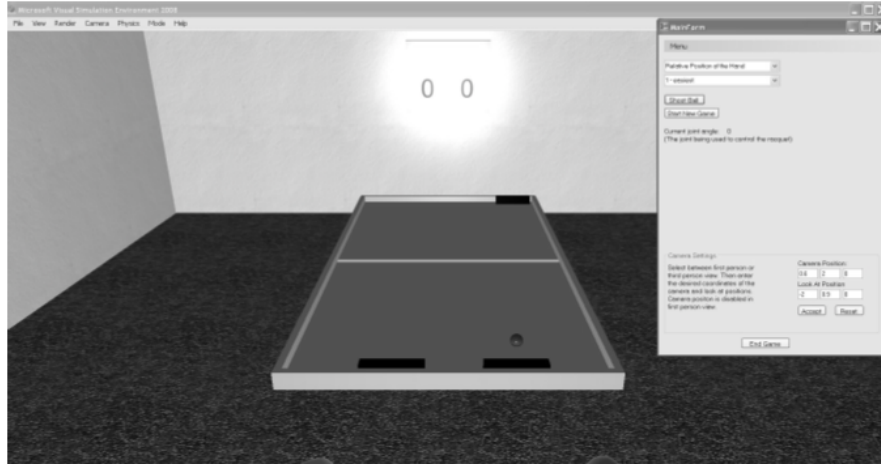


Figure 4.8: The pong game. The pong table is shown at the center of the screen. The paddles can be controlled using one of the 7 joints or the hand.

4.3.3.5 Circle

The circle game is similar to pong except that the game is played on a cylindrical platform (see Fig. 4.9). The platform constrains the paddle's motions within the circular edge of the cylinder. The paddle is free to move on the entire circumference of the circle in unilateral mode. In bilateral mode the circular edge is divided into two halves, left and right half, and two paddles are used where the paddles' motion are constrained only on its side of the circle. Similar to the pong game, the paddles are controlled using any of the 7 joints or the hand.

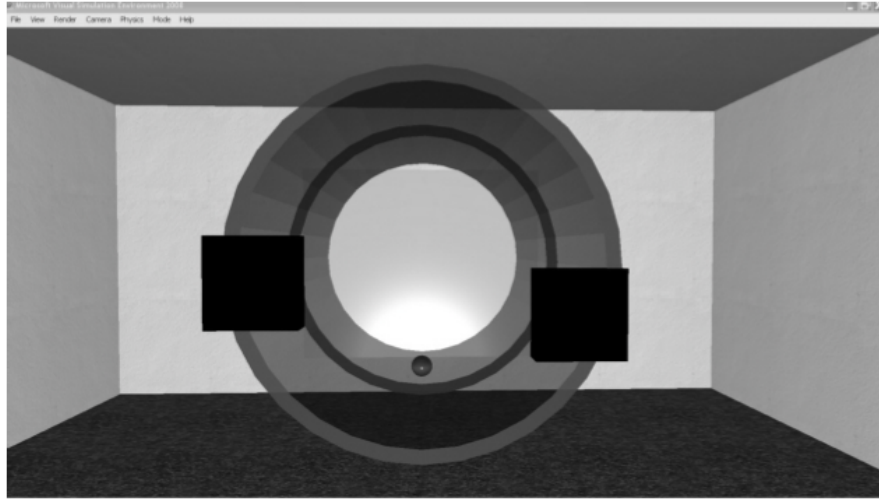


Figure 4.9: The circle game in bilateral mode showing two paddles represented by block cubes at the left and right of the cylindrical platform. Only one paddle is shown for unilateral mode

4.3.3.6 Pinball

This is a traditional pinball game where the goal is not to let the ball go through the hole by blocking or hitting it with the flippers (see Fig. 4.10). The control mechanism used for this game is similar to pong and circle game in both unilateral and bilateral mode. The difficulty of the game is set by varying the inclination angle of the pinball table. The stiffer the angle the faster the ball drops consequently increasing the difficulty of hitting the ball.



Figure 4.10: The pinball game. At the center is the pinball table and the flippers can be controlled by choosing the control mechanism in the drop down menu shown on the left.

4.3.3.7 Hand Ball

The goal of this game is to hit a bouncing ball back to the wall. The court is enclosed with walls (see Fig. 4.11) to constrain the movement of the ball. The ball is spawned on the other side of the room and bounces towards the human model. If the player fails to hit the ball back, the ball is regenerated at its initial location. The direction of the trajectory is randomly chosen each time the ball is spawned.

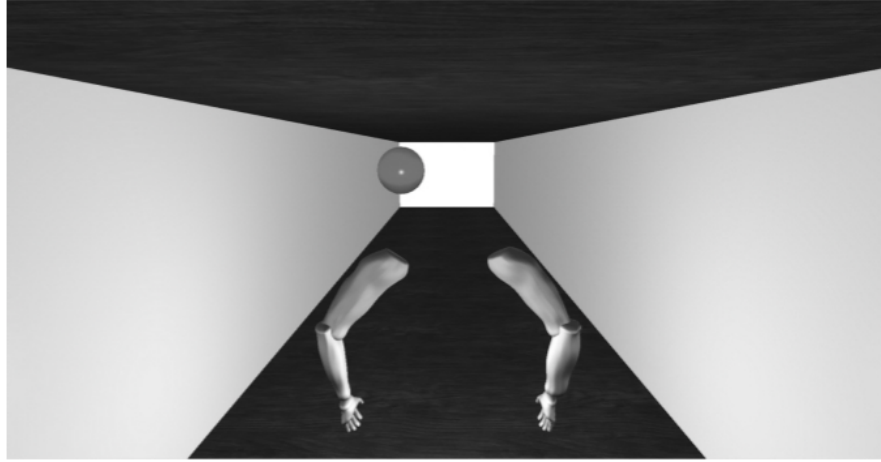


Figure 4.11: The handball game. Two arm models are shown where the player is free to move both arms

In unilateral mode, only the affected arm is used. Since the human model does not move and thus lacking the ability to reach the ball if it bounces to the side of the healthy arm, the trajectory of the ball is designed such that it is attracted towards the affected side of the human model. Both arms are used in bilateral mode.

4.4 Limitations and Future Work

Throughout the implementation process, we identified a couple of limitations. First, the information about MSRDS, including Microsoft documentation and available on-line forums are limited. The last software release was in 2011 [21] and the updates are not announced. Second, the design required to override physical properties of certain entities. However, because of the proprietary nature of the software, developers are prohibited from altering the library. Third, the physics engine is unreliable and failed

several occasions. Objects reaction to collision tends to poorly simulate real world behavior when the collision is under certain angle. Instead of bouncing off another object at the same angle at which the object collides with the other one, it bounces along a trajectory, which is perpendicular to the surface of the collided object. Finally, some properties of entities in the environment could not be dynamically altered once the entities have been instantiated, for example the color property.

The limitations prompted a proposal to re-design the software and use Chai3d as the base library. Chai3d does not have the complexity of MSRDS and lacks the mechanism of a robotic programming language package that MSRDS has. However, the exoskeleton application at its current iteration does not require complex concurrency. Currently, data exchange between the exoskeleton, the gaming environment (visual rendering), simulation engine, and user interface are required. At minimum, it needs a process to handle the simulation loop that will contain the data exchange method and a process for the user interface. In this design, the simulation loop will be the main thread, processing the input data from the exoskeleton and also handle the physics calculations and environment interactions. For real time applications, a thread for sending and receiving data and possibly another thread for long running calculations may be added. Chai3ds architecture already contains two threads, one for the simulation loop and the other for visual rendering. In addition, another disadvantage of the current implementation in MSRDS is that input/output data exchange method is a polling method where the exoskeleton data are actively sampled, which has the disadvantage of missing information that is received at the wrong time. Making it fully event driven

will resolve this issue especially for a safety critical exoskeleton device that interacts intimately with human operators.

The open source nature of Chai3d also means that the developer has the freedom to dig deeper in the source code. With OpenGL as the API for graphics rendering developers are not constrained to a small set of rigid body entities and have the ability to alter visual entities all the way to its pixel level.

Chai3d is developed for haptics and visualization application which is a good fit for the exoskeleton project especially when force feedback capability is included. Several haptics properties are readily available and, in fact, several commercially available haptics hardware is already supported by Chai3d. This means that supporting the exoskeleton, at minimum would require the creation of custom interface.

Chapter 5

A Low-Dimensional Dissimilarity Analysis of Unilateral and Bilateral Stroke-Impacted Hand Trajectories

This chapter is a preprint to the paper:

- Roldan, J.R., Milutinović, D., Li, Z., and Rosen, J., "A Low-Dimensional Dissimilarity Analysis of Unilateral and Bilateral Stroke-Impacted Hand Trajectories", *ASME Journal of Dynamic Systems, Measurement and Control*.

5.1 Introduction

Stroke is the number one cause of long-term disability in the United States [66]. While it is known that the functionality of the impaired limb can be recovered through rehabilitation therapies, they come with a high price; it is an annual cost of

34 billion dollars each year [66]. Improving rehabilitation and streamlining it towards patient-specific needs are important to expedite the recovery progress and improve its outcome.

The difficulty of recovery progress tracking during rehabilitation therapies is a major roadblock in establishing proper therapeutic plans[79]. Over the years, a wide spectrum of clinical assessment tests and tools were developed to evaluate the current state of a patient’s sensory and motor performance, as well the outcome of a rehabilitation treatment. Among the methods are: Action Research Arm Test (ARAT) [36, 68], Arm Mobility Arm Test (AMAT) [40], Ashworth Scale (AS) [9], Assistive Technology Device Predisposition Assessment ATD-PA [15], Box and Block Test (BBT) [68], Canadian Occupational Performance Measure (COPM) [4], Fugl Meter (FMA) [83, 68], Motor Activity Log (MAL) [82], Motor Assessment Scale (MAS) [69], Nine-Hole Peg Test (NHPT) [57] and Wolf Motor Function test (WMFT) [65]. These assessments are primarily subjective assents [29, 20, 74] that may or may not require prior training. In particular, the FMA assessment tool ranks the performance of a patient during a series of tasks on a discrete scale of 0,1,2. The patient needs to improve by 33% in order to be ranked higher on the scale. As such, this scale is not sensitive enough to changes that may result from a rehabilitation treatment.

In tracking the changes, the sensitivity is not the only factor. A method of tracking should be able to distinguish the progress in the direction of recovery towards healthy motions [42, 49] from the direction in which subjects use compensatory strategies to achieve motion goals. The latter is not the goal of successful recovery plans, since

though the subjects may be able to perform some daily activities, their motions would be different from those of healthy subjects.

In this paper, we present a quantitative approach to aid the tracking of recovery during a rehabilitation process using high-rate motion capture system data. The approach is focused on the quality of movements and task performance of the end effector [49]. In the process of developing the approach, we analyzed reaching trajectories of healthy and stroke-impacted hemiparetic subjects. The analysis relies on reaching trajectories, therefore, all subjects in our study were screened for their capability of performing such tasks. We first focused on trajectory characteristics in the vertical direction and used only the z-axis component of the data. This provided information about the complexity of trajectories and showed that for a better insight into the data, a more complete analysis of trajectories is required.

The method of analysis of the trajectories proposed in this paper is multidimensional scaling (MDS)[11, 10]. The MDS method has been used in various studies as a tool for clustering and characterizing the evolution of certain parameters [44, 5, 33]. It proved to be particularly useful for the analysis of lab assays producing data on a real-valued approximate dissimilarity measure, which is of a type that is generally considered unsuitable for quantitative analyses [77].

In this paper, the area between hand trajectories is introduced as an approximate measure of trajectory dissimilarities. Based on the measure, the MDS produces a map in which each trajectory is represented by a point. The distance between any two points of the MDS map reflects the dissimilarity of the corresponding two trajec-

tories, therefore, the map reveals the structure of dissimilarities among trajectories. In every MDS map depicting dissimilarities among trajectories for reaching a specific target we are able to identify a dense cluster of points corresponding to healthy trajectories. Trajectories of hemiparetic subjects are usually spread over the map and we can quantify their difference and variability with respect to the cluster of healthy trajectories. In this way, the difference and variability of trajectories are quantified and can be followed on scales that are fully compatible with the observed data. Our analysis includes trajectories from healthy and hemiparetic subject groups and results are compared to trajectories of a single subject from the hemiparetic subject group.

The paper is organized as follows. The data collection and experiment protocol are explained in Section 2. Section 3 describes the methods and results of the vertical component analysis. The methods and results of the multidimensional scaling analysis are detailed in Section 4. Section 5 provides a discussion of our results and their interpretation. Section 6 gives conclusions.



(a)



(b)

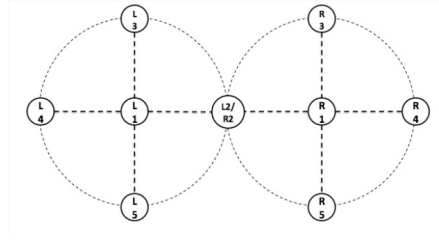
Figure 5.1: Marker placement. (a) Nine reflective markers are attached to each of the left and right arm (light gray circles). Four markers are attached to the torso (dark gray circles). (b) Subject holds a T-shaped pointer with a marker attached at the tip.

5.2 Data Collection And Protocol

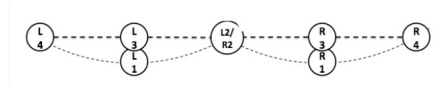
The data were captured using a Vicon motion capture [85] system with ten cameras. Nine infra-red reflective markers were attached to the left and right arm of the subjects, see Fig. 5.1. Since some stroke-impacted hands are characterized by flexed wrist and clenched fist, the subjects held a T-shaped pointer with a marker attached at the tip (Fig. 5.1b). Additional four markers were attached to the subjects' torsos and backs for a total of 24 markers. The Vicon's Bodybuilder [84] software was used to create a biomechanical model of the arms and torsos. The motion capture system captured data at a sampling rate of 100Hz with submillimeter accuracy. The subjects were seated and cameras were positioned at the ceiling pointing directly towards the subjects. The experiment protocol is approved by the University of California, Santa Cruz institutional review (DHHS IRB Registration Number IRB00000266, #HS 1821).

Ten subjects composed the control group, and nine unhealthy, hemiparetic subjects participated in the experiments. Both subject groups underwent a screening process prior to participating in the study. For the control group, both arms had to be injury free and without any pain or discomfort. The hemiparetic group was composed of stroke survivors in their chronic phase with a disability lasting more than two months since they had stroke. They were able to perform reaching movements with observable impairment. Specifically, with their impaired arm, the subjects were capable of (1) bending the elbow at 90 degrees without support and keeping it there; (2) reaching up and touching their ears; (3) moving the wrist up and down; (4) grasping objects; and

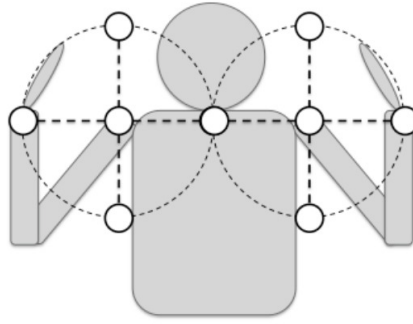
(5) raising the arm in front at 90 degrees with the thumb pointing up.



(a)



(b)



(c)

Figure 5.2: Target workspace setup. (a) Front and (b) top view of the target workspace.

The left workspace is composed of targets L1-L5 and the right one is composed of targets R1-R5. (c) The subject's shoulders are aligned with the center of the left and right workspaces.

Out of the nine subjects, only eight were included in the analysis. One of the subjects had difficulty of reaching the targets that are above the shoulder (R3 and L3,

see Fig. 5.2).

Both subject groups performed reaching tasks to targets in a 3 dimensional workspace. The workspace and targets are shown in Fig. 5.2. During the experiment, each subject sat on a chair with their torso straight and both hands resting on the chair handles (Fig. 5.1a). The chair was positioned so that the subjects could comfortably reach all ipsilateral targets. According to the experimental protocol, the subjects were instructed to start each arm movement from a position where their hands were rested on the handles of the chair (Fig. 5.1a), whereas the wrist positions of the hands were aligned with the end of the chair handles. Two modes of reaching tasks were performed, unilateral and bilateral. For the unilateral mode, the subjects were asked to reach targets R1 – R5 using their right hand, and then L1 – L5 using their left hand. For the bilateral reaching mode, the subjects were instructed to reach simultaneously symmetric targets in the workspace. There were 5 repetitions for each target in both modes for a total of 25 trajectories. That resulted in 50 trajectories per subject for the right and left arms of the control group, 50 trajectories per subject for the impaired and healthy arms of the unhealthy, hemiparetic group, and 50 trajectories per subject for the bilateral reaching mode. In both unilateral and bilateral modes, the subjects were instructed to perform the reaching motion after a sound signal. Reaching motions were performed at speed comfortable to the subjects. To avoid fatigue, the subject were given time to rest between the reaching motions.

Our trajectory data are sequences of all trajectory point coordinates from the initial hand position to the time point at which the subject touched the target with the

tip of the pointer. The subjects were oriented to face the positive y-axis with their right side towards the positive x-axis direction of the reference coordinate frame. Examples of the collected trajectory data are shown in Fig. 5.3.

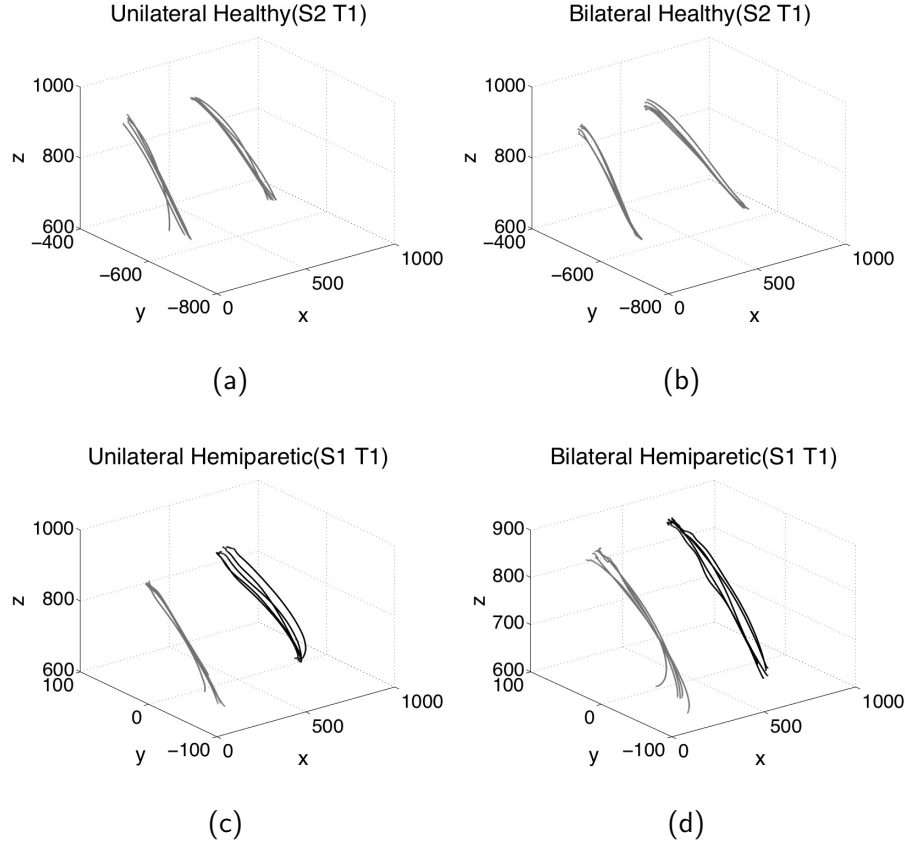


Figure 5.3: Sample of the collected trajectory data relative to the motion capturing system coordinate frame. The relative position and orientation of the target workspace with respect to the chair on which the subjects sat were kept unchanged. (a) Unilateral mode trajectory data of Subject 2 from the control group. Both right and left trajectories are shown. (b) Bilateral mode trajectory data of Subject 2 from the control group. (c) Unilateral mode trajectory data of Subject 1 from the hemiparetic group. Both healthy (light gray) and unhealthy (dark gray) trajectories are shown. (d) Bilateral mode trajectory data of Subject 1 from the hemiparetic group.

5.3 Analysis of Vertical (Z-Axis) Component Of Human Hand Trajectories

Unconstrained human reaching trajectories to a target are not straight lines. From the collected data, one of the observed characteristics is that some subjects put more emphasis on upward motion at the beginning of their trajectories and then move their hands towards the target. Because of that, we first analyzed the z-axis profile of hand trajectories using two methods. The first is the *area ratio* method, which is based on the ratio of the areas above and below the trajectory (see Fig 5.4). The second is the *polynomial fit* method, which is based on a polynomial model of the hand trajectory.

For the *area ratio* data analysis, the data are first normalized based on the task completion measured by the travel distance to reach the target. The areas a_a above and a_b below the trajectory are calculated as a sum of products of the increments ΔS_k of the traveled distance S in the xy-plane between trajectory data points and the height h_k^a above and h_k^b below the trajectory, see Fig. 5.4. The area ratio is calculated as the ratio of the two areas:

$$Ratio = \frac{a_a}{a_b} = \frac{\sum_{k=1}^N \Delta S_k h_k^a}{\sum_{k=1}^N \Delta S_k h_k^b}, \quad \Delta S_k = S_k - S_{k-1} \quad (5.1)$$

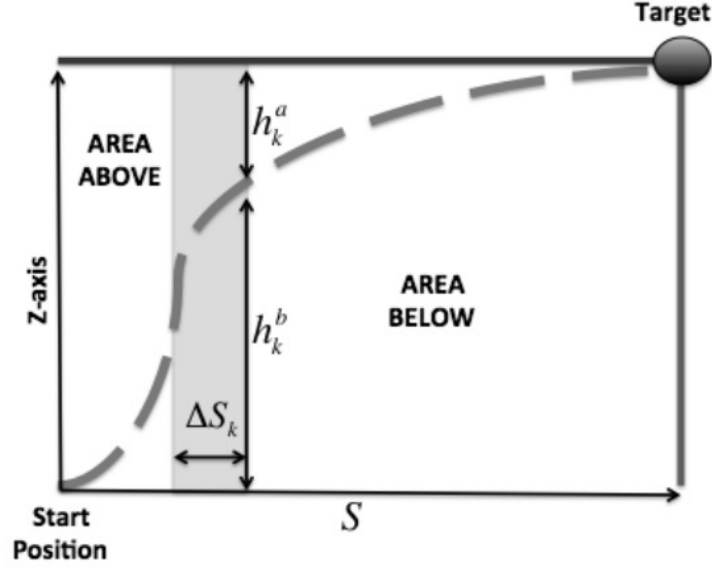


Figure 5.4: Area ratio calculated as the ratio of the areas above and below the trajectory: S axis represents the traveled distance in the xy -plane and ΔS_k are increments of the traveled distance between trajectory data points.

Polynomial Fit: The normalized data are averaged per trajectory groups. A polynomial model of the travel distance in the xy -plane S versus the height h is estimated. The degree of the polynomial is chosen based on the model that fits the trajectory group best.

The results of vertical component data analysis of our data are presented in Section 5.5.

5.4 Multidimensional Scaling Analysis

In order to compare the trajectories based on their three-dimensional shapes, here we introduce a measure of trajectory differences and apply the method of multidimensional scaling (MDS). The method is capable of visualizing data in a lower dimensional space and is used for exploratory data analyses.

We apply the classical MDS method, which is based on the measure of difference a_{ij} between the trajectories i and j . The measure must be (1) zero if the trajectories i and j are identical; (2) non-negative; and (3) symmetric, which means that the difference a_{ij} is the same as the difference a_{ji} . As a result of the MDS method, every two trajectories i and j are mapped into the points T^i and T^j of the lower dimensional space with the distance that corresponds to a_{ij} . Mathematically, the trajectories are mapped into the points as the result of the following minimization

$$J = \min_{T^i, T^j} \sum_i \sum_{i \neq j} (a_{ij} - \|T^i - T^j\|)^2 \quad (5.2)$$

where $\|\cdot\|$ corresponds to the euclidean norm of the lower dimensional space. To measure the difference between the two trajectories, we use the area between them, which can be approximated based on sampled trajectory points. This area is depicted in Fig. 5.5 together with the trajectories i and j and sampled points.

Figure 5.6a depicts two pairs of subsequent sampled trajectory positions from the trajectories i and j . The area among them can be approximated as the area S'_k of the two triangles that have the common side connecting the points $(x_{k+1}^i, y_{k+1}^i, z_{k+1}^i)$

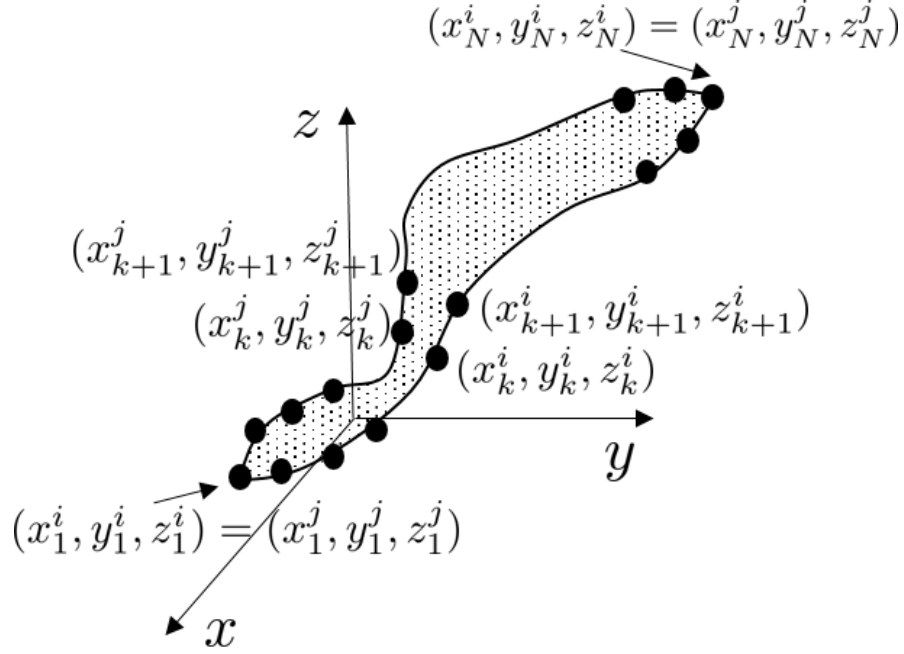


Figure 5.5: Two 3D trajectories with the same number of points. The coordinates of the k th sample point of the i th and j th trajectories are (x_k^i, y_k^i, z_k^i) and (x_k^j, y_k^j, z_k^j) , respectively. The measure of difference between the trajectories is based on the area between the trajectories (shaded).

and (x_k^j, y_k^j, z_k^j) . This approximation is

$$S'_k = \frac{1}{2} \|\vec{r}_{k,k+1}^i \times \vec{r}_{k,k}^i\| + \frac{1}{2} \|\vec{r}_{k+1,k+1}^j \times \vec{r}_{k,k+1}^j\| \quad (5.3)$$

where $\times$ denotes the vector product and $\|\cdot\|$ the euclidean norm of a vector. However, the same area can be approximated as the area S''_k of the two triangles that have the common side connecting the points (x_k^i, y_k^i, z_k^i) and $(x_{k+1}^j, y_{k+1}^j, z_{k+1}^j)$, see Fig. 5.6b, in which case

$$S''_k = \frac{1}{2} \|\vec{r}_{k,k+1}^j \times \vec{r}_{k,k}^i\| + \frac{1}{2} \|\vec{r}_{k+1,k+1}^j \times \vec{r}_{k,k+1}^i\| \quad (5.4)$$

with the obvious relations $\vec{r}_{k,k}^i = -\vec{r}_{k,k}^j$ and $\vec{r}_{k+1,k+1}^i = -\vec{r}_{k+1,k+1}^j$ that are not exploited for the sake of clarity. Using the expressions for S'_k and S''_k , we define the measure of difference between the trajectories i and j as

$$a_{ij} = \sum_{k=1}^{N-1} \frac{S'_k + S''_k}{2} \quad (5.5)$$

which is the sum of average of the two approximations and N is the number of sample points of each trajectory.

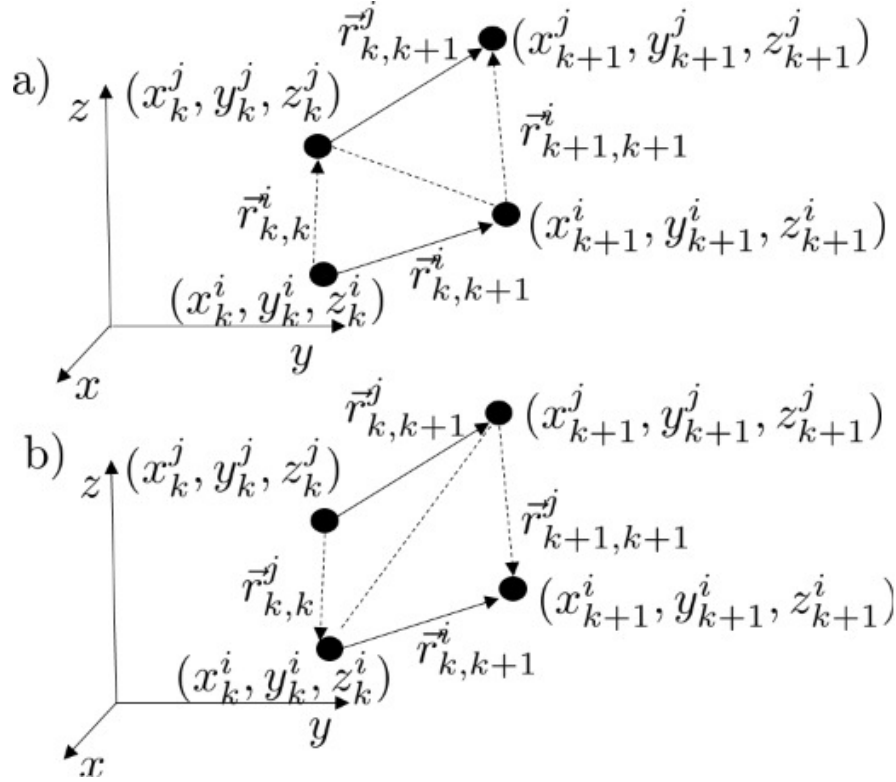


Figure 5.6: Approximations of the area between two trajectories: (a) the area is approximated as a sum of two triangles sharing the side connecting (x_k^j, y_k^j, z_k^j) and $(x_{k+1}^i, y_{k+1}^i, z_{k+1}^i)$ (b) the area is approximated as a sum of two triangles sharing the side connecting (x_k^i, y_k^i, z_k^i) and $(x_{k+1}^j, y_{k+1}^j, z_{k+1}^j)$.

The measure a_{ij} defined by expression (5.5) is zero only if all the sampled points of the trajectories i and j are equal. It is also nonnegative and symmetric in all cases, including the situation in which the initial and final trajectory points are not the same. However, the final trajectory points are always the same since the subjects reach to the same targets. Moreover, to compensate for the variability of human subject body sizes and variability of the chair position (see Fig. 5.1a), we pre-process the trajectories to match the trajectory initial points. First, the final trajectory points are translated to the origin. Then, the trajectories are scaled by dividing each data point coordinate by the absolute value of the length of the trajectory along each axis

$$x_k^i = \frac{\hat{x}_k^i}{|\hat{x}_N^i - \hat{x}_1^i|}, y_k^i = \frac{\hat{y}_k^i}{|\hat{y}_N^i - \hat{y}_1^i|}, z_k^i = \frac{\hat{z}_k^i}{|\hat{z}_N^i - \hat{z}_1^i|} \quad (5.6)$$

where $\hat{x}_k^i$, $\hat{y}_k^i$ and $\hat{z}_k^i$ denote the originally recorded coordinates of the trajectory i points.

Once we compute all mutual differences a_{ij} for a specific target, we use the MATLAB command ‘cmdscale’ to compute an MDS map of the trajectory data for each target.

5.5 Results

In this section, we present data analysis results using the methods of vertical component and multidimensional scaling trajectory analyses described in sections 5.3 and 5.4, respectively.

5.5.1 Vertical Component Data Analysis

The results of the area ratio analysis of the subject groups are summarized in

Fig. 5.7. The polynomial fit analysis results are shown in Fig. 5.8.

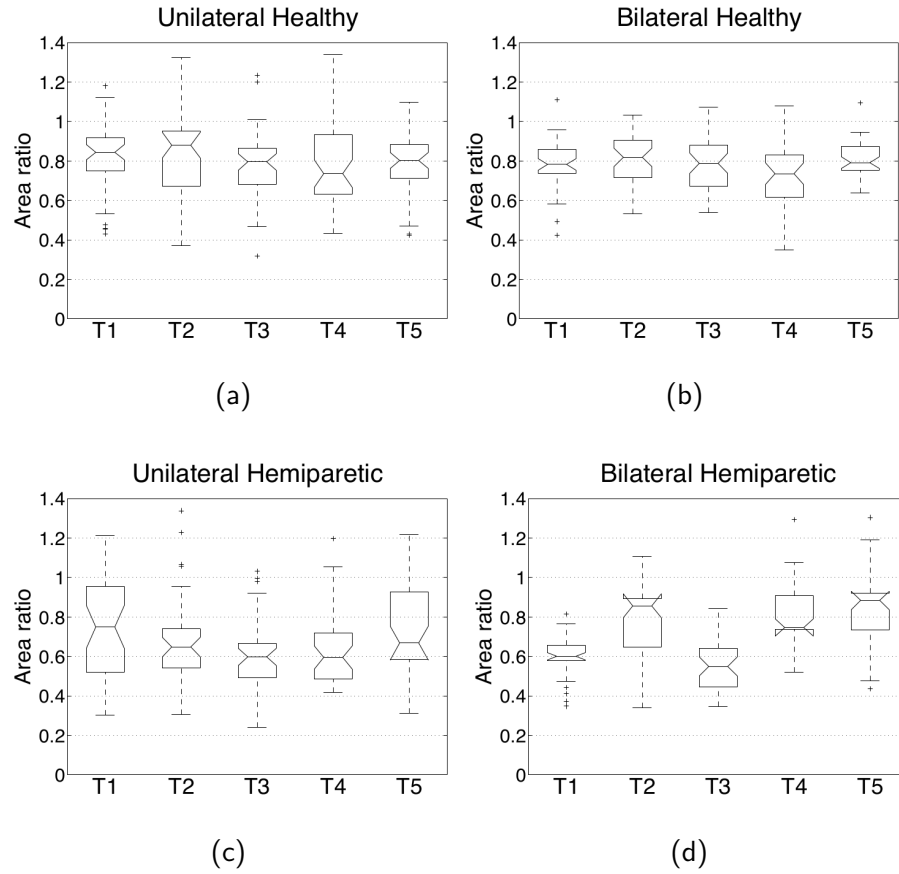


Figure 5.7: Boxplots of the area ratio per target for two reaching modes and two groups of subjects. A ratio less than 1 means that there is an upward motion at the start of the trajectory followed by a forward motion towards the target.

For all targets and all subject groups, the area ratio is below 1 with a 95% confidence interval. The ratios of trajectories from the hemiparetic subjects are smaller

than the ratios of corresponding trajectories from the healthy subjects except in the case of targets 2 and 5 in the bilateral mode. Targets 2 and 5 have the highest median in the bilateral mode for the healthy group. In addition, there is a significant difference between the unilateral and bilateral reaching modes of the hemiparetic group for targets 2, 4, and 5 with consistently higher ratios for the bilateral reaching mode trajectories.

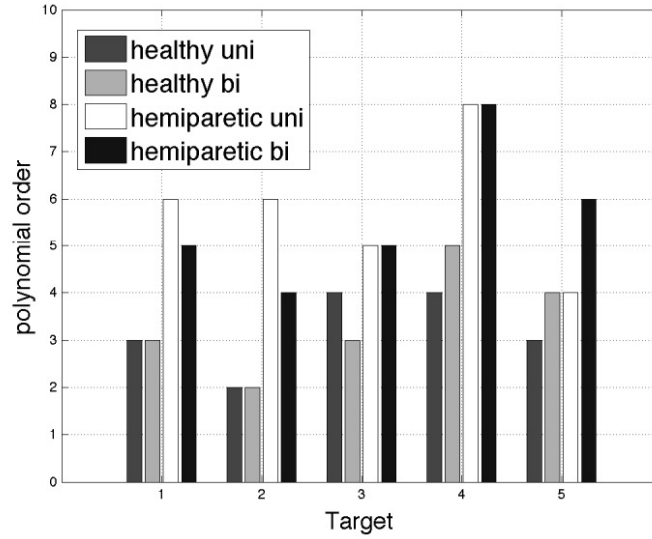


Figure 5.8: The polynomial order per target for the trajectories from two reaching modes and two groups of subjects.

Assuming that the trajectory height could be modeled as the 2nd order polynomial, this would be an indication that the trajectory tends to have more of an upward motion at its onset. The results of the polynomial fits of the height versus distance are shown in Fig. 5.8. The trajectories from the healthy subjects can be modeled with the 2nd to the 5th order polynomials. In both unilateral and bilateral reaching modes, the

trajectories to target 2 show the lowest polynomial order while the highest polynomial order is for trajectories in bilateral reaching mode to target 4. The trajectories from the hemiparetic subjects are more complex with polynomial orders ranging from the 4th to the 8th. The trajectories to target 2 in the bilateral mode and to target 5 in the unilateral mode are with the 4th polynomial order. The highest 8th polynomial order is for the trajectories to target 4 of the hemiparetic subjects. These findings show that in general the trajectories cannot be modeled as the 2nd order polynomials. The trajectories to targets 2 and 5 of the hemiparetic subjects have the largest differences (which are 2) in the polynomial order between the trajectories from unilateral and bilateral reaching modes.

The trajectories of healthy subjects tend to follow a straight line towards a target in both unilateral and bilateral reaching modes. The trajectories to target 4 are excluded from this since they are somewhat similar in shape to the trajectories of hemiparetic subjects to the same target. In general, the hemiparetic trajectories are more curved, which supports the findings from the analysis of the area ratio.

5.5.2 Multidimensional Scaling Analysis

The results show that most of the maps can be represented in one dimension. For a better visualization, we choose to display the maps in two dimensions.

The MDS maps of the trajectories for the five targets are shown in Fig. 5.9. For each target, the points corresponding to the trajectories of healthy subjects form a distinctive cluster of points in one area of the map. Instead of plotting all points of the

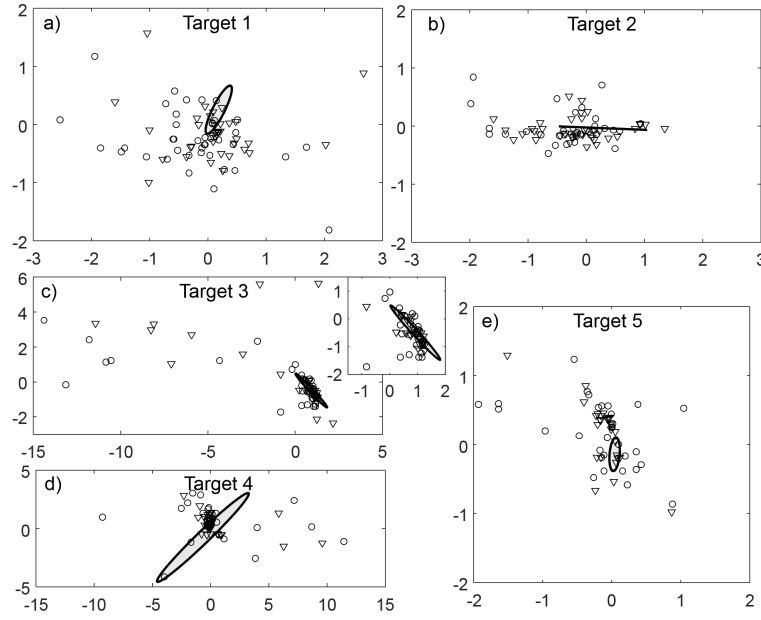


Figure 5.9: The MDS maps for all trajectories for targets 1 to 5 are depicted in (a) to (e), respectively: the ellipse with the shaded area describes the 95% area for the cluster of the trajectories of healthy subjects, the points corresponding to the trajectories of hemiparetic subjects in unilateral (∇) and bilateral ($\circ$) reaching modes.

cluster, we depict the cluster using ellipses representing the 95% area for the points in the cluster. For each target, the ellipses are elongated and, in the case of target 2, the cluster of healthy subject trajectories is practically a line.

The points corresponding to the arm trajectories of hemiparetic subjects are spread over the map, which indicates their variability across all subjects. The distance between a point from these subjects and the center of the healthy subject trajectory cluster can be used as a measure of how much the trajectory is “unhealthy” and to follow the progress of rehabilitation. Because of the natural variability of healthy subject

trajectories, their cluster is elongated in one direction. When computing the distance, this direction needs to be taken into account with a smaller weight.

Let us consider a given target and denote all healthy subject trajectory points with 2-dimensional vectors T_h^i , $i = 1, 2, \dots, N_h$, where N_h is the number of healthy subject trajectories. Then, the center, i.e., the mean μ_h value and 2×2 covariance matrix Σ_h of the cluster can be estimated as

$$\hat{\mu}_h = \frac{1}{N_h} \sum_{i=1}^{N_h} T_h^i \quad \text{and} \quad \hat{\Sigma}_h = \frac{1}{N_h - 1} \sum_{i=1}^{N_h} (T_h^i - \hat{\mu})(T_h^i - \hat{\mu})^T \quad (5.7)$$

where $\hat{\cdot}$ denotes the estimated value, i.e., $\hat{\mu}_h \approx \mu_h$, $\hat{\Sigma}_h \approx \Sigma_h$ and T denotes the transpose of the vector. Based on the singular value decomposition (SVD), we know that the covariance matrix estimation can be represented as

$$\hat{\Sigma}_h = \underbrace{\Phi \Lambda \Phi^T}_{\Lambda} = \Phi \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \Phi^T, \quad \Phi^T \Phi = I \quad (5.8)$$

where I is the unity 2×2 matrix, Φ is the matrix composed of unit intensity vectors aligned with the minor and major axes of the ellipse, while $\sqrt{\lambda_1}$ and $\sqrt{\lambda_2}$ are their lengths. Therefore, to measure the distance $d(p)$ between a point p of the MDS map and the center of the healthy subject cluster, we formulate the distance as

$$d(p) = \|(\sqrt{\Lambda})^{-1} \Phi^T (p - \hat{\mu}_h)\|, \quad \sqrt{\Lambda} = \begin{bmatrix} \sqrt{\lambda_1} & 0 \\ 0 & \sqrt{\lambda_2} \end{bmatrix} \quad (5.9)$$

which can be written as

$$d(p) = \left((p - \hat{\mu}_h)^T \underbrace{\Phi (\sqrt{\Lambda})^{-1} (\sqrt{\Lambda})^{-1} \Phi^T}_{\Sigma_h^{-1}} (p - \hat{\mu}_h) \right)^{1/2} \quad (5.10)$$

and because of $\Phi^T \Phi = I$ and $\hat{\Sigma}_h^{-1} = (\Phi \Lambda \Phi^T)^{-1} = \Phi^T \Lambda^{-1} \Phi$, we obtain

$$d(p) = \sqrt{(p - \hat{\mu}_h)^T \hat{\Sigma}_h^{-1} (p - \hat{\mu}_h)} \quad (5.11)$$

If we introduce $\hat{\mu}_{uni}$ and $\hat{\mu}_{bi}$ as the centers of the clusters of hemiparetic subject trajectories in unliateral and bilateral reaching modes, then their center distances to the center of healthy subject trajectory cluster are $d(\hat{\mu}_{uni})$ and $d(\hat{\mu}_{bi})$, respectively.

These distances are presented in Fig. 5.10a for each target. From it, we can find that the largest one is for target 3 and that in all other cases the distances are comparable, which is in agreement with Fig. 5.9 showing that the points corresponding to hemiparetic subject trajectories in unilateral and bilateral modes overlap with the healthy ones except in the case of target 3, where the unilateral mode trajectories are dispersed all over the map, see Fig. 5.9c.

To get a quantitative insight into the variability of trajectories, we compute the standard deviations of trajectory points over a certain distance from the center of the healthy subject trajectory cluster. We first compute $d(T^i)$ for any point representing a trajectory from the group of unilateral trajectories, and then compute the standard deviation σ_{uni} of the distance

$$\sigma_{uni} = \sqrt{\frac{1}{N_{uni} - 1} \sum_{i=1}^{N_{uni}} (d(T^i) - \bar{d}_{uni})^2}, \quad \bar{d}_{uni} = \frac{1}{N_{uni}} \sum_{i=1}^{N_{uni}} d(T^i) \quad (5.12)$$

where $\bar{d}_{uni}$ is the mean value of the distance. Similarly, we compute the standard deviation σ_{bi} of the distance

$$\sigma_{bi} = \sqrt{\frac{1}{N_{bi} - 1} \sum_{i=1}^{N_{bi}} (d(T^i) - \bar{d}_{bi})^2}, \quad \bar{d}_{bi} = \frac{1}{N_{bi}} \sum_{i=1}^{N_{bi}} d(T^i) \quad (5.13)$$

for bilateral trajectories. The standard deviations for each target are presented in Fig. 5.10b. We note that the dispersion of the points in the healthy subject cluster is the smallest, which is also supported by Fig. 5.9 across all the targets. We can also confirm that the dispersion of target 3 unilateral trajectories is comparable to their distance in Fig. 5.10a, which is also in agreement with the map in Fig. 5.9c.

From Fig. 5.10b, it follows that the variability of trajectories is comparable among unilateral and bilateral trajectory types for target 1 and target 4. A significant difference in the variability in these types of trajectories is observed in target 5 with the pattern of more variable bilateral trajectories than unilateral trajectories. The same pattern can be also clearly seen for target 2 and target 3. However, targets 3 and 4 have consistently high variabilities in both modes, which means that for these targets the hemiparetic subjects consistently express a high level of unhealthy synergies in their motion.

Overall, figures 9 and 10 show that the major difference between the trajectories of hemiparetic and healthy subjects is in a strong consistency of the second ones for each target, which is illustrated well by their MDS map clusters of points. In other words, all healthy subject trajectories are similar to each other. Such a level of similarity does not exist among the hemiparetic subject trajectories since they are typically dispersed over the MDS maps.

However, once we focus on a specific subject from the hemiparetic group, we can find its MDS trajectory points less dispersed over the map, which indicates consistency in motion. For example, subject 2's MDS maps per target are shown in Fig. 5.11.

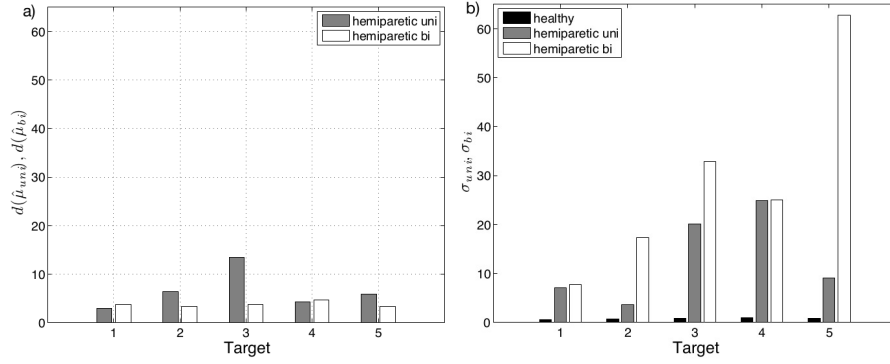


Figure 5.10: The distances of the centers of points corresponding to the unilateral and bilateral hemiparetic trajectories to the center of the healthy subject cluster (a) and the standard deviation (b) of the distance to the center of the healthy trajectory cluster. The bar graphs show the distances and standard deviation per type of the trajectory and target.

The maps for targets 1 to 5 show an obvious dissimilarity of the subject's trajectories in unilateral and bilateral reaching mode since the corresponding MDS points are easily separable. In the case of targets 3 and 4, the MDS trajectory points for both modes, with a few exceptions, overlap with the clusters of the healthy subject trajectories. If this happened for all targets, we would conclude that subject 2 is fully recovered. However, the MDS maps for targets 1, 2 and 5 show that the subject's reaching trajectories for these targets are different from the healthy. Interestingly enough, subject 2 belongs to the group of hemiparetic subjects and, for targets 3 and 4, the group shows consistently the largest dispersions of the MDS map points in both reaching modes. This indicates the importance of individual therapy plans since the high level of unhealthy synergies of the hemiparetic group for targets 3 and 4 is not characteristic of subject

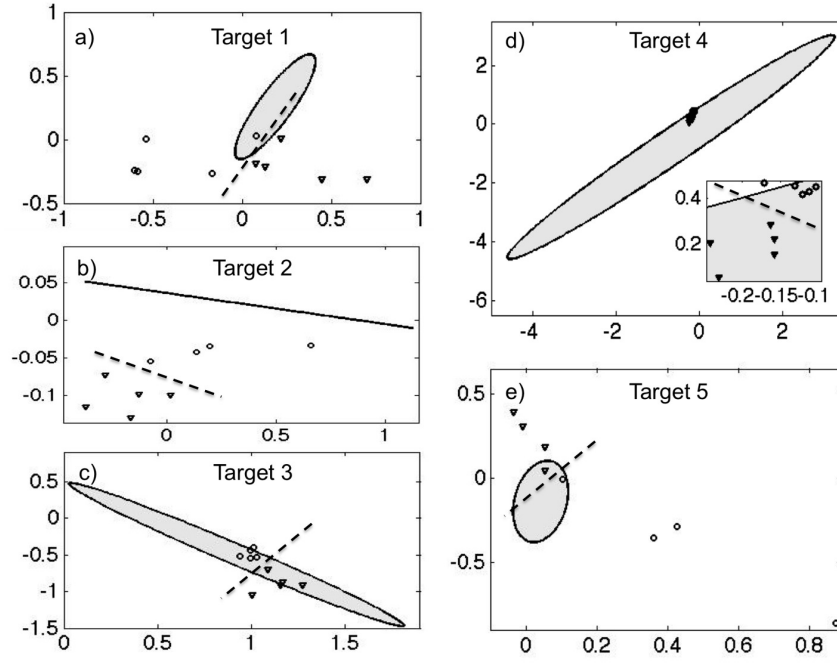


Figure 5.11: Subject 2 map for all targets are shown in (a) to (e). (∇) represents the bilateral trajectories and ($\circ$)'s are unilateral reaching trajectories of subject 2. The dashed lines illustrate the separation between the unilateral and bilateral trajectories. The ellipses with the shaded areas describe the 95% area for the cluster of healthy trajectories.

2's trajectories.

From this, for example, we can conclude that subject 2 should have a therapy that would emphasize motions necessary to reach targets 1, 2 and 5. In that case, we would also give a slight preference to a therapy that engages two arms simultaneously because of considerably larger distances of the MDS map points for target 2 in the bilateral reaching mode.

Naturally, the impact of our analysis to therapy planning is speculative in nature and should be further investigated. However, we clearly show that for a specific subject our analysis can pinpoint specific targets creating problems in reaching motions.

5.6 Discussion

Although the polynomial fit method indicates that z-axis profile trajectories are more complex than the 2nd order polynomials, both area ratio and polynomial fit analyses are in agreement that trajectories tend to move upward on the onset and then forward. Based on the area ratio, the trajectories to targets 2 and 5 have the biggest departure from that pattern especially in bilateral reaching mode. While the position of targets plays a critical role, the latter can be explained only by a higher demand on subject's attention [32] which impacts visual and proprioceptive feedbacks contributing to reaching motions. The z-axis profile analyses also show that the trajectories of hemiparetic subjects have a higher-order polynomial model than the trajectories of healthy subjects. The highest-order polynomial model is required for hemiparetic bilateral reaching mode trajectories. This can be explained by both muscular weakness and unhealthy synergies [2, 8, 74, 19, 18] that result into more complex reaching trajectory patterns. While these may be useful results, the overall attempt to analyze the data along the z-axis does not show the potential to reveal characteristics of individual subject trajectories.

With the aim to use complete 3D data about the trajectories, we introduced

the area between two trajectories as a measure of their dissimilarity and explored the data using the MDS method. The method was applied to hemiparetic and healthy subject trajectories in both reaching modes, and resulted in the MDS maps with up to two dimensions for each target. The MDS maps showed that, contrary to the healthy subject trajectories, the hemiparetic subject trajectories did not group into distinctive clusters, which means that they are all different from each other.

The differences between unilateral and bilateral reaching mode trajectories of the hemiparetic subject group are evident from Fig. 5.10b. It shows that unilateral mode hemiparetic subject trajectories are consistently closer to the healthy than the trajectories from the bilateral mode. Also, the farther ipsilaterally the target is, the higher the variability of unilateral mode trajectories of the hemiparetic subjects is. The highest variability of trajectories is in bilateral reaching mode of the hemiparetic subjects for target 5. However, targets 3 and 4 have consistently high variabilities in both modes. This characteristic does not show in the analysis of subject 2 that belongs to the hemiparetic group and based on this we can conclude that the therapy for subject 2 cannot be equal to the other subjects of the same group. By this, we underline the importance of individual subject analyses and therapy plans.

Multidimensional scaling analyses not only reveal the dissimilarity structure of the trajectory groups, but also provide an insight into the variability of subject trajectories per target by measuring the dispersion of the MDS points per trial of a subject. The significance of variability is in the evaluation of the strategy that an individual is using in the process of recovery. The strategies can be compensatory in

nature or reflect true recovery. Compensatory strategies are employed to accomplish daily activities, however this hinders true recovery in that it disregards the training of natural joint configurations [3, 13, 70].

When multiple trajectories of one patient to a specific target are represented in the MDS map, they form a set which can be compared to the the cluster of points corresponding to the healthy subjects, and there are three outcomes that can be identified: (1) the patient's set has a low dispersion and overlaps with the cluster of healthy subjects, which indicates the fully recovered patient; (2) the patient's set has a low dispersion and it does not overlap with the cluster of healthy subjects, which indicates that the patient is functionally recovered , i.e., has consistent trajectories, but uses a compensatory motion strategy resulting in trajectories that are different from those of the healthy subjects; and (3) the patient's set has a high dispersion, with or without the overlap with the cluster of healthy subjects, which indicates the inconsistency of motion associated with an early phase of, or non-responsiveness to the therapy. The size of overlap between the patient's set and the cluster of healthy subjects measures only a degree of dissimilarity of the patient's trajectories to the healthy subject trajectories.

In spite of the data reduction resulting from the MDS map, a therapist may have access to the original trajectory while comparing it with trajectories of healthy subjects. The z-axis component of the trajectory may provide an insight regarding muscle strength compensating gravitational loads, while the xy-components of the trajectory provide information regarding the muscular coordination during the reaching task. Assessing in this context may affect the treatment regime that is unique to each patient

under evaluation. As the patient progresses through the rehabilitation treatment, it is anticipated that the dispersion of the MDS points will provide a quantitative measure of the progress, while their distance to the cluster of healthy trajectories will indicate the direction of the progress towards a full, or functional recovery.

5.7 Conclusion

Our aim to quantitatively analyze hand trajectories has led us to the novel method of characterizing the trajectories by using the multidimensional scaling (MDS). With the MDS, we were able to generate the map that visualizes dissimilarities between the trajectories in a two dimensional space. In the map, each trajectory is represented by a point and the healthy subject trajectories are mapped into a distinctive cluster of points. The analysis of the MDS points provided us the valuable insight into the differences among the trajectory groups and the variability of group trajectories. In order to identify the level of accuracy of this quantitative, data-driven objective tracking in the context of standard expert-based, subjective assessment methods such as Fugl-Meyer, or Wolf Motor Function test, it is necessary to perform a larger study, which can be a part of our future work.

Quantifying the differences and variabilities of trajectory groups is significant because it can guide therapists in establishing different therapeutic plans. For example, a high variability of trajectories in a reaching task to a target can be used to emphasize the part of therapy that will decrease their variability. After a period in the therapy, the

therapist can use the MDS map to detect if the subject uses compensatory strategies, or shows the progress towards true recovery. With this, the effectiveness of the therapy can be evaluated and the therapist can potentially use it to steer the direction of the rehabilitation plan.

Chapter 6

Conclusion

In this thesis, we presented our contribution to the development of the rehabilitation software sub-system together with a proposed recovery identification and tracking method applicable to the EXO-UL7 exoskeleton arm towards a complete rehabilitation system. We started by presenting the theory behind human arm reaching and coordination and introduced the current design of the exoskeleton device. A detailed technical report of the software systems is presented, detailing the design and implementation of each component, the rehabilitation games, and a discussion of its limitations and future work. Lastly, we introduced a novel recovery tracking method using MDS. Starting from observed data patterns, we progressively developed our method from the analysis of the z-axis component of hand trajectories, and then formulated a richer quantitative, objective recovery assessment and tracking method based on trajectory dissimilarity map.

The software system consisting of the control, data acquisition, and the virtual

environment and rehabilitation games was developed for the EXO-UL7 extending its application as a rehabilitation device. The virtual environment and rehabilitation games specifically set the system apart from other exoskeleton devices in that it was designed for the sole purpose of encouraging neuromuscular recovery taking traditional upper limb intervention concepts and applying them into virtual tasks. The development effort opened pathways for research studies to be conducted that produced several papers in the field of human-robot interaction and stroke rehabilitation. It facilitated the comparison of unilateral and bilateral kinematics data analysis of post-stroke patients [37, 71], provided new understanding on the design and evaluation of rehabilitation games interfacing with robotic systems [76, 75], and added yet another evidence on the advantage of robot-aided therapy compared to conventional training [12].

Our proposed recovery identification and tracking method based on MDS is developed as a quantitative and objective measure of recovery that tracks progress and effectiveness of the therapy. Our method creates a dissimilarity map of hand trajectories that was able to quantify a patient’s hand trajectory consistency, variability, and degree of impairment. Based on these three parameters, it can distinguish a trajectory if it is compensatory or true recovery. In addition, it was able to measure the difficulty of the target workspace by identifying the variability of individual patient for each target. A patient’s performance could be evaluated based on his or her trajectory variability per target and a plan can be created to focus on targets that have high trajectory variability or difficulty. Furthermore, the detection of compensatory strategies based on variability per trial could provide an idea on the effectiveness of the therapy. The eventual appli-

cation of our method can be applied to the exoskeleton system as a means of guiding rehabilitation game design or as an underlying assessment mechanism embedded in a robot-guided therapy, providing the system information on how to progressively provide assistance or resistance in different workspace locations and/or which mode of reaching should be emphasized.

In the process of pursuing a novel assessment method, the research effort in understanding the kinematics and dynamics of the human arm have produced several research publications [38, 53, 50, 54, 51].

Further integration of the MDS based recovery assessment method with the rehabilitation games and exoskeleton system will be part of our future work. Additionally, the clinical effectiveness of each game could be analyzed in comparison with each other. A next generation 10-DOF exoskeleton system is currently under development using Chai3d as the base library for rehabilitation games. This integration of the exoskeleton system, the rehabilitation software, and an objective measure of identifying and tracking recovery based on MDS provide for a complete robotic rehabilitation system that covers all the fundamental factors of rehabilitation – intervention and recovery assessment.

Appendix A

IRB Protocol

UNIVERSITY OF CALIFORNIA, SANTA CRUZ

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SANTA BARBARA • SANTA CRUZ

OFFICE OF RESEARCH COMPLIANCE ADMINISTRATION
TEL: (831) 459-1473
orca@ucsc.edu

SANTA CRUZ, CALIFORNIA 95064

RE: Reaching and Grasping Movements of the Stroke-Impacted Upper Arm
UCSC IRB Protocol # 1999
UCSC Principal Investigator: Li, Zhi
Approval Date: 3/4/2013

Dear Investigator:

The Human Subjects review committee has reviewed the proposed use of Human Subjects in the project referenced above and has determined that the project is approved for a period of three years. There is no need to submit an annual renewal form before the expiration date.

This approval will expire on 3/2/2016. You should reapply for review at least one month prior to the expiration date in order to continue conducting your research beyond that date.

Please remember that modifications to the protocol must be reviewed and approved by the IRB prior to being initiated.

Additionally, it is your responsibility to promptly notify the IRB of any unanticipated problem that occurs during the research, including any breach in confidentiality or data security that places participants or others at a greater risk of harm.

The UCSC Institutional Review Board operates under a Federalwide Assurance approved by the DHHS Office for Human Research Protections, FWA00002797. Our DHHS IRB Registration Number is IRB00000266.

Sincerely,

A handwritten signature in black ink that reads 'Alice Kindheart'.

Alice Kindheart
Office of Research Compliance Administration
(831) 459-1473
orca@ucsc.edu

Appendix B

Phone Interview Questionnaire

Interview for Participation In: Reaching and Grasping Movements Of the Stroke-impacted Upper Arm

Research being conducted by the Bionics Laboratory at the University of California, Santa Cruz
Sponsored by: Jacob Rosen, PhD
Investigator: Zhi Li, PhD candidate

The following questions will be asked over the phone, in person, or by email. Responses will not be documented during the interview. However, if the candidates are determined to be suitable subjects they will complete a hard copy questionnaire at the start of their first scheduled session. The following format is in question "Q" response "R" format.

1. Q: What is your age?
R: If the candidate's is under the age of 18 they are ineligible.

Question 1 will be asked for all candidates. The following questions do not apply to healthy candidates.

2. Q: Was your impairment caused by a stroke?
R: If the impairment was caused by an injury other than a stroke they are ineligible.
3. Q: Do you still have noticeable impairment in your left or right arm?
R: If impairment is too mild, or the candidate has fully recovered they are ineligible.
4. Q: How long ago did you have your stroke?
R: If less than 2 months they are ineligible.
5. Q: Can you bend the elbow to of your affected arm 90 degrees without support and keep it there?
R: If the subject can not perform this task they are ineligible.
6. Q: Can you reach up and touch your ear?
R: If not the candidate is ineligible.
7. Q: Can you move your wrist up and down?
R: If the subject can not move there hand up and down they *might* be ineligible pending further review.
8. Q: Can you open and close your hand? Can you grasp objects?
R: If they can not open their hand, or particularly if they can not close it, they *might* be ineligible.
9. Q: Can you sit in a chair with your affected arm pointed straight down at your side?
R: If no the subject *might* be ineligible.
10. Q: Can you raise your arm in front of you at 90 degrees with your thumb pointing toward the ceiling and your elbow straight?
R: If not, the subject *might* be ineligible pending further review.
11. Q: Have you undergone any procedures involving Botox injections in your affected arm?
R: If yes the candidate *might* be ineligible pending further review.
12. R: At the conclusion of the interview the candidate will be told that they will be contacted regarding their eligible. If there is doubt about one of the responses, particularly questions 7 through 9 the investigator will research the question and provide a timely response to the candidate. If the candidate is deemed a suitable subject they will be scheduled for a session and logistical considerations will be discussed. The interview is then concluded with a statement of appreciation for the candidate or subject taking interest in this research.

Appendix C

Interview Questionnaire

Questionnaire for Participation In: Reaching and Grasping Movements Of the Stroke-impacted Upper Arm

Research being conducted by the Bionics Laboratory at the University of California, Santa Cruz
Sponsored by: Jacob Rosen, PhD
Investigator: Zhi Li, PhD candidate

Information collected in this questionnaire is strictly confidential and is collected on the understanding that it will be held confidentially and not disclosed to third parties without the prior written consent of prospective subjects for this research study. The research subject may elect not to answer any or all of the following questions.

Please indicate the following:

1. Age: _____
2. Gender: Male () Female ()
3. Handedness Right Handed () Left Handed ()
4. Do you have any impairment in your left or right arm?
 Yes () No ()

If you answered yes to the previous question, please complete questions 5 through 9

5. Was the impairment in question 4 caused by a stroke?
Yes () No ()
6. Was the stroke caused by a blockage (ischemic) or caused by bleeding (hemorrhagic)
 Ischemic () Hemorrhagic () Not Sure/Other ()

If "Other" please explain: _____

7. Number of months or years since your stroke: _____
8. Affected side[s]: Left () Right ()
9. Have you undergone any procedures or are using any devices that might affect the movement of your affected arm? Examples might include Botox injections for muscle spasticity or electrical stimulators.
 Yes () No ()

If "Yes" please explain: _____

Participant Signature/Date: _____

Investigator Signature/Date: _____

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